Harnessing Artificial Intelligence, Digitalization and Data Governance for Food Security and Nutrition

Background note for the Committee on World Food Security's High-Level Forum, 30 June 2026 in Rome, Italy

By the High Level Panel of Experts on Food Security and Nutrition (HLPE-FSN)

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Acknowledgments

The High Level Panel of Experts on Food Security and Nutrition (HLPE-FSN) would like to express its appreciation to the many people who provided advice and guidance during the preparation of this document. The note was authored by the HLPE-FSN Steering Committee members and the Artificial Intelligence Expert Tristan Wiessalla with the support of the secretariat.

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Referencing this paper: HLPE. 2026. *Harnessing Artificial Intelligence, digitalization and data governance for food security and nutrition – Background note for the Committee on World Food Security's High-Level Forum in June 2026 in Rome, Italy.* Rome, FAO.

HLPE-FSN

The High Level Panel of Experts on Food Security and Nutrition (HLPE-FSN) is the United Nations body for assessing the science related to world food security and nutrition.

The HLPE-FSN is the science-policy interface of the Committee on World Food Security (CFS) and provides independent, comprehensive and evidence-based analysis and advice at the request of CFS. It elaborates its studies through a scientific, transparent and inclusive process.

EXECUTIVE SUMMARY

This background note informs the CFS High-Level Forum on Harnessing Artificial Intelligence (AI), Digitalization and Data Governance for Food Security and Nutrition. Building on prior work by the Food and Agriculture Organization of the United Nations (FAO), the World Bank, the United Nations Development Programme (UNDP), CGIAR and CFS itself, it focuses on what has been observed in deployment rather than future potential not yet supported by evidence and aims to provide a **shared technical basis** for the discussions at the Forum.

The term "AI" covers a spectrum of technologies, from narrow, task-specific machine learning (ML) to general-purpose generative systems. The note simplifies this into **specific-purpose AI** and **generalist AI**, since the two carry different infrastructure requirements, application risks and governance implications. Most proven advances are made by specific-purpose tools embedded in existing physical and institutional systems. Generalist AI offers complementary value, particularly as a human-language interface to data and expertise, but its deployments in high-stakes FSN functions remain limited and its benefits less consistently demonstrated.

The FSN dimensions whose impacts are the most documented are availability, through increased productivity, and stability thanks to better early warning systems. The effects on accessibility are very context specific. The effects on other dimensions like utilization, especially for nutrition are not well documented yet. Agency is the dimension most under threat because of unequal access to AI and because of the risks posed by potentially redelegating decisions to opaque algorithmic systems weakening accountability and contestability in food governance.

AI and digital tools amplify existing institutional and social capacity rather than substituting for it. Where that capacity is present, the right tools can accelerate progress; where it is absent, no digital tool alone can supply it. The World Bank's "4Cs" (**Connectivity, Compute, Context and Competency**) describe the cumulative preconditions for adoption, adaptation or innovation and many countries do not yet meet baseline conditions.

Three categories of risk are attached to deployment regardless of context: **Operational risks**, including **hallucinations** and a documented gap between vendor claims and observed benefits. **Social and political risks**, including algorithmic exclusion in areas of low contextual data availability ("**data deserts**") that often coincide with areas of threatened food security (e.g. Sahel, Horn of Africa), reduced institutional agency and power asymmetries between multi-billion-dollar private firms and public sector institutions. **Competition for resources**, with projected AI data-center investment far exceeding the UN estimate to end world hunger and the large environmental footprint of AI. These risks compound on those most vulnerable and least likely to capture the benefits of adoption: smallholders, women and Indigenous Peoples.

Across these findings, a **strategic lever is data**. Technical infrastructure, however well-engineered, serves whoever controls the underlying data. Regulatory frameworks for FSN data exist in some countries but often lack international coordination and technical implementation in the form of dataspaces that operationalize sovereignty, fair benefit-sharing and contestability.

The note's way forward starts from the recognition that adoption is already underway, often ahead of the conditions that make it serve the public. This requires public and institutional capacity with digital public infrastructure that is publicly owned, democratically governed and built with those it serves and sustained investment in local competency and in the hybrid technical-policy expertise needed to specify, procure, audit and contest digital systems. The note also emphasizes a discipline for AI use: **framing problems precisely** before selecting tools, choosing the simplest and potentially analogue solution that fits, **evaluating against final FSN outcomes** rather than usage metrics, and **accompanying data strategies with concrete technical implementations** (Boxes 1 and 2). Three areas of action are proposed at this stage for CFS: further exploring the issue through exchanges of experiences and further work of the HLPE, disseminating good practices; revisiting and expanding the CFS 2023 data recommendations regularly in light of AI related developments; and coordinating with the UN bodies emerging from the *Governing AI for Humanity* process.

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1. INTRODUCTION

The Committee on World Food Security (CFS) is organizing a High-Level Forum (HLF) on "Harnessing Artificial Intelligence, Digitalization and Data Governance for Food Security and Nutrition", focusing on enhancing equity and inclusiveness in food systems. The Multi-Year Programme of work of the CFS (MYPoW) notes that "innovations such as artificial intelligence (AI), digital platforms and big data analytics have the potential to enhance productivity, improve early warning systems, support climate adaptation and strengthen value chains. At the same time, these technologies also bring new challenges, including concerns around data privacy, equity, algorithmic bias, digital exclusion and lack of governance mechanisms". The purpose of this background note from the CFS High Level Panel of Experts on Food Security and Nutrition (HLPE-FSN) is to inform the event and provide the basis for discussions during the forum.

It builds upon the substantial body of work produced by international organizations, including the World Bank, FAO, UNDP, CGIAR and CFS itself, aiming to distinguish proven contributions from unsubstantiated promises and to identify the structural conditions under which digital tools can genuinely promote food security and nutrition (FSN).

The note briefly explains what "AI" refers to in practice, distinguishing between specific-purpose and generalist systems, and provides a high-level perspective on these technologies (Part 1). It then describes some documented uses in food production, supply chains, market access, nutrition advice and policymaking (Part 2), before describing challenges, risks and limitations found in documented use (Part 3). Finally, as a way forward, it highlights some central questions to ask when considering adoption and after adoption has taken place (Part 4).

1.1 Scope and methodology

This note avoids, as much as possible, common narratives about what technology can or could potentially do. Instead, it aims to present objective and, where possible, empirical assessments of actual impact. It draws on relevant scientific literature and reports by UN organisations and other international bodies. Its purpose is to support a shared understanding of where digital and AI tools are already used and assessed in food systems, and of available evidence of their impact on FSN. Many of these technologies are being adopted rapidly, often without independent evaluation. Most of the documented examples below rely on scientific assessment and technical benchmarking. Direct and indirect FSN outcomes will need to be assessed more comprehensively in future work. This note therefore advocates for more thorough empirical assessment of the actual impacts of individual technologies on FSN outcomes prior to and during adoption. Where specific technologies or their effects on particular dimensions of FSN are not discussed, this generally reflects a lack of available evidence. The HLPE-FSN welcomes feedback and looks forward to the discussions at the Forum to identify areas where further analysis is needed.

1.2 AI – A spectrum of technologies

In this note AI is used in its broad sense, referring to computer systems performing tasks that were previously associated with human cognition, such as logic operations, pattern recognition, language processing, learning and reasoning. The term AI thus encompasses a broad range of tools, from narrow, task-specific machine learning[1] and computational systems (here referred to as Specific-Purpose AI) to general-purpose generative models that produce text, images, audio or video (Generalist AI).

Fig. 1 (adapted from (World Bank, 2025a)) serves as an orientation of where to place some of the more known innovations into this spectrum. No clear line separates specific-purpose AI and Generalist AI, but as a rule of thumb Generalist AI can be described as data-intensive, computationally demanding and tending to increase dependency on external cloud and energy- and resource-intensive data-center infrastructure. This reduces user agency and raises governance and privacy concerns. Specific dimensions to consider are training data control, the ability to audit and contest outputs, interoperability versus lock-in, local hosting feasibility leading to questions of political sovereignty over deployed systems and ongoing operational costs. Generalist systems are often praised as a universal solution to a multitude of problems. These silver bullet narratives are tempting, but risk distracting attention from a clear analysis of and solution for those problems. Specific-Purpose AI, on the other hand, is generally much less computationally demanding, increasing its applicability and controllability in resource-constrained contexts such as regions with low compute capacities or in edge computing[2]. Table 1 (see Appendix) presents some characteristics of specific purpose versus generalist systems.

It is, therefore, important to avoid treating AI as a single class and instead assess which types of AI applications are appropriate for specific functions, policy goals and local contexts.

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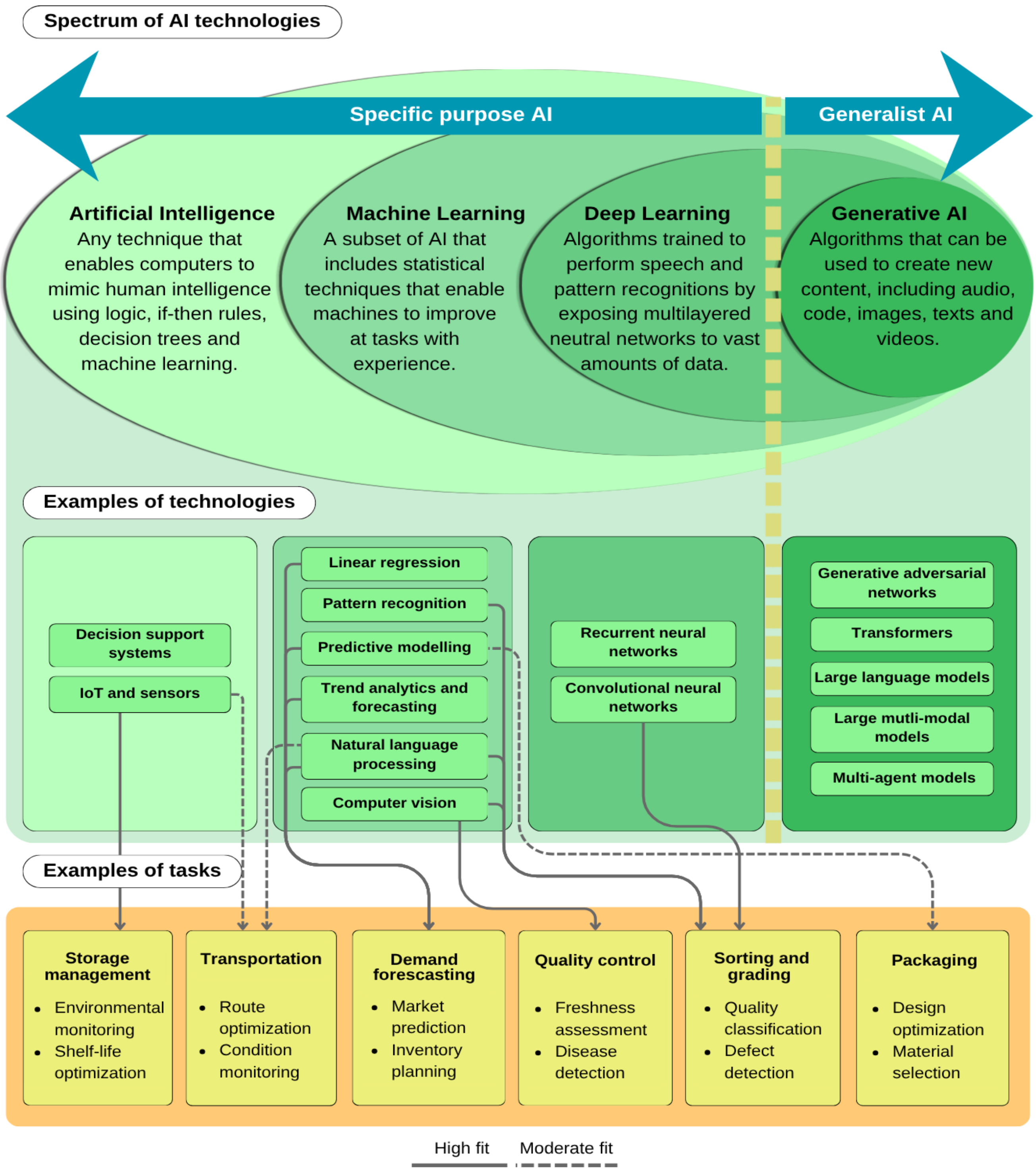
[1] Machine learning describes computational systems that improve tasks through training on data, enabling predictions about previously unseen inputs within the domain they were trained on. It encompasses a wide array of algorithms

[2] Distributed IT architecture that processes data near its source rather than in a centralized cloud or data center.

Fig. 1. Spectrum of artificial intelligence technologies and example applications in post-harvest tasks



Note: Special-purpose technologies are not small in all cases and the line separating deep learning approaches from generative AI is increasingly blurred, as indicated by the shading. The example mapping to tasks in post-harvest management is adapted from (Shao and Marwa, 2025). Source: Adapted from (World Bank, 2025a).

2. USES OF DIGITAL AND AI TOOLS IN FOOD SYSTEMS

The purpose of this section is to examine examples of uses of artificial intelligence (AI) and related technologies in food systems, particularly in relation to enhancing productivity, improving early warning systems, supporting climate adaptation and strengthening value chains. These technologies are commonly presented as drivers of change across production, exchange, governance, and consumption. Leapfrogging[3] is documented most clearly in the uptake of mobile connectivity in Africa, which speeded up access to mobile extension services, financial information and information services to people who have never used fixed-line infrastructure. New waves of digital technologies from blockchain to AI remain predominantly described as pilots or potential and did not display leapfrogging dynamics, with limited documented impact on FSN outcomes (Malabo Montpellier Panel, 2019; Mutiso, 2025). This shows that digitalization, specifically when it comes to software, is the most effective when optimizing existing workflows, value chains and processes. Rarely does an app or a prediction tool solve problems from the ground up. Primary production, for example, is fundamentally physical and applications in this domain depend on data collected from the physical environment.

A recent survey of a decade of agricultural AI research by INRAE (INRAE, forthcoming) confirms that most effective solutions have clear problem statements and specific-purpose approaches at heart. The central observation is not that specific-purpose tools predominate, but that a precise problem statement typically renders them the simplest and most reliable response. In some cases, Generalist AI offers clear benefits, particularly in communicating results to non-technical end users, bridging the "last mile" between humans and machines, or combining heterogeneous data modalities. Yet, even in these applications, effectiveness depends on precise problem framing and availability of relevant contextual data, making Generalist AI, in practice, less general-purpose than the label implies. In food systems, agentic systems[4] could eventually coordinate logistics, procurement, and risk assessment across fragmented supply chains. However, as noted in the introduction, meaningful deployment remains rare, and the accountability, reliability, and bias concerns that accompany simpler AI tools are amplified when systems act with greater autonomy. Many of the examples mentioned below coordinate multiple AI systems, but do not do so fully independently.

[3] The direct adoption of recent technologies without passing through intermediate stages.

[4] Agentic systems or AI interface directly with computer systems with minimal human supervision. Often, they consist of a central coordinating model that is able to start tasks for other specialized models or on the hardware it operates on.

2.1 Enhancing productivity

Digital innovations are increasingly applied to improve the efficiency and resilience of primary production (crops, livestock, forestry, fisheries and aquaculture), notably through decision support systems, monitoring and automation. The most credible near-term benefits for food security arise where these tools are embedded in existing supply chains (e.g. optimizing existing irrigation- or agrivoltaics systems).

Accordingly, the benefits of the technologies mentioned are conditional; they depend on the local capacity such as energy and telecommunications infrastructure, maintenance capacity, as well as the level of mechanization and digital literacy amongst primary producers.

2.1.1 Improving research efficiency: the example of crop and livestock selection

Setting up optimal breeding and identifying desirable alleles to select more resistant and higher yield and nutritionally more balanced crops as well as livestock have recently seen a lot of progress in biological and agricultural sciences due to a better understanding of the (epi-)genome and improved prediction models. They can also use, for instance, image analysis for plant phenotyping (Li, Zhang and Huang, 2014), considerably facilitating phenotypes' assessments. These approaches are typically R&D[5]-intensive and concentrated in well-resourced institutions, especially large agri-food corporations. They can contribute to improved resistance to heat, drought, pests, and diseases, and better feed efficiency, productivity and nutritional quality (e.g. micronutrient density) traits if innovations are translated into locally appropriate varieties/breeds and governed in ways that safeguard equity, biosafety, and access. As for most research and innovation there is a risk of concentration on the most profitable productions. However, AI use may enable reductions of costs that can benefit research in species that have smaller commercial markets. Public policies can also prioritize neglected species that have other public benefits for nutrition and system resilience. Direct beneficiaries of AI use include researchers, as well as seed and other genetical material producers. There is a notable risk of inequitable access to and use of genetic resources, impacting smallholder farmers negatively. This is discussed in Section 3.5. Table 2 (Appendix), which mentions the International Maize and Wheat Improvement Center (CIMMYT) research as an example for the fact that genomic prediction is typically based on statistical models that are complemented by more complex or generative AI.

[5] Research & development.

2.1.2 Land and water management

Remote sensing using tools ranging from phone cameras to drones and satellite-based analytics is widely used for land and water management, including crop type mapping, yield estimation and land cover classification (Wu *et al.*, 2023). Table 3 (Appendix) summarizes that the well-documented solutions in this field are products of international collaboration and benefit international organisations and local governments most directly.

2.1.3 Precision farming, aquaculture and fisheries

A prominent set of applications focuses on decision support for producers and advisors across land- and water-based production systems. In crop and livestock systems, these include irrigation scheduling, fertilizer and pesticide optimization, forage and pasture planning and animal health and welfare monitoring. In aquaculture, equivalent tools combine automated feeding systems, water-quality monitoring and underwater computer vision to optimise feed conversion, monitor animal health and detect disease early (Fini *et al.*, 2025; O'Donncha *et al.*, 2021). Another innovation cluster concerns mechanization and automation, ranging from precision sprayers and weeding technologies to drones and robotics for monitoring and targeted operations. In mechanization, the most important benefits are often shared-access and service models for mechanized tools (leasing, contractor services or cooperative ownership). Digital platforms can help match demand and supply for equipment services, schedule maintenance, and lower transaction costs. AI-enabled perception systems can also upgrade non-smart machines through add-on sensors, sometimes in the form of smartphones. Shared-access, bulk-buying and upgrading existing machinery can potentially benefit small-scale producers (SSPs) directly, while developments in precision agriculture are dependent on data collection mechanisms and digital infrastructure. Table 4 (Appendix) lists currently employed approaches in precision farming and aquaculture and supporting scientific literature. As for many other transformations, development of digital solutions is easier for simple and mechanized production systems. Also, most digital innovations have been designed in the context of high-income countries (HICs) and large commercial farming systems. Few digital innovations were designed specifically for Low- and Middle-Income Countries (LMICs) and SSPs. There are fundamental barriers to adoption, such as accessibility to mobile Internet, limited coverage and usage gap, with sub-Saharan Africa and South Asia seeing some of the largest gaps. Today, this gap is more often caused by limited usage rather than coverage: 90percent of those who remain unconnected live in areas that have available coverage, rural areas in LMICs are 25percent less likely to use mobile internet than their urban counterparts, women are 14 percent less likely than men to be connected (GSMA, 2025). The underlying barriers (coverage, costs, digital literacy, trust and safety) must be overcome to realize the potential of digital agriculture for SSPs (Chandra and Collis, 2021; Petraki *et al.*, 2025).

2.2 Risk management

Risk management systems encompass tools that combine weather data, satellite imagery, field observations, and farm records to generate risk alerts and recommendations. Typical functions include early warning of pests and diseases and monitoring of drought and flood risks. The strongest immediate use is often situational awareness: improving estimates of cultivation areas, vegetation condition and likely production outcomes at local to national scales and thus risks of food insecurity. Such outputs can inform preparedness, targeted support (e.g. inputs, cash, or feed), and logistics planning. A particularly well-documented example is FAO's desert locust surveillance system (eLocust/SWARMS) has been operating for several decades on invasions covering North Africa, the Horn of Africa, the Arabian Peninsula and Southwest Asia (FAO, undated). This system has progressively integrated advanced digital tools, satellite imagery, meteorological models, IoT sensors on the ground, mobile applications for field agents while maintaining intergovernmental governance under FAO control. Related operational systems include FAO's Global Information and Early Warning System (GIEWS), which monitors food supply and demand conditions worldwide and issues regular reports on countries facing food insecurity (FAO, undated), and WFP's Hunger Map, which combines remote sensing, news data and household survey results to produce near-real-time estimates of acute food insecurity at sub-national resolution in over 90 countries (WFP, undated).

2.2.1 Climate change resilience

Climate change increases the frequency and severity of extreme weather events and changes agroecological conditions in ways that often render traditional approaches to farming and disaster prevention outdated. AI-enabled tools are developed to improve climate and weather predictions, dynamically map land and classify agroecological zones, improve the speed and accuracy of disaster response. Weather and disaster prediction are now increasingly done by large and complex deep-learning models that compete with more traditional statistical models, Table 5 (Appendix). A concrete application is famine early warning. FEWS NET, the primary operational early warning system for acute food insecurity, has long combined remote sensing (rainfall, evapotranspiration, vegetation indices) with land surface models to produce IPC[6]-compatible phase classifications and food security outlooks up to 8 months ahead. Recent ML research has extended this further: an International Food Policy Research Institute (IFPRI)/United Nations International Children's Emergency Fund (UNICEF) model trained across 29 countries produces IPC-phase forecasts up to 12 months in advance using over 100 real-time indicators (Constenla-Villoslada *et al.*, 2025). A further class of models uses news text and

[6] Integrated Food Security Phase Classification (IPC)

event data to detect emerging crises in data-scarce environments (Balashankar, Subramanian and Fraiberger, 2023).

A comprehensive study (Rolnick *et al.*, 2019) described that most contributions of AI in tackling climate change could be made by small, specific-purpose models. The author later stressed that it is well possible to focus on those impactful models without using Generalist AI at all (Rolnick, 2025). An investigation financed by environmental interest groups into the claims made by Generalist AI vendors that their models will have a net positive impact on the climate found a similar pattern (Joshi, 2026): smaller, more specific-purpose AI might help solve specific problems, but no substantial proof of large Generalist AI having such a positive impact can be found yet.

These advances come with an important caveat. Climate-driven signals — vegetation, rainfall, soil moisture — are readily captured by satellite and sensor data, and models trained on them perform well for drought-related crises. But conflict is now the primary driver of acute food insecurity in at least 20 of the 59 countries tracked by the Global Report on Food Crises (2024). A 2025 European Union (EU) Joint Research Centre systematic review of ML-based acute food insecurity forecasting found that conflict data is used in only 4 of the reviewed studies and accounts for just 1–10 percent of model explainability despite its outsized real-world role (Machefer *et al.*, 2025). A Horn of Africa ML model failed entirely to predict the Tigray famine triggered by the November 2020 conflict outbreak, even though conflict data signals appeared three months before the crisis became visible in IPC classifications (Busker *et al.*, 2024). In short: these tools extend useful lead time for climate-driven crises but remain structurally blind to the crises most likely to reach Integrated Food Security Phase Classification (IPC) Phase 4–5.

2.2.2 Food security early-warning systems

The global food price crises of 2007–08 and 2010–11 — during which wheat prices tripled and rice prices quadrupled within five years — demonstrated both the severity of price volatility for FSN outcomes and the inadequacy of existing monitoring systems: a study of 1.27 million pre-school children across 44 LMICs found that a 5 percent increase in food prices raises the risk of child wasting by 9 percent and severe wasting by 14 percent, yet the international system lacked tools capable of anticipating these spikes in time to trigger preventive action (Headey and Ruel, 2023; Lele, Agarwal and Goswami, 2021). A structural limitation of current early warning models, as discussed in the section above, is that they are trained predominantly on satellite-derived agroclimatic data and are largely blind to conflict and epidemic shocks, which are now the primary drivers of IPC Phase 4–5 emergencies (Busker *et al.*, 2024; Machefer *et al.*, 2025). Two tools are directly addressing this gap: a World Bank ML system providing real-time price estimates across 1 200 markets in 25 countries (Andree, 2021), and a news-stream model by Balashankar et al. that uses 11.2 million news articles to improve district-level IPC predictions up to 12 months ahead across 21 food-insecure countries (Balashankar, Subramanian and Fraiberger, 2023), extended using unsupervised neural networks and validated with FAO (Van Wanrooij, Cruijssen and Olier, 2024).

2.3 Supply-chain management.

Traceability and information systems can considerably improve value chain management, oversight, compliance, and market information. It is however important to consider that the way these systems are designed and managed can have significant impacts on power and value distribution along value chains and on access of small-scale actors to markets and information.

2.3.1 Commodity price prediction

Commodity price prediction aims to anticipate short- to medium-term movements in staple and cash-crop prices to support farmer planning (crop choice, timing of sales, storage decisions), risk management (insurance design, credit decisions), and public action. Approaches range from simple statistical models to machine-learning systems that combine historical prices with explanatory signals such as weather anomalies, input prices, freight and fuel costs, exchange rates, trade policy events, conflict/port disruptions and remote-sensing indicators of crop conditions and production prospects. Pricing information or facilitating access to certain markets gives operators of these tools power over other actors, including farmers. Without adequate competition and regulatory safeguards, it risks reproducing or intensify existing power asymmetries. Table 6 (Appendix) shows that price information alone might not be sufficient to assist farmers and that explainability of these models is of central importance.

2.3.2 Supply chain tracing (accountability, adherence to regulation and production conditions)

Traceability and provenance systems, linking products to verifiable information on origin, handling, and production practices, are a use case for blockchain protocols, particularly where supply chains are fragmented and trust needs to be ensured. Uptake of blockchain tools for supply chain tracing in agriculture is still relatively low, even though many pilot projects exist (Singh and Singh, 2020). They can be a suitable tool to document adherence to various requirements relating to supply chains, ethics or carbon credit generation (FAO and WUR, 2021).

2.3.3 Supply chain optimization

Digital tools are also used to optimize food distribution by improving routing, network design, and inventory decisions, particularly in the case of perishable products. In humanitarian operations, optimization tools are applied to improve delivery networks and routing to increase coverage and reduce costs. Table 7 (Appendix) lists some examples.

2.3.4 Food quality, safety and food waste prevention

Farm-to-fork traceability systems (including blockchain-based provenance records mentioned above) can strengthen food safety by improving the speed and reliability of traceback during contamination events and by supporting verification of handling conditions along the chain. Additionally, descriptive and predictive analytics can support estimating the likelihood or concentration of foodborne pathogens. From a public-health perspective, AI-enabled approaches are also being explored to improve surveillance and enforcement targeting: predicting which food outlets may have poor hygiene compliance, identifying likely sources of outbreaks, and supporting faster hypothesis generation about patients zero and contamination pathways (Qian *et al.*, 2023). These innovations matter in a context where foodborne diseases remain a large and recurring burden globally, as the World Health Organization (WHO) estimates that roughly one in ten people fall ill each year due to contaminated food (WHO, 2025).

Closely coupled to this are AI-enabled tools used to reduce post-harvest losses and food waste by (i) predicting shelf life and spoilage risk, (ii) optimizing storage and cold-chain conditions, and (iii) improving operational decisions in retail and food services. A recent review has found good alignment between machine-learning capabilities and tasks that need to be performed in order to limit post-harvest losses. They performed technology-task fit (TTF) analysis, a tool that could be employed more systematically to assess other FSN dimensions in this report in future works on the topic (Shao and Marwa, 2025). Finally, in hospitality and institutional catering, AI-assisted waste tracking[7] is used to quantify and categorize waste in real time, supporting menu redesign, procurement adjustments, and staff feedback loops that have shown substantial reductions in measured waste in some deployments (Clark *et al.*, 2025). Shelf-life prediction using imaging combined with machine-learning models can enable more accurate first-expired-first-out inventory practices, dynamic discounting, and safer redistribution decisions (Rashvand *et al.*, 2025). AI systems can support cold-chain and retail refrigeration optimization, maintaining food-safety temperature constraints while reducing energy use and preventing temperature-driven spoilage (Onoufriou *et al.*, 2019). Most of the scientifically documented tools use more traditional machine learning approaches (Gbashi and Njobeh, 2024). Table 8 (Appendix) lists examples and related scientific literature.

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[7] Generally, these systems use a combination of photo or video recordings in combination with scales weighing the food, summarized in the source as camera and scale systems.

AI and machine learning are also being applied to optimize food processing itself, with demonstrated applications in process monitoring, product formulation and nutritional value retention across bakery, dairy, beverage and meat processing (Agrawal *et al.*, 2025; Canatan *et al.*, 2025).

2.4 Digital public infrastructure and intelligence systems

Digital public infrastructure (DPI)[8] (UN, 2024a) including interoperable digital ID, payments, registries and data exchange layers can strengthen the design and delivery of food-related public policies by improving targeting, coordination, and monitoring across agencies and levels of government. In food systems, this can support shock-responsive social protection, input and subsidy programs, disaster relief, food safety oversight, and the monitoring of food availability and prices. More broadly, digital services can also facilitate access to services and reduce time spent on doing so, particularly in areas remote from physical service infrastructures. However, these benefits are conditional on robust data governance (clear purpose limitation, privacy protection, accountability, and redress), institutional capacity to use and audit systems, and safeguards to prevent exclusion, discrimination, or capture by private interests. In fact, there is rising concern that the growing role of private actors in building and operating DPIs risks replicating the asymmetries of data extractivism and sovereignty that DPI was originally framed to correct (CIPESA, 2025; IPES-Food, undated). The criticism levelled at India's AgriStack, that centralises personal information of farmers in the hands of private firms without meaningful consultation of farmers and farmer associations (Gurumurthy *et al.*, 2025), illustrates how the DPI label can lend public legitimacy to arrangements that grant private firms more benefits than individual producers. Table 9 (Appendix) lists two examples, highlighting that centralization and agglomeration of data about individuals also bear risks around data protection.

2.5 Food environments and nutrition

Digital tools increasingly shape consumer information and purchasing environments. A systematic review showed the importance of social and media influence in the adoption of fad diets (Spadine and Patterson, 2022). This calls for means to protect consumers from manipulation and misinformation ensuring clear and fair information. It requires both public regulation and engagement of the multiple stakeholders involved.

[8] In an analogy to public infrastructure, digital public infrastructure (DPI) describes foundational digital solutions that form the basis for economical and societal digital development. A simple example is comparing fibreglass data cables with road infrastructure. The Digital Impact Alliance qualifies DPI as maximizing public value creation, following open, modular, interoperable and extensible design principles and giving people agency over data usage and participation in the data economy.

A growing set of "precision nutrition" initiatives and services use AI models to generate individualized dietary guidance. Several consumer-facing applications and research prototypes now allow users to photograph a meal and receive approximate caloric and nutrient breakdowns. Others work through collection of biomarker measurements and meal logs. However, it remains unclear how far this progress has been taken by consumers, and independent validation of accuracy in real-world, culturally diverse dietary contexts is still limited (Agrawal *et al.*, 2025). Table 10 (Appendix) lists commercial implementations. Many of these approaches are however not suited to improve the nutrition on the population level for any country, due to costs and complexity of individual data collection. There is a risk that such AI-driven precision nutrition shifts attention away from population-level determinants of nutrition and public health and focuses on individualized approaches that are more possible for affluent populations. In contexts where undernutrition and micronutrient deficiency are the primary concern, the digital nutrition tools with documented use are categorically different. The predominant approach is SMS-based behaviour change communication. A recent review of 53 digital nutrition interventions in LMICs found that SMS, mobile apps, and social media are the main platforms, predominantly studied in Asia. These interventions have shown to have positive impacts on physical activity and healthy food consumption, but less clear impacts on biological variables. The review criticizes a lack of theoretical frameworks in intervention design and highlights the need for commitment by policymakers in integrating these tools meaningfully into national public health agendas (Kurniawan *et al.*, 2025). However, impact on maternal and child nutrition outcomes remains inconsistent across trials (Barnett *et al.*, 2025), also because education and wealth are determining factors in the successful uptake of the information and adoption of the technologies (Cunningham *et al.*, 2024), which is a theme consistent in digital development aid (Toyama, 2011; World Bank, 2025b). The implementation of precision nutrition tools in LMICs faces challenges of funding, affordability, resources, awareness, training, suitable tools, and safety) (Bedsaul-Fryer *et al.*, 2023). In the Lao People's Democratic Republic, the National Information Platform for Nutrition (NIPN) has integrated an AI system trained on the country's nutrition data holdings to process large volumes of information and translate complex multisectoral analyses into accessible summaries for non-technical policymakers, automatically flagging data gaps and inconsistencies (NIPN, undated). A complementary application is the use of AI for regulatory enforcement: the Virtual Violations Detector (VIVID), developed by Alive & Thrive and deployed initially in the Socialist Republic of Viet Nam, uses supervised machine learning and natural language processing to scan social media and websites for violations of the International Code of Marketing of Breast-milk Substitutes. During over twelve months of monitoring in 2022, VIVID detected more than 3 000 online advertisements contravening Vietnamese law, averaging 9.5 violations per day (Backholer *et al.*, 2025).

2.6 Potential impacts of digital tools and AI use in food systems on food security and nutrition

As shown above, digital tools and AI can have immediate impacts in improving productivity, especially in primary production, and along value chains. It is worth noting that the type of AI that is employed is generally in the form of machine learning or statistical tools and not Generalist AI. Successful use of these tools requires a lot of existing infrastructure and know-how.

It is important that adoption of any tool be accompanied by critical questions and empirical assessments throughout. This needs to go beyond the " human in the loop" that is being put in place to bear responsibility for errors made by the tool. Critical thinking and observation cannot be done by any digital tool. Users and decision-makers must not yield their responsibility and expertise to a tool but ask the tough questions before adopting it and closely monitor outcomes.

The uneven empirical evidence reviewed in this part also points at the need for independent assessment of FSN outcomes of digital tools that are publicly accessible. Addressing this requires investment in shared learning systems that allow governments, research institutions and producers' organizations to compare, validate and build on each others' assessments. Without such infrastructure every new deployment effectively starts from scratch, deepening the information gap between users and vendors.

The current pace and promise of development of digital technologies alongside the already observed downsides and criticisms lead to some critical questions:

- Do specific digital innovations deliver measurable improvements in FSN or have their benefits been overstated by vendors?
- Who captures value and power from digital innovations in food systems, and who absorbs their costs and risks?
- Which food system models, production systems, practices, and diets are privileged by prevailing digital innovations, and which are marginalized or are invisible?
- Under what conditions can different actors meaningfully own, control, use, and shape digital technologies, rather than merely adapt or passively access them?

3. CHALLENGES AND LIMITATIONS TO ALIGN DIGITAL INNOVATIONS WITH THE PUBLIC GOOD IN FOOD SYSTEMS

This part starts with listing basic technical requirements, before going into the more complex social problems that come with the use of AI tools. Areas with little existing data (“data deserts”) often coincide with those where FSN is threatened the most. This means that even the best digital tools will not perform well in these contexts unless sufficient data is collected. This creates a structural case for prioritizing investment in basic data collection infrastructure in the highest-FSN-need contexts, ahead of and as a precondition for deploying predictive tools. "Data deserts" sometimes simplify the situation: much FSN-relevant data is already stored in data silos, and new collection must respect normative human rights frameworks (CFS, 2023) to avoid many of the risks described below. Additionally, investment in digital infrastructure and data collection must not compete with the existing Official Development Aid (ODA) budgets but needs to be added to them.

3.1 Preconditions: digitalization, infrastructure and basic conditions

AI has considerable potential to improve the efficiency of food systems. However, the realization of this potential and its impact on FSN are very dependent on contextual conditions and on the specific situation of different categories of actors.

Many AI applications require substantial investments in energy infrastructure, connectivity, data systems, institutional capacity and digital literacy. These requirements are often underrepresented in narratives that present AI as the stand-alone solution to problems. The International Monetary Fund (IMF) publishes an AI preparedness index that illustrates the cumulative result of those requirements. On the one hand, there are high- and some middle-income countries that generally have a high preparedness index and often national or super-national strategies on AI, digitalization and data governance in place. On the other hand, there are lower- and low-income countries that do not meet the baseline conditions to adopt AI tools, let alone adapt or invent them (IMF, undated). This observation of disparity is generally described as the “digital divide”[9]. Such disparities exist both between countries and inside countries, including between rural and urban areas.

The World Bank specifies the necessary pre-conditions for each country to leverage AI as the 4Cs: **Connectivity, Compute, Context and Competency**. They describe country-level economic

[9] The digital divide characterizes the gap between those who have access to telecommunications and information technologies and those who do not. This ranges from access to high-speed internet, to mobile coverage, literacy and the skills needed to operate and use apps and devices.

preconditions for adopting, adapting or innovating with AI. They do not in themselves specify the policy choices needed to ensure that benefits are distributed fairly within or across countries. **Connectivity** encompasses reliable digital and energy infrastructure, device access and ownership. This can be broadly described as digitalization and is the basic precondition to leverage AI-enabled tools. **Compute** refers to processing power as AI chips, servers, data centres and cloud services, which are necessary to train and deploy AI-enabled tools. **Context** is specified as training data, models and applications that reflect local realities like language, culture, needs and governance frameworks. It is essential to create solutions that cater for specific needs, and that are trusted and adopted. Finally, **Competency** is the set of digital skills that are indispensable for adopting, adapting and innovating with AI. Depending on which of those three activities is suitable for a given country or region and the complexity of the tools chosen for the task, the relative importance of the four preconditions varies (World Bank, 2025b). These preconditions must be considered on top of and combined with the major constraints of cost and accessibility. They apply with diverse degrees to both specific-purpose and Generalist AI. Crucially, the report suggests that LMICs do not need to replicate the trajectory of early adopters: countries prioritizing adoption over innovation can selectively deploy proven tools and policies while building the connectivity and competency foundations that make those tools sustainable.

3.2 Operational Risks: Intrinsic inaccuracies and lack of measurable real-life impact

Many high-impact functions in food systems such as early warning, extension advice, nutrition guidance and supply-chain control require contextual sensitivity, accountability, uncertainty handling and reliability. Generalist AI tools are prone to confident but incorrect outputs and cannot reliably signal uncertainty, which poses specific risks when used for decision-making affecting livelihoods, food access or health. Hallucinations (outputting confident falsehoods rather than admitting ignorance) are an intrinsic feature of how Generalist AI is trained, i.e. by evaluating them against standardized test benchmarks (Banerjee, Agarwal and Singla, 2024; Kalai *et al.*, 2025), and thus how they generate output. Risks of hallucinations have been reported in areas such as food safety, nutrition and plant pest identification (Arslan, 2025; Tan, 2025). Additional FSN-specific documentation of hallucination risks remains sparse, which is in itself a major concern: tools such as AI-based extension chatbots and nutrition advisory systems are being deployed faster than they are being evaluated. Research shows that besides hallucinations, model output is highly unpredictable with small changes of input parameters causing significant changes of the output (Mirzadeh *et al.*, 2025). This reliability gap is visible even in information summarization scenarios for which Large Language Models (LLMs) are often used: a large cross-market evaluation by the European Broadcasting Union (22 public-service media organizations across 18 countries and 14 languages) found that 45 percent of AI-assistant responses to news questions contained at least one significant issue, and 81 percent contained at least some issue; sourcing problems were the most frequent driver of significant issues (31 percent), followed by accuracy-related problems (20 percent) (EBU, 2025). In other words, fluent text generation can coincide with systematically weak verifiability and factual reliability – properties that are central for policy-relevant communication and decision-making. Statistical and machine learning models have an advantage in explainability, precision and reproducibility and can be integrated with LLMs to improve their reliability. Regardless of the precise technology used, performance heavily depends on relevance and amount of training data available, as discussed further below. Early initiatives such as the Institute for Agriculture and Artificial Intelligence (IAAI), launched in late 2025, aim to develop agriculture-specific benchmarks that allow systematic comparison of model performance on domain tasks rather than relying on general-purpose evaluations (AI AgriBench, undated; MBZUAI, undated). Beyond technical benchmarks, public institutions will still need to work towards assessing ultimate real-life impacts on food security of these technologies.

Evidence from early adopters in the private sector already suggests that reliability is not only a theoretical concern. In PricewaterhouseCoopers' (PwC) 29th Global CEO Survey (published on 19 January 2026), 56 percent of CEO's report sees neither higher revenues nor lower costs from AI to date (with only 12 percent reporting both improvements) (PricewaterhouseCoopers, 2026). The Massachusetts Institute of Technology (MIT) State of AI in Business report characterizes enterprise results as highly skewed, claiming 95 percent of organizations in its dataset see zero return from Generalist AI efforts until 2025 (Challapally *et al.*, 2025). Ranganathan and Ye's eight-month field study, in a United States technology firm with around two hundred employees, finds Generalist AI use can intensify work rather than reduce it: employees work faster, take on a broader scope of tasks, and extend work into more hours of the day, often without being asked. These dynamics (scope creep, boundary creep, and higher cognitive load) can make early speed gains difficult to convert into durable, organization-level productivity gains (Ranganathan and Xingqi, 2026). Equivalent evaluations in public-sector FSN contexts are not yet available, but the pattern from early private-sector adopters warrants caution before significant institutional investment.

3.3 Social and political risks

The considerable investments in AI and the limited number of big private actors that drive them create a potential risk of increased corporate concentration including applications that influence food systems. This can reinforce existing power imbalances in favour of extractive agriculture models. Digital innovations are not neutral technologies. They are developed, deployed, and governed within specific economic and institutional models, and as such tend to reproduce existing power relations in food systems. Any AI system reproduces statistical patterns present in its training data, and is therefore inherently backward-looking, generating predictions about the future based on past observations. This means AI and digital solutions in general cannot substitute for structural societal change needed to address inequality, discrimination or power imbalances. In the context of food systems, particular caution is required because algorithmic systems trained on historical data likely reproduce existing biases in access to extension services and public support programmes, or implicitly favour extractive, intensive and monocultural agricultural models. Unbiased training data does not largely exist by default and would need to be collected specifically with representativeness in mind. Post-hoc technical debiasing methods exist and can reduce specific measured disparities, but they cannot address the structural inequalities embedded in the underlying data-generating processes, involve trade-offs between competing fairness criteria, and risk creating an appearance of fairness without changing real outcome (Mehrabi et al., 2021; UNDP, 2025).

3.3.1 Accountability, contestability, and institutional capacity

Where AI is introduced into public decision-making, the central risk is institutional accountability. Decision-making tasks include e.g., targeting assistance, grievance redress, and inspection prioritization. The questions that need to be answered are who is responsible when systems fail, how are errors detected and whether affected people can appeal errors. UNDP explicitly warns that outsourcing core capacities like information gathering, triage, and prioritization to AI tools that governments do not own, train, or fully control can erode institutional capacity (also referred to as “de-skilling”). For instance, allowing an external model to make all decisions on triage during disaster response can result in the institution no longer being able to perform that function without such a model (UNDP, 2025).

Furthermore, the institutions’ work risks becoming more prone to automation bias (deference to model outputs) and less able to explain or contest decisions. At the institutional level, this can weaken state capacity and increase vendor dependency, which is particularly problematic in high-stakes FSN functions where accountability and auditability are essential. A related political risk is performative participation. “Listening platforms” can create an appearance of inclusion while weakening genuine participation if inputs are collected but do not change decisions (“engineered inclusivity”). AI-based summarization and filtering can also flatten minority or dissent voices and amplify centrally preferred narratives (UNDP, 2025). Institutional use needs to follow the normative human-rights baselines (UN, 2018) to ensure that the right to adequate food is guaranteed.

3.3.2 Financial risks and related power imbalances

The ability to develop and deploy Generalist and big deep learning models is currently in the hands of very few companies. Relevant layers of the AI technology stack such as data centres, cloud infrastructure and proprietary models are in the hands of few, mostly private actors, due to the high investment and infrastructure barriers involved (World Bank, 2025b). AI infrastructure has the structural characteristics of industries that tend towards concentration: very high fixed costs, strong network effects, substantial economies of scope across applications, and steep learning curves that advantage incumbents. Under these conditions, monopolization is a tendency of the market rather than an anomaly that cannot be regulated away. Resolving the resulting unequal bargaining power, reduced policy autonomy and vendor lock-in require structural alternatives rather than regulation along, e.g. digital public infrastructure designed to embody human rights, public values and democratic accountability. Building and operating AI systems take up a huge amount of compute, prompting the biggest investments in any technology to date. AI data centre investment is projected to reach USD 6.7 trillion (McKinsey, 2025), while vendors are still looking for pathways to get returns on their investments (Deloitte US, 2026). Operating large Generalist AI systems does not profit from the effects of scale, that is provisioning a service to 10 times more users does take much less than 10 times the cost, because each user prompt triggers an expensive computation (Ji and Jiang, 2026; O'Donnell and Crownhart, 2025). It is projected that this will have to lead soon to advertisement and increased costs for the end users (Claburn, 2026). This is of high relevance for FSNrelated objectives: the underlying technology solving a specific task might become prohibitively expensive or might prioritize or recommend responses and content that reflect the interests of system providers rather than those of end users. Consequently, models might end up propagating extractive, intensive and monocultural models disregarding their long-term effects. An example of the influence of commercial interests is Plantix, an agricultural advisory application, originally claiming to aim at reducing pesticide usage. Their pivot towards becoming also pesticide vendors to satisfy their investors has raised questions on conflicts of interest (Miller, 2024).

Small, specific-purpose AI models can be developed with less upfront investment and related risk. The central cost factor for them is data collection and curation. They can be rendered more accessible to non-technical users by adding interfaces of open, small language models operated locally.

3.3.3 Bias, exclusion and data deserts[10]

Unequal digital access and unequal representation in data can translate into unequal performance and unequal service delivery. Data-driven services tend to work best where digital traces are abundant (connectivity, device access, transaction records, sensor data and, crucially, training data in the local languages). This creates a systematic risk that smallholders and remote communities become underrepresented in training data and thus underserved or mis-served by models and targeting

[10] A data desert refers to a systematic absence of reliable, representative data about a specific population or location, resulting in their exclusion from data-driven policy and decision-making.

systems (Mehrabi *et al.*, 2021). The UNDP cautions that large segments of the population can become effectively invisible to algorithms where digital records are sparse, incomplete, or biased, creating risks of algorithmic exclusion and reinforcing deprivation (UNDP, 2025).

This is true even for inequalities within countries: Rising capital costs, as well as persistent barriers related to access, awareness, trust, accessibility, affordability and digital literacy mean that different categories of actors might see different degrees of benefits or disadvantages from digitalization efforts. For instance, in rural India, consequences of limited access to and use of mobile phones by women were amplified by digital systems relying on mobile phones to access government entitlements, banking and civic participation (Scott *et al.*, 2021). Avoiding digital exclusion in model predictions requires deliberate investment in representative datasets and in rights-respecting data governance, rather than attempting debiasing outputs after deployment. Digital divides also shape who uses general-purpose tools and who benefits from them. For example, women are severely under-represented in Generalist AI's training data (Norori *et al.*, 2021). This can compound existing inequalities for women, whose nutritional knowledge and decision-making authority over household food purchases and preparation are among the strongest determinants of child nutrition outcomes (FAO, 2023). AI tools that systematically underserve or misinform women carry disproportionate consequences for household food security.

3.3.4 Data sovereignty, vendor lock-in and resulting power imbalances

Collection and analysis of data are essential to management and decision-making. States have progressively developed rules and principles on data collection, management and conservation for public purposes. Digitalization and increasingly performant AI have considerably facilitated these operations, making it easier to collect and manage data and also adding value to it. In fact, the shift towards a data economy has also resulted in major changes in who collects and holds data. In many cases data is now predominantly collected, processed and held by private firms, traded as a commodity and integrated into proprietary systems that serve commercial ends. The risk is that it also becomes increasingly easy to cross-reference and connect large amounts of data, giving data owners a lot of insights and subsequently power to private firms over the sources of that data, ranging from individuals to states.

Weak and fragmented regulatory frameworks enable large corporations to collect and process data at scale, often leaving producers, workers and smaller actors with limited rights over data access, use, privacy, cybersecurity and the resilience of the digital systems they depend on. A revealing asymmetry has emerged around intellectual property: firms claim that training models on others' data is permissible, while simultaneously arguing that AI-generated outputs and trained models should receive proprietary protection (Stuart D. Levi and Shannon N. Morgan, 2023; Sweney and Milmo, 2025). Even though a US-based class action lawsuit by authors has been settled by a payout of USD 1.5 billion (Associated Press, 2025), consolidation of this position would amount to a one-directional extraction of value from data originators to model operators.

In FSN contexts this asymmetry has direct consequences. AI-assisted genomic prediction and marker-assisted selection (Section 2.1.1) are used by public institutions such as the International Maize and Wheat Improvement Center (CIMMYT) and CGIAR for public-interest breeding, but also by the consolidated agrochemical and seed sector to build proprietary genomic databases and patent portfolios that progressively narrow the genetic resources available to farmers and public breeders (Kloppenburg, 2010). New Genomic Techniques (NGTs) such as CRISPR-[11]based gene editing extend this dynamic: because NGT-edited plants are potentially indistinguishable from plants produced by conventional breeding or natural variation, patents on AI-identified and NGT-derived traits risk extending to peasant and conventional seeds carrying the same sequences. Farmers' rights to seeds – recognized under Articles 9 and 12 of the ITPGRFA (*International Treaty on Plant Genetic Resources for Food and Agriculture*, 2001) and Articles 19 and 28 of the United Nations Declaration on the Rights of Peasants and Other People Working in Rural Areas (UNDROP) (UN, 2018) – and the broader right to adequate food are thus being progressively constrained by Internet Protocol (IP) regimes that AI is accelerating, a tension reflected in unresolved Dispute Settlement Issues (DSI) negotiations under the Convention on Biological Diversity (CBD) and ITPGRFA (Conference of the Parties to the Convention on Biological Diversity, 2022). Where regulatory capacity is low, these gaps are compounded by vendor lock-in: legal instruments based on copyright protection considerations currently allow hardware manufacturers to restrict owners' ability to install, modify or repair the software running on equipment they have purchased (e.g. mobile phones, tractors or irrigation controllers), not only blocking independent repair or third-party integration but importantly also controlling the flow and storage of data collected using this equipment. Over time, these constraints raise switching costs, weaken the bargaining position of users and governments alike, and entrench dependency on a narrow set of providers (FTC, 2021; *Memorandum of Law in Support of Plaintiffs' Motion for Preliminary Approval of Settlement with Defendant Deere & Co., Certification of the Proposed Settlement Class, and Related Relief*, undated).

The concentration of data, compute, talent and frontier models in a small number of firms translates into risks that extend well beyond market power. At the geopolitical level, it can produce asymmetric bargaining power and long-term dependency that the UNDP characterizes as a digital-colonialism dynamic in which countries must pay recurring subscriptions or surrender data to access capabilities

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[11] Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR)

(UNDP, 2025). Cloud-hosted data raises direct sovereignty concerns: providers may be legally compelled to share data stored on their infrastructure with their home governments, regardless of the data's origin or sensitivity. As knowledge, analytical capacity and decision-making are progressively transferred to digital systems controlled by these corporations, the risk is not only economic dependency but the narrowing of policy autonomy and food-systems agendas towards frameworks that reflect corporate rather than public interest. This is reinforced by dominant narratives that frame digitalization itself as a primary solution to food insecurity, potentially leading to uncritical policy adoption and unmanaged conflicts of interest where the same firms that sell the tools also shape the policy discourse around them.

Finally, the centralization of sensitive datasets and expanded data flows create operational risks that compound the structural ones. "Functional creep" – the repurposing of data and systems beyond their original mandate – becomes more likely as integrated platforms make cross-referencing technically trivial. National security as well as individual privacy risks rise with the centralization of sensitive agricultural, demographic and logistical data, and the heightened cyber-risk surface created by expanded digital integrations means that breaches, when they occur, can expose entire systems rather than isolated datasets.

3.3.5 Labour displacement and change in labor dynamics

In economies where agricultural employment is the primary income source for poor households, productivity gains obtained through automation can coexist with a degradation of food security if incomes fall faster than food prices (Headey and Ruel, 2023).

Beyond displacement, digital tools introduce new forms of workplace control. In large-scale farming operations and food processing, real-time surveillance systems, e.g. biometric sensors, GPS tracking and algorithmic performance scoring, are deployed to intensify work , monitor individual output and identify underperforming workers (Berg, 2018; Klauser, 2018).

3.3.6 General risks of digital critical infrastructure

A further dimension of data governance that requires attention in FSN policy debates is operational security: the set of practices required to ensure that digital systems and data remain available, intact, and interpretable over time (Digital Preservation Coalition, 2015). Three categories of risk deserve explicit consideration. First, cybersecurity (Kulkarni *et al.*, 2025): digital systems underpinning public FSN functions are exposed to the full spectrum of malicious interference, from ransomware to state-sponsored intrusion, and require the same institutional investment in defense, redundancy, and incident response as any other digital infrastructure. Second, physical and geopolitical threats (Harding, 2026): data centers are critical infrastructure for modern societies and have emerged as strategic targets in recent conflicts. Concentration of FSN-critical data in a small number of commercial data centers therefore constitutes a resilience risk, beyond the data sovereignty concern. Third, long-term archival integrity (Digital Preservation Coalition, 2015): digital records degrade and become inaccessible through physical data degradation, hardware failure, format obsolescence, and the discontinuation of proprietary systems. These risks accumulate silently over the years and are rarely budgeted for. FSN-related data carry policy-relevant value over decades, a lifespan that far exceeds typical hardware and software cycles. Without active migration policies, open-format standards, and geographically distributed storage, the institutional memory on which evidence-based FSN policy depends can be quietly lost. Taken together, these risks imply that data governance frameworks for FSN must extend beyond questions of ownership and access to encompass the full lifecycle of data integrity.

3.4 Competition for resources

The development of AI requires important resources, energy and water, with potential consequences on FSN particularly in areas where water is scarce. Estimates are that a single ChatGPT query consumes roughly 25 times as much energy as a Google search and half a liter of water is used for cooling the computers processing every 29-50 ChatGPT queries (The Brussels Times, undated). There is a huge variance of energy consumption for different types of queries (text-to-image generation consumes 1000 times as much as simple text generation) and these considerations do not factor in the hundreds of Megawatt-hours needed to train the models (Ji and Jiang, 2026; O'Donnell and Crownhart, 2025). Electricity and water usage of datacentres are generally used as a proxy to estimate the environmental impact of AI, with the International Energy Agency (IEA) estimating that currently 15 percent of existing data centre demand is caused by AI applications. The IEA reports that data centres accounted for around 1.5 percent of the world's electricity consumption in 2024, which is expected to double by 2030. In water-stressed regions, where food insecurity is most severe, the water demands of data centre cooling create a direct dilemma: either compete for scarce water resources to host Generalist AI infrastructure domestically, or accept dependence on externally-hosted cloud systems and the sovereignty risks that accompany it (IEA, 2026).

Besides those direct emissions caused by operating AI, short hardware half-life of 2-3 years (Kshirsagar, 2025) and construction of new data centres and associated power plants (Nutt, 2025) have largely negative environmental impacts.

Notably, the investment into Generalist AI also contributes to the competition for already scarce financial resources in development aid, food security and nutrition. Ongoing investments into Generalist AI are unprecedented in their extent, with the estimate of USD 6.7 trillion until 2030 (McKinsey, 2025). This not only concentrates funding in the sectors of AI and IT in the hands of very few companies, but, more importantly, far exceeds the UN's estimate of USD 93 billion a year to end world hunger (UN News, 2025), roughly a fourth of what Amazon, Microsoft, Google and Meta spent on datacentres in a single year (IEA, 2026). In FSN contexts, the total Official Development Assistance (ODA) for food security and nutrition amounts to roughly USD 76 billion annually, of which only around a third directly addresses the drivers of food insecurity and malnutrition (FAO *et al.*, 2024); at the same time, the Development Assistance Committee (DAC) bilateral ODA fell by 6 percent in real terms in 2024 (OECD, 2025). In this context, institutional investments in Generalist AI tools with undemonstrated returns displace nutrition programmes, smallholder support, and data infrastructure within the same finite envelopes.

3.5 Cross-cutting risk impact on the most vulnerable

All of the risks described above, ranging from missing digital infrastructure to data deserts, and information and power imbalances, compound on those who are most vulnerable: Low-income smallholders and rural workers, women and indigenous peoples. They face sparse digital infrastructure, underrepresentation in training data, weak institutional protections, a lack of economic and political bargaining power against platform operators and the risk that these technologies do not serve them. Those who face the highest risks of adoption are least likely to capture its benefits.

In purely profit-driven contexts marginalized people are difficult to monetize as customers but valuable as sources of data. A concrete trajectory is that widespread adoption of technological tools imposes significant costs on smallholders, be it through hardware purchase or software access subscriptions. This would directly conflict with spending on food consumption and -production.

At the same time, vendors are extracting community knowledge. Converting intelligence, previously held by the public, communities and individuals into a resource only accessible for a fee has already been described as a path to profitability for LLMs (Rev, undated). The current market capitalizations of the biggest AI vendors show the immense value of extracted and consolidated public knowledge, yet little of it was remunerated. This collected knowledge and intelligence is used to reassess land values, adjust insurance pricing, inform credit scoring or guide speculative investment in farmland (Bludnik, 2022; Fraser, 2019). Food security can be threatened by resulting increases in land access costs, reduced tenure security or pressure smallholders into cost-intensive technology adoption. The strategic advantage is afforded by those who have capital to comprehensively analyze and act on it, not those who generated it (Hackfort, Marquis and Bronson, 2024).

The UN existing normative frameworks, such as the UN Declaration on the Rights of Peasants (UNDROP, 2018) and the UN Declaration on the Rights of Indigenous Peoples (UNDRIP, 2007) provide directly applicable standards for agricultural data governance, regarding consent, benefit-sharing and the right to refuse technologies incompatible with one's livelihood. Their application in design and adoption of new digital technologies does not only benefit the marginalized but creates a safe foundation for digital tools for FSN that leave no one behind.

4. WAY FORWARD

Digitalization and AI adoption in food systems is already underway, but often outpacing the development of conditions needed to ensure these tools benefit the public, especially those most in need. Making sure that if adoption is happening it benefits the public requires public and institutional capacity. DPI must be publicly owned, democratically governed and build with those it serves, especially women and marginalized groups. This requires sustained investment in local competency and hybrid tech-policy expertise. Today digital expertise sits overwhelmingly in the private sector, which means the translation of public rules into working systems risks being superseded by de-facto standards provided by privately engineered tools. Independent public capacity to specify, procure, audit and contest digital systems is needed as much as international exchange of the insights gathered.

The key to digitalization that has real impact on FSN and low risks is to frame problems well and to rely on local human ingenuity to contribute to targeted solutions. This might be more demanding upfront but will pay off in creating local expertise and strengthening local and institutional problem-solving skills. Technology amplifies existing human and institutional capacity rather than substituting for it (Toyama, 2011), a finding that the high failure rates of externally designed digital systems in developing countries have repeatedly confirmed (Heeks, 2002, 2003). The cases and evidence reviewed in this note show the same for recent AI technologies and FSN specifically: approaches that invest in local problem-framing, human capacity, and controllable infrastructure outperform those that prioritize speed of adoption over depth of ownership.

The cross-cutting foundation when thinking about equity and participation is data is often superficially treated as the "oil of the information economy", but the more meaningful perspective is that it is the main point of control of digital systems, making data the strategic lever to establish control and regulation from the beginning. It is important to appreciate that it is the data, not the ingenuity of the models, that gives power.

Governments have a critical role to play (see box 1), particularly in designing appropriate data governance. The Federative Republic of Brazil has framed government data as a public good within its broader digital government strategy, using Open Government Data (OGD) as an instrument to advance the SDGs and support digital transformation (Galdino de Magalhães Santos, 2024). This includes attention to data governance capabilities, privacy, transparency and ethics. The Federative Republic of Brazil has committed to "Open Agricultural Data" through its Open Government Partnership action plans, with agencies such as the National Supply Company (CONAB) and the Brazilian Agricultural Research Corporation (EMBRAPA) mandated to collect, systematize and publish agricultural data and to share publicly funded research data under open science initiatives. These efforts coexist with Brazil’s General Data Protection Law (LGPD), which strengthens data protection but also raises new tensions between transparency and privacy in the use of government data (Abigayle Erickson, 2019). The Federative Republic of Brazil has also launched a Gaia-X Hub, whose goal is trusted, interoperable and sovereign data ecosystems across national borders (Gaia-X, 2025). The Global Open Data for Agriculture and Nutrition[12] (GODAN) initiative highlights the power of Open Data for transforming agriculture driving sustainable development through knowledge sharing and data-driven systems.

Creation of predictive systems is becoming increasingly easy. Making sure that the data used for those predictions is used in the public interest to ensure and protect food security requires robust regulatory frameworks accompanied by actual technical implementations of them, i.e. dataspaces[13]. These dataspaces must reflect the same values CFS has long promoted for physical food systems: fair remuneration for producers, transparency across value chains, protection of smallholders and individuals from exploitative market structures, and accountability of actors with disproportionate power. Data governance frameworks must, therefore, reflect these same standards: sovereignty over what one produces, participation in decisions about how it is used, fair benefit-sharing, and the technical dataspace implementations to make these rights enforceable rather than aspirational.

A key response to individual vulnerability in data governance is the collective ownership and management of data through trusted community structures, allowing people to assert their rights collectively rather than in isolation. Community representation in negotiating data ownership and management varies by local context. For instance, measuring thirty of Canada's Data Strategy Roadmaps for the Federal Public Service commits the federal government to support Indigenous-led data strategies, enables timely data sharing, and strengthens protections while respecting Indigenous governance over data (Canada School of Public Service, 2025). These commitments are operationalized through Indigenous-led institutions and frameworks. The First Nations Information Governance Centre provides a data sharing platform (The First Nations Information Governance Centre, undated) that adheres to the Ownership, Control, Access, Possession (OCAP®) principles. Inuit organisations, including Nunavut Tunngavik Incorporated, advance Inuit data governance through tools such as the National Inuit Data Strategy (ITK, undated), while Métis organisations are developing their own data sovereignty frameworks (Métis Nation, 2025). In India, Panchayats have been proposed as the local self-governance institutions that should represent local farmers (Baksi *et al.*, forthcoming).

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[12] https://www.godan.info/

[13] A dataspace is an interoperable framework, based on common governance principles, standards, practices and enabling services, that enables trusted data transactions between participants.

Taken together, these examples illustrate an emerging model of community-governed data spaces that offer a meaningful alternative to both state-centric and corporate approaches to data control.

The CFS Data collection and analysis tools for food security and nutrition recommendations (CFS, 2023) stated that FSN data should be accessible, circulated and used in the public interest, while also preserving the rights of data originators and data owners, ensuring data protection and privacy, and taking steps to address imbalances in power among actors with respect to generating, accessing, collecting, storing, processing, sharing and using FSN data. Most existing regulatory frameworks for data around the world reflect these values with different emphasis, but actual technical implementation is often lacking. The public already faces the risk that private firms create systems that serve corporate rather than public interest and thus dataspaces supporting public interest by implementing law and regulations into technology are urgently needed.

At regional level, the African Union published its Data Policy Framework describing a shared African data space in 2022. It places equitable access to and benefit sharing from data at its centre (AU, 2022). The Digital Transformation Strategy for Africa 2020-2030 (AU, 2020) builds on that concept and provides a blueprint for an African single Digital Market. One of its central interests is to "allow regional and continental integration of African data markets through open standards, while taking into account that security and regular upgrading of these tools must be guaranteed". It proposes the creation of an e-Government Inter-operability Technical Framework. The framework shall propose core standards for data flows and information integration and management, both for the public and private sector. Eventually the African Union (AU) aims to "ensure commercial rights of the use of personal data of Africa's citizens staying in Africa or provide a fair commercial share to Africa" while guaranteeing "inclusion, security, privacy and data ownership in digital identity systems". Digital Agriculture is one of the central pillars in this conceptual framework. At the level of practical implementation support, the Commonwealth's National Agricultural Data Infrastructure (NAgDI) framework provides countries with a structured approach to building data systems, governance arrangements and institutional capacities needed to manage agricultural data as a national asset. It has been piloted in Bangladesh, Ghana, Malawi and the Caribbean, illustrating that data infrastructure and management can be thought from a systems approach viewpoint and interconnecting diverse institutional starting points (Commonwealth Secretariat, 2025).

Finally, there is the major challenge of keeping up to date with the sheer pace of change in the fields of digital technologies, data and AI innovation and getting information on them that is independent and usable, including on proven impacts, positive and negative, on the various dimensions of FSN. The UN multi-stakeholder High-level Advisory Body on Artificial Intelligence has highlighted the need for a globally shared common understanding of AI developments as the essential foundation for international capacity building and regulation. This led to its first recommendation in the *Governing*

AI for Humanity report (UN, 2024b): The foundation of an international scientific panel on AI. CFS could consider performing recurring scientific analyses of the use of AI in food systems and proven impacts on FSN. This could mean disseminating recurring publications, convening events like this forum regularly and liaising with the UN AI Advisory Body's scientific panel as appropriate.

Box 1: Considerations when designing policies related to the use of AI for FSN

People and their national representatives must have the ultimate say over the use and control of their data, and not private firms or other countries. Regulations and dataspace implementations must reflect that.

Publicly-funded efforts should result in publicly accessible, FAIR (Findable, Accessible, Interoperable, and Reusable) data.

Existing normative frameworks (OHCHR, 1966; UN, 2007, 2018) need to be the starting point for development and use of digital tools in FSN.

Sovereignty strategies do not need to imply full domestic self-sufficiency. The World Bank notes that small states may seek economies of scale through regional collaboration and approaches such as data embassies[1] (legal control over data hosted abroad), while emphasizing the high trust and complex legal requirements involved (World Bank, 2025b).

Digital public infrastructure must become the foundation of digital innovation world-wide. This is necessary to keep monopolies from stifling innovation elsewhere. Specifically, creation of interfaces, modularization and increasing interoperability must be actively supported and not be rendered illegal.

Hardware (e.g. mobile phones, tractors, sensors) must not enforce which software runs on it. People and their representatives must be able to choose freely which software tool serves their needs while protecting their rights regardless of hardware vendors' commercial interests.

A clear separation should be maintained between advisory and solution providers. An actor that recommends which intervention is needed should not also be the one that supplies it, so that advice is not shaped by the incentive to sell. Procurement and conflict-of-interest rules should enforce this separation rather than leaving it to good practice.

Source: Authors' own elaboration.

"Responsible AI" in food systems is not only a question of technical safeguards, but of institutional design: inclusive access, purpose limitation, contestability and appeal, transparency of model and data provenance, and procurement that preserves public agency and exit options.

The conditions for AI and digital tools to genuinely serve food security and nutrition are sequential and cumulative. At the beginning a clear framing of the problem and assessment of available solutions arise. It is important to always keep in mind that technologies can contribute to progress, but only where structural conditions are in place and where problem framing precedes tool selection. Box 2 proposes a series of good practices that can guide the design of AI solutions for FSN. Every technical solution requires physical and digital infrastructure. Without sound data governance, the infrastructure serves whoever controls the data. Without regulation of platform power, even well-governed data infrastructures risk serving actors who did not build them for the target audience's public good. These considerations highlight that tackling the systemic and societal issues threatening food security is more important than the choice of a particular technology .

Digital and AI solutions for many issues related to FSN exist today. Harnessing them requires dissecting which technologies can be leveraged to solve which problems. Effectively leveraging "AI", requires recognizing that it encompasses a spectrum of technologies ranging from narrow, task-specific systems developed decades ago to the large generalist models that are dominating recent public debate. Being specific in describing and assessing these technologies is essential: many of the most pressing challenges in food systems (e.g. early warning, yield estimation or supply chain optimization) can be addressed by specific-purpose AI that is computationally modest, broadly deployable under local conditions, and governable by the institutions that use it. Generalist AI can offer genuine complementary value, particularly as an interface to data and expertise, but carries higher infrastructure requirements, greater dependency risks, and less predictable behavior in high-stakes contexts. Decision-makers need to assess carefully in each individual case if these added costs are justified for the expected and observed returns.

Box 2: Considerations when designing AI solutions for FSN

- For good problem framing experts and practitioners across sectors need to be involved.
- Consider which analogue approaches are available/could work better. Is the digital solution supporting them?
- Digitalization needs to be thought of as one dimension of optimization of existing systems. These systems need to exist before they can be optimized. A good combination of enabling access to tools and goods are shared-access models. Apps and digital systems can bundle smallholder demand to serve areas that would otherwise not be of sufficient economic interest for vendors of machinery, pesticides or fertilizer.
- Apply Ockham's razor logic: What is the simplest possible solution to a problem? “Simple” doesn't mean simple for the decision-maker ,e.g. let a chatbot fix all of our communication problems, but the solution that is most impactful and controllable and has the smallest footprint and highest maintainability.
- Rollout needs to happen at small, measurable steps that avoid overcommitment.
- Technology is a tool, an extension of human capabilities. It cannot be held responsible. Do not replace central decision-making with machines.
- Accompany data strategies with effective technical implementations pathways.
- Ensure clear and direct rewards for data contributors, down to individual farmers. Data collection must not be extractive.
- The evaluation of the performance of digital tools should be done exactly as for analogue approaches. It should measure final outcomes (and not only interest in the tool such as user numbers or clicks). In FSN these could be, for instance, the Household Dietary Diversity Score (HDDS), Food Insecurity Experience Scale (FIES) or Household Food Insecurity Access Scale (HFIAS). In primary production direct measures like yield increase are easier to obtain.

Source: Authors' own elaboration.

4.1 Considerations for CFS

Digitalization, data and AI are increasingly used in almost all human activities, influencing the six dimensions of food security and nutrition. The potential impacts of AI, positive and negative, on FSN cannot be ignored. CFS is well positioned to play a convening, monitoring and evidence-synthesis role as these technologies continue to develop. Given the pace of commercial product cycles and the persistent gap between vendor claims and independently assessed outcomes, there is real value for a multilateral, multistakeholder, evidence-based body to regularly monitor empirical evidence on the FSN impacts of digital tools, distinguishing demonstration pilots from scaled implementations. Digitalization, data and AI should also be systematically included into considerations regarding any topic related to FSN.

The HLPE-FSN wishes to draw the attention of CFS members and participants on four potential areas of action. The first one is for governments and other relevant actors to revisit and implement the CFS Data collection and analysis tools for food security and nutrition report recommendations (CFS, 2023) in light of the added value and power that AI can give to data, as well as the set of considerations when designing policies related to the use of AI for FSN proposed in Box 1. Second, clear assessments of actual impact of digital tools need to be agreed upon and implemented to validate claims from vendors seeking public procurement. The third one is for all actors to consider developing some good practices, expanding on those proposed in Box 2 when designing AI solutions for FSN. Finally, the CFS should follow the UN Secretary-General's call for interdisciplinary exchange and coordinate with the Office for Digital and Emerging Technologies, the High-Level Advisory Body on AI, and the emerging independent international scientific panel on AI to connect CFS's substantive expertise on food systems with the digital governance expertise those bodies carry.

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APPENDIX

Table 1: Characteristics of specific purpose technologies versus generalist systems

Dimension	Specific-purpose AI	Generalist AI
Generality vs Specificity	Task-specific. Excels at one well-defined task. Performance degrades sharply outside trained distribution. Requires retraining for new tasks.	Generalist. A single model can answer questions, write code, summarise documents, and reason across domains. Enables agentic[14] workflows with multi-step autonomous execution.
Compute Footprint	Low. Runs on microcontrollers, mobile CPUs, locally.	High. Requires GPUs/TPUs datacenters. Training runs consume megawatt-hours.
Data Requirements	Structured (tabular). Labelled data, hundreds to thousands of examples sufficient.	Unstructured at scale. Pre-trained on internet-scale corpora. Requires billions to trillions of data points.
Modality	Single modality. Each model is purpose-built for one data type.	Multimodal. Handles text, images, audio, video within a single model.
Energy & Scale Consumption	Low. Inference can run on milliwatts. Suitable for always-on IoT[15], wearables, embedded systems.	High. A single LLM training run can emit hundreds of tonnes of CO_2. Consumer-scale inference (millions of queries/day) demands significant data centre capacity and cooling.
Deployment & Infrastructure	Locally deployable. Embedded directly into devices, apps, or on-premises servers. No cloud dependency, works offline.	Requires specialised HPC infrastructure. Typically cloud-hosted on dedicated GPU clusters. Self-hosting requires significant capital expenditure. Most organizations consume via application programming interfaces (API).

[14] Agentic systems or AI interface directly with computer systems with minimal human supervision. Often, they consist of a central coordinating model that is able to start tasks for other, specialized models or on the hardware it operates on.

[15] IoT (Internet of Things) describes physical objects that are embedded with sensors, processing ability, software, and other technologies that connect and exchange data with other devices and systems over the Internet or other communication networks.

Dimension	Specific-purpose AI	Generalist AI
Interpretability	High. Rule-based models produce auditable reasoning paths.	Low. Effectively black boxes.
Cost	Cheap. Local training is feasible. Prediction costs near-zero. Total cost is highly predictable.	Expensive. API costs accumulate rapidly at scale. Fine-tuning and hosting frontier models require large cloud budgets.
Privacy & Data Sovereignty	Strong. Data never leaves the device or on-premises environment. Suitable for healthcare, finance, and defence where data residency is mandatory.	Requires governance. Cloud-based inference means sensitive data may leave organisational boundaries.

Source: Authors' own elaboration.

Table 2: Examples of specific purpose AI used for genetic resources improvement

Name	Description
Genomic selection for climate-resilient crops (e.g. CIMMYT Mining Useful Alleles for Climate Change Adaptation)	Statistical genomic prediction models identifying climate-adaptive alleles are complemented by machine learning. Current target crops are wheat, maize, sorghum, cowpea, and rice. (MacNish *et al.*, 2025)

Source: Authors' own elaboration.

Table 3: Examples of specific purpose AI used for land and water management

Name	Description
Sen2-Agri (ESA)	Open-source crop mapping system from satellite imagery. Reached 90% overall prediction accuracy in national maps for Ukraine, Mali and South Africa. (Defourny *et al.*, 2019)
Global Agro-Ecological Zones land suitability mapping (GAEZ, FAO)	Statistical analysis of biophysical potential of land for crop production incorporating various datasets on climate, soil, land cover and related ecological observations. (Fischer, 2021)
CropWatch	Crop condition monitoring system indicating crop situation, farming intensity and stress. (Wu *et al.*, 2015)
NCCAG	National Color-Coded Agricultural Guide Map overlaying soil, elevation, rainfall, temperature and climate hazard data for 20 crops. Supports land use planning and climate adaptation at local government level. (Department of Agriculture (Philippines), undated)

PRiSM	Satellite-based rice monitoring system integrating remote sensing, crop modelling and ICT. Operational since 2014, used by the Department of Agriculture for planning, disaster response and supply outlook. 85–93% accuracy in rice area mapping. FAO-recognised in 2025. (Labbi, 2020; Mabalay *et al.*, 2022)

Source: Authors' own elaboration.

Examples of AI tools in FSN mentioned in part II.

Table 4: Examples of specific purpose AI used for precision farming

Name	Description
Uber for tractor businesses (e.g. HelloTractor)	Platform for on-demand equipment access using an app. Enables demand planning and pooling, combination with satellite data and sensors measure area served and maintenance needs. (Daum *et al.*, 2021)
Farmonaut	Modular machine learning pipelines analyzing multispectral satellite imagery. Yield prediction accuracy up to 95% when compared to post-harvest ground truth. (Farmonaut, 2026; Patel, 2025)
Plant disease detection (e.g. Plantix, PlantVillageNuru)	Phone apps using computer vision and machine learning to detect plant diseases based on photos. Often requires internet connectivity. Generally disease detection accuracies around 70-85% are reported. (Ng *et al.*, 2021; Ramcharan *et al.*, 2017; Shafay *et al.*, 2025)
Aquaculture monitoring (e.g. salmon farming in Chile and Norway (Christian Molinari, 2025))	AI monitoring of fish feeding, fish wellbeing and water quality in aquaculture. Machine learning performs well in many of these areas, while deep learning[16] and generative AI has increased performance (e.g. more reliable 3D-tracking of individual fish.) (Fini *et al.*, 2025; O'Donncha *et al.*, 2021)
Integrated sensors IoT (e.g. Zenvus)	IoT sensors coupled with traditional machine learning analysis performs well in crop recommendation and soil health monitoring. (Islam *et al.*, 2023)
Farming drones (e.g. XAG, DJI)	Computer vision, AI flight control, machine learning and deep learning-controlled variable-rate spraying. Reported 46-75% decrease in pesticide use. (Li *et al.*, 2025; Nguyen *et al.*, 2025a; Zhu *et al.*, 2024)

LLM-based advisory for farmers (e.g. Farmer.Chat, Kisan e-Mitra, UlangiziAI, AgriLLM)	Main application of Generalist AI: Used in communication of analytical results and data to extension workers in multiple languages. Projects are not yet reporting agronomic outcome data beyond user numbers and satisfaction. (De Clercq *et al.*, 2024)

Source: Authors' own elaboration.

Table 5: Examples of specific purpose AI used for climate and weather forecasting

Name	Description
Weather forecasting (e.g. GraphCast, Pangu-Weather)	Deep learning approaches for global weather forecasts reach accuracy of numerical forecasting with a smaller compute footprint. (Bi *et al.*, 2023; Lam *et al.*, 2023)
Multi-Hazard Early Warning Systems (e.g. UNDRR DesInventar, Famine Early Warning System Network, WFP HungerMap, EC-JRC MARS)	Machine learning models are being tested to extend traditional analysis and reporting systems(Hrast Essenfelder, Toreti and Seguini, 2025; Machefer *et al.*, 2025)
Satellite-based crop insurance and agricultural finance (e.g. SatSure, IBFI/IWMI)	Machine learning models integrating satellite imagery, weather, and IoT data to enable index-based insurance and credit scoring for smallholder farmers. (Benami *et al.*, 2021; Nguyen *et al.*, 2025b)

Source: Authors' own elaboration.

Table 6: Examples of specific purpose AI used for commodity prices prediction

Name	Description
Market information systems for smallholders (e.g. SMS-based price alerts)	SMS-based market information are not AI-based. Studies in Ghana and Malawi have found small effects on earnings improvements for smallholders. (Chikuni and Kilima, 2019; Soldani, 2014)
Commodity price prediction models (e.g. agricultural futures forecasting in China (Zhang *et al.*, 2024))	Machine learning and deep learning models are used to predict prices of staple crops. deep learning tools outperform simpler machine learning solutions, but the latter remain more explainable. (Manogna, Dharmaji and Sarang, 2025; Theofilou *et al.*, 2025)

Source: Authors' own elaboration.

Table 7: Examples of uses of blockchains along value chains

Name	Description
Moyee Coffee blockchain	Blockchain coffee for transparency and fair pricing. (Moyee Coffee, undated)
BlocRice (Oxfam)	Blockchain tracing of organic rice production origins and supply chain conditions in Cambodia. (Oxfam, undated)
AgriLedger	Ledger-based services for development objectives. Notable case study in Haiti in 2019 claims great improvements on farmer productivity and supply chain efficiency. (Bhusal, 2021)

WFP Route The Meals	Optimization tool for delivery networks and routes. (WFP, 2025)

Source: Authors' own elaboration.

Table 8: Examples of specific purpose AI uses for food quality and -safety assessments

Name	Description
Vision-Based Methods for Defect Detection and Grading (e.g. IntelloLabs ShelfEye)	Machine learning, specifically computer vision is used to extract relevant features from images of shelved food. They perform well at detecting physical defects. (Intello Labs, undated; Liakos *et al.*, 2025)
Nemesyst (retail refrigeration AI)	Deep learning tool optimizing retail refrigeration while ensuring food safety temperature limits. (Onoufriou *et al.*, 2019)

Source: Authors' own elaboration.

Table 9: Examples of FSN data exchanges

Name	Description
AgriStack India	Federated farmers' database linking land records, crop data, and input access. Farmer representatives criticized it for centralizing farmer data in private hands without consultation. (Balkrishna *et al.*, 2023; Subramaniam, 2021)
KIAMIS Kenya	Digital public infrastructure that links farmer registry, subsidy management and agro-meteorological data. It currently reaches 130,000 farmers. (AIRC, 2026; World Bank, 2025a)
Smart Milk Platform (Kazakhstan)	Sector data-sharing platform linking dairy farmers, processors and service providers for traceability, food-safety compliance and value-chain coordination; illustrates governance arrangements for data sharing. (FAO, 2020)
China rural e-commerce / digital agriculture ecosystem	Digital marketplaces, logistics, payments and agricultural data platforms connecting smallholders to markets. (Hernandez *et al.*, 2024)

Source: Authors' own elaboration.

Table 10: Examples of generalist AI applications providing nutritional advice:

Name	Description
ZOE	Personalized nutrition programme combining at-home testing with digital coaching to improve metabolic health markers and dietary habits. (Bermingham *et al.*, 2023; ZOE Limited, 2026)
Viome	At-home microbiome testing with AI/machine learning-driven analysis and personalized diet/supplement recommendations. (Viome Life Sciences, Inc, 2026)
American Gut	Open citizen-science microbiome research platform; large-scale microbiome dataset enabling research

	and downstream nutrition/health insights. (McDonald *et al.*, 2018)
NutriGen	Personalized meal plan generator leveraging large language models to improve dietary and nutritional adherence. (Khamesian *et al.*, 2025)
NIPN Lao PDR	AI-enabled national nutrition information platform that processes multisectoral data and generates plain-language policy summaries. Government-owned, EU/UNICEF-supported. Not consumer-facing. (NIPN, undated)
VIVID (Alive & Thrive / FHI 360)	Supervised ML and NLP tool monitoring digital marketing of breastmilk substitutes for violations of the WHO International Code. Deployed in Viet Nam and extended to nine countries. Detected 3,000+ violations over 12 months. (Backholer *et al.*, 2025)
Image-based dietary assessment (research prototypes)	Deep learning (CNN) models for food image classification, portion size estimation and nutrient content prediction. High accuracy on benchmark datasets; limited real-world consumer uptake and validation outside high-income food cultures documented so far. (Agrawal *et al.*, 2025)

Source: Authors' own elaboration.

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