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ARTIFICIAL INTELLIGENCE FOR AGRICULTURAL SUPPLY CHAIN RISK MANAGEMENT:

CONSTRAINTS AND POTENTIALS

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CGIAR Platform for Big Data in Agriculture

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ABSTRACT

Supply chains of staple crops, in developed and developing regions, are vulnerable to an array of disturbances and disruptions. These include biotic, abiotic and institutional risk factors. Artificial intelligence (AI) systems have the potential to mitigate some of these vulnerabilities across supply chains, and thereby improve the state of global food security.

However, the particular properties of each supply chain phase, from "the farm to the fork," might suggest that some phases are more vulnerable to risks than others. Furthermore, the social circumstances and technological environment of each phase may indicate that several phases of the supply chains will be more receptive to AI adoption and deployment than others.

This research paper seeks to test these assumptions to inform the integration of AI in agricultural supply chains. It employs a supply chain risk management approach (SCRM) and draws on a mix-methods research design.

In the qualitative component of the research, interviews are conducted with agricultural supply chain and food security experts from the Food and Agricultural Organization of the UN (FAO), the World Bank, CGIAR, the World Food Program (WFP) and the University of Cambridge.

In the quantitative component of the paper, seventy-two scientists and researchers in the domains of digital agriculture, big data in agriculture and agricultural supply chains are surveyed. The survey is used to generate assessments of the vulnerability of different phases of supply chains to biotic, abiotic and institutional risks, and the ease of AI adoption and deployment in these phases.

The findings show that respondents expect the vulnerability to risks of all but one supply chain phases to increase over the next ten years.

Importantly, where the integration of AI systems will be most desirable, in highly vulnerable supply chain phases in developing countries, the potential for AI integration is likely to be limited.

To the best of our knowledge, the methodical examination of AI through the prism of agricultural SCRM, drawing on expert insights, has never been conducted. This paper carries out a first assessment of this kind and provides preliminary prioritizations to benefit agricultural SCRM as well as to guide further research on AI for global food security.

KEYWORDS
Artificial Intelligence, Agriculture, Supply Chain Risk Management, Food Security

TABLE OF CONTENTS

01 INTRODUCTION

Food security has been defined by the Food and Agricultural Organization of the UN as a state in which all people, at all times, have access to food to meet their dietary needs and preferences.[1] This state can only be sustained by the continuous production, processing and provision of nutritionally adequate, safe and affordable agricultural commodities.

Therefore, global food security depends on effective, efficient and risk-resilient agricultural food supply chains.[2,3,4,5,6,7,8,9,10,11] That being so, agricultural supply chain risk management (SCRM) is crucial for achieving global food security.[12]

The crux of supply chain risk management is the identification of supply chain vulnerabilities, the assessment of risks that the supply chain may be exposed to, and the actions prescribed to mitigate vulnerabilities and risks; actions referred to as either ex-ante or ex-post risk management measures.[13,14,15,16,17,18,19] An extensive catalogue of ex-ante and ex-post measures is proposed in the literature to mitigate risks in agri-food supply chains.[20,21,22,23,24,25,26]

More recently, scientists have recognized that emerging technologies can contribute to the mitigation of different types of supply chain inefficiencies, losses and risks, and to improve the overall agri-food system's resilience, in order to achieve global food and nutritional security. "It is essential," note Cole et al., "to explore how innovations from [...] data science, robotics, artificial intelligence [...] impact on food security."[27]

Of these emerging technologies and techniques, artificial intelligence (AI) systems are likely to have significant applications for SCRM, and thereby to improve the state of global food security.

1.1 ARTIFICIAL INTELLIGENCE

AI refers to a set of technologies that carry out functions that we traditionally think of as requiring human intelligence. They are computer systems that are used to identify objects, recognize patterns and anomalies, solve problems, allocate resources optimally, navigate, predict failures, make personalized recommendations, and learn.[28] For certain cognitive functions, such as patterns and anomalies recognition, several AI systems can exceed human performance.[29,30,31] *

AI is often used to control robots, autonomously or under the direction of a human. With robotics, AI could replace or aid humans in routine work in industrial-scale production, in domains where manual work can be done by robots; this is referred to as robotics process automation (RPA).

1.2 ARTIFICIAL INTELLIGENCE IN AGRICULTURAL SUPPLY CHAINS

Over the next decade, the time frame allotted to meet the second sustainable development goal of ending hunger, AI systems are expected to have the potential to benefit the global agricultural system in numerous important ways. They can increase crop and livestock yields, decrease food loss and waste, and allocate resources optimally.[32,33,34,35,36,37,38]

Several studies have outlined and illustrated these options, and AI systems and networks, in combination with smart sensors, communication technologies, big data sets and robotics, are already being experimented with and integrated in various phases of the global food chain.†

Examples include detection and diagnostics of plant diseases and pests,[39,40,41,42,43] protection of aquaculture from bacteria,[44] modelling soil physicochemical properties and composition,[45] simulating and evaluating future degradation of the biophysical environment emanating from land clearing for food production,[46] supporting farmers' choices in crop cultivation through the analysis of data collected and transmitted by sensors,[47] substituting animal pollination in farming with artificial pollinators,[48] informing national agricultural policies through prediction of gaps between food production and eating,[49] tracking and tracing agricultural commodities along shipping routes,[50] targeting food-insecure populations,[51] detecting real-time outbreaks of food-borne diseases, [52] recognizing and assessing risks to yields under warmer temperatures and climate variability, simulating future yield performance in different environments, and identifying improved agricultural management practices.[53]

Given that AI systems show potential for widespread applications across supply chains, there is a need to conduct a more comprehensive examination of deployment constraints and deployment potentials of AI through the prism of SCRM.

Several motivations warrant such a systemic analysis. First, the theory of SCRM notes that some phases of the supply chain are more vulnerable than others. Different phases are exposed to different types of risks and disturbances. These risks have different probabilities of occurrence, and an array of possible detrimental consequences.[54]

* As a category, AI encompasses a range of different types of systems, such as rule-based systems, in which human-crafted sets of rules are used to manipulate information and produce outputs, and machine learning systems, in which algorithms and statistical models rely on large quantities of data, referred to as big data, to carry out pattern identification and inference, producing predictions, decisions or actions for a particular task. Rule-based AI, and other AI techniques are all used, at times in combination, in a wide range of contexts. However, AI systems cannot be applied in all contexts, and typically require various types of additional information and infrastructure. Machine learning (ML), for example, typically requires carefully curated training datasets in order to train a model to perform well on a task, as well as 'live' data relating to the task in question in order to take the correct actions. Rule-based systems require a high degree of expert knowledge and design relating to the task to be used in the design and application of the system. Therefore, for AI systems to be applied successfully, additional resources may be necessary, such as high-quality labelled and unlabeled data, computing hardware, sensors for collecting input data, and actuators for taking action in the world. Human expertise on the use and limitations of AI is also necessary.

† In this paper, the concepts "agricultural supply chain", "food supply chain", "agri-food supply chain" and "food chain" are used interchangeably.

An assessment of supply chain phases of disproportionate vulnerability should inform policies for the implementation of appropriate vulnerability mitigation measures.[55,56,57]

Relatedly, the risk literature acknowledges distinctions between food chains in developing countries and developed ones in terms of institutions, inefficiencies, vulnerabilities, and risk-environments. This acknowledgement has led to a series of studies focused on supply chains in developing countries.[58,59,60,61,62,63,64]

To this end, not all supply chain phases will present conducive environments for immediate AI integration. Constraints such as insufficient, inadequate or otherwise scarce technological infrastructure, for example sensors and broadband internet, human capital, for instance technological literacy, or operational standardizations of processes and data – will limit the opportunity for near-term application of AI.

It is significant that not all agricultural activities are food-related. For example, crops are often cultivated for fibers and fuels. Importantly, within the broad category of food and feed crops, a minority of just four cultivars, wheat, maize, rice and soybean, comprise approximately 50 percent of total croplands. Global food security is overwhelmingly dependent on these four staple crops, and as a result the integration of AI in agriculture should be prioritized for the supply chains of these staple crops first. In this regard, it should be stated that supply chains of storable, calorie-dense staple crops, i.e. high in starches, fats and proteins – the focus of this paper – are different from the supply chains of more perishable products such as fruits and vegetables.

In view of the above, it is reasonable to hypothesize that entire supply chains, and specific phases along supply chains, for which AI systems are most readily applicable may not be the most desirable ones, in terms of vulnerability and urgency.

Therefore, when the deployment of AI across the supply chains of staple crops is considered, supply chain phases should be assessed in two respects: (a) vulnerability and (b) receptiveness to AI. In particular, it is necessary to draw distinctions between supply chains of staples in developed countries, and those in developing ones.

02 METHODS AND MATERIALS

This paper assumes that differences between supply chain phases in developed and developing countries, in relation to vulnerability and ease-of-AI-deployment, exist. To test this assumption, the paper employed the SCRM perspective and a mixed-methods research design was preferred combining qualitative and quantitative approaches.

2.1 QUALITATIVE RESEARCH COMPONENT

First, we articulated a staple crops supply chain model.‡ The model, consisting of eight phases, was jointly created with five global agri-food supply chains and SCRM experts: two agricultural SCRM specialists at the Institute for Manufacturing in the University of Cambridge, one agri-food chains specialist from the Food and Agriculture Organization (FAO), one agri-food chains specialist from CGIAR, and one agri-food chains expert formerly with the World Bank and the UN World Food Program (WFP).

The supply chain that was eventually proposed and used in this research (see figure 1) is necessarily a simplified one.

Simplification of phases and functions was designed to provide a degree of generality so that the model would represent the four staple crops, wheat, maize, rice and soybean, and other cereals and legumes supply chains.

‡ Based on the view that, at present, global food security, the access to sufficient, safe and nutritious food that meets people's dietary requirements, depends on the production, processing and provision of a handful of agricultural commodities. Of the primary one-hundred global cultivated crops by land area, just four items comprise approximately 50% of total croplands (FAO STAT, 2017). These four items, wheat, maize, rice and soybean are considered the main plant-source foods (PSF) and are also referred to as global staple crops. In addition, the livestock industry and animal-source foods (ASF), which are comprised of chicken (and eggs), pork, beef (and milk) and fish, rely on cereal and legume crops as feed sources, primarily maize and soybean. These foods currently provide over a third of global protein intake and additional essential micro-nutrients. These dependencies narrow down the number of agri-food supply chains that ought to be prioritized for risk management – and in the context of this paper, for the integration of advanced technologies, namely AI – to just four supply chains (i.e. wheat, maize, rice, and soybean). This set or priorities sets clearer boundaries for the scope of the research.

FIGURE 1. AGRI-FOOD SUPPLY CHAIN MODEL

AGRI-FOOD SUPPLY CHAIN PHASES AND FUNCTIONS, IN DEVELOPED AND DEVELOPING COUNTRIES

	Supply chain echelons	Key functions in each echelon
1	PRODUCTION OF FARMING INPUTS	Particulary seeds - seed research - plant breeding - seed production - inspection and distribution
2	AGRICULTURAL PRODUCTION (FARMING AND HARVEST)	Soil testing - monitoring - preparation - farming inputs (seeds, fertilizers, pesticides) - cultivation and crops management - irrigation - harvest - initial handling and labeling
3	POST-HARVEST AGGREGATION, LOCAL TRANSPORT AND STORAGE	Transport to post-harvest storage at country elevators - warehouse and silos near field - warehouse and silos near field- sampling and inspection for defects - ventilation and moisture management - fumigating - grading and classification
4	TRADE AND MARKET INTERMEDIARIES	Price setting - trade at rural primary markets - assembly markets - wholesale markets
5	NATIONAL AND INTERNATIONAL TRANSPORT AND STORAGE	Temporary storage in lorries/trains - ventilation and moisture control - storage in warehouse in bulk cargo or in containers - hygiene and safety sampling and examining defects - grading, cleaning and certificacion - vessel inspection - cargo load and fumigation - cargo ventilation and moisture control on route - records keeping - sea voyage - ship discharge - inspection - transport of grain and legume for processing and manufacturing
6	PROCESSING AND MANUFACTURING	Primary and secondary processing - milling - refining and quality control for feed/food ingredients - livestock production and processing - food production and processing - packaging
7	RETAIL	Inventory management and forecasting - food ordering from manufacturers - food receival at distribution centers - customer demand forecasting - food receival at stores and markets
8	COMSUMPTION AND WASTE	Direct consumption from the farm - or indirect consumption from rural primary markets - assembly markets - wholesale markets - or retailers - waste management of sanitary surplus food from retailers and restaurants

2.2. QUANTITATIVE RESEARCH COMPONENT

In the second stage of the research, and with the supply chain model as a shared point of reference, we investigated how seventy-two scientists and researchers in the domains of digital agriculture, big data in agriculture and agricultural supply chains assess (a) the expected vulnerabilities of supply chains to risks and (b) the expected receptiveness of supply chain phases to AI systems.

Respondents were recruited from the 15 research centers of CGIAR. The analysis in this paper was based on data collated from an anonymized survey of those respondents. All respondents were members of one of six Communities of Practice (CoP) of CGIAR's Platform for Big Data in Agriculture. Therefore, all respondents were involved in initiatives to develop and deploy big data resources, and algorithms and models for the analysis of data sets, in agriculture and agricultural supply chains.

Some 51 of the 72 respondents attended CGIAR's Big Data in Agriculture 2019 Convention in India, led by the International Center for Tropical Agriculture (CIAT), the International Food Policy Research Institute (IFPRI) and hosted by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). Invitations to take part in the survey were sent out by email in the run-up to the convention in India via the CoP network, as well as in the proceedings of the convention. Experts were surveyed either online or at the convention. In both circumstances, participants were given at least three days to complete the in-depth questionnaire.

We used a standardized questionnaire based on the staple crops supply chain model (figure 1). The survey comprised three sections, with two questions in the first section, two questions in the second section, and a third section in which personal information was elicited for screening purposes.

After obtaining respondents' consent to participate, we asked respondents to carefully review the agricultural supply chain model, its phases and functions. Respondents reviewed the supply chain model again, before each of the four questions.

The first section of the survey assessed staple crops supply chain vulnerabilities. In the first question, we instructed respondents to deliberate over various categories of vulnerabilities of the eight-phases supply chain model, and provided them with vulnerability categories and risk examples. These included biological, environmental, weather-related, infrastructural, operations-related, economic, institutional, and social and political vulnerabilities and risks.

We then asked respondents to assess the expected vulnerability of each supply chain phase in developed regions and countries which lead staple crops production, processing and provision, focusing on North America; the US and Canada, within the next ten years.

Respondents provided a numerical value on a scale of 1-100, where 1 is "not at all vulnerable to risks", and 100 is "extremely vulnerable to risks". In addition, numerical value was situated within one of five score bands: 1-20 for "not at all vulnerable to risks", 21-40 for "slightly vulnerable to risks", 41-60 for "moderately vulnerable to risks", 61-80 for "very vulnerable to risks", and 81-100 for " extremely vulnerable to risks". This allowed the generation of a heat map (see section 3, Findings).

The second question in the first section requested experts to assess the expected vulnerability of each supply chain phase in the next ten years, this time focusing on developing regions and countries which lead staple crops production, processing and provision: South East Asia and South America; China, India, Bangladesh, Indonesia, Vietnam, Brazil and Argentina.

The second section of the questionnaire focused on the ease of AI deployment across the same supply chain phases, in different regions.

In the first question of the second section, respondents were asked to score each supply chain phase in developed regions and countries, focusing, again, on North America; the US and Canada, by the expected receptiveness of the supply chain phase to AI integration over the next ten years. Respondents used a scale of 1-100, where 1 represents "not at all receptive to AI integration", and 100 represents "extremely receptive to AI integration". The numeric value for each supply chain phase was situated within one of five score bands: 1-20 for "not at all receptive to AI integration", 21-40 for "slightly receptive to AI integration", 41-60 for "moderately receptive to AI integration", 61-80 for "very receptive to AI integration", and 81-100 for "extremely receptive to AI integration".

Before respondents made assessments, they were asked to deliberate over the state of information and communication technology (ICT) infrastructures in developed regions today, and over the next ten years, as well as the non-technical factors influencing technological spread and access over the next ten years – i.e. availability and affordability of AI systems for each agricultural supply chain phase, AI supporting infrastructures, and the ability of individuals to apply and use AI systems, machines and networks as well as their knowledge of such systems.

We provided a definition of AI, followed with a short description of the infrastructure typically needed to support the use of AI systems. We defined AI as a set of technologies that mimic cognitive functions. They are computer systems that have some of the qualities that the human mind has, such as the ability to identify objects, recognize patterns and anomalies, solve problems, allocate resources optimally, , navigate, predict failures, make personalized recommendations, and learn. We defined AI supporting infrastructure as the devices necessary to accumulate and analyze big data for decision making including data collection, transmission, storage, processing, cleaning, and analysis apparatuses, for instance, sensor technology, broadband internet, satellite technology, mobile technology and global positions systems.

In the second question of the second section, respondents scored each supply chain phase for ease of AI deployment in the previously-examined group of developing regions and countries: South East Asia, including China, India, Bangladesh, Indonesia and Vietnam, and South America, including Brazil and Argentina.

The third part of the survey contained questions about employment and the educational background of participants. We did not elicit additional personal characteristics of respondents, such as gender and nationality. We excluded questionnaire respondents who were not employed with CGIAR and did not meet the professional and educational level criteria from our sample. Since most CGIAR centers are in developing regions, we were able to avoid potential knowledge biases.

Data analysis was carried out using descriptive statistics. The complete and anonymized data elicited in the questionnaire is available in a supplementary file (see AI in Ag-SCRM Experts Survey Output Data 2019).

03 FINDINGS

Questionnaire results indicate that, within the next ten years, experts anticipate nearly all phases and functions in all regions will become more vulnerable to risks. With the sole exception of Pre-Production of Farming Inputs in developed countries, no phase was found "not at all vulnerable" to disturbances.

Put differently, over the next ten years, in the production, harvest, handling, processing and provision of staple crops, everywhere, vulnerability to risks is expected to increase, thereby jeopardizing global food security.

3.1. VARYING DEGREES OF VULNERABILITY

Results have confirmed the research assumption, and varying degrees of vulnerability across supply chain phases were registered.

With comparatively high mean score, symbolized here with $\bar{x}$, and comparatively low standard error of the mean score, symbolized here with σ_{M}., the phases of Agricultural Production ($\bar{x}$ =64.15, σ_{M}.=1.8 in developed countries; $\bar{x}$ =75.75, σ_{M}.=1.5 in developing countries), Post-harvest Aggregation, Local Transport and Storage ($\bar{x}$ =52.06, σ_{M}.=1.63 in developed countries; $\bar{x}$ =69.29, σ_{M}.=1.93 in developing countries), and National Transport and Storage ($\bar{x}$ =47.69, σ_{M}.=1.86 in developed countries; $\bar{x}$ =51.58, σ_{M}.=2.23 in developing countries), were noted for greater vulnerability to risks in both developing and developed countries, warranting particular attention.

Results further indicate that there exist significant differences between supply chain vulnerabilities in developing countries and developed ones: every single supply chain phase in developing countries received an average vulnerability score higher than the same phase in developed countries, standard errors taken into account.

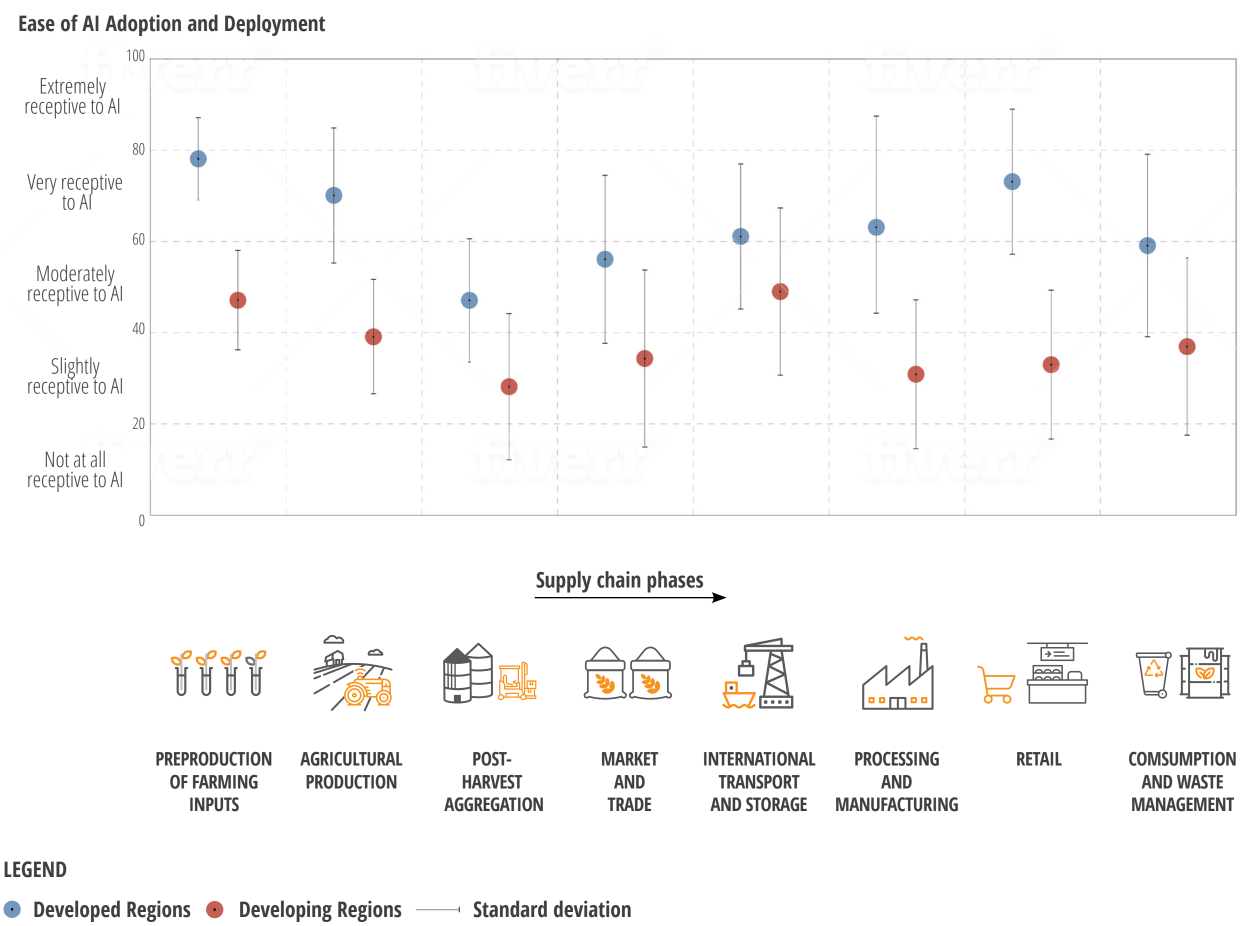
3.2. AI DIVIDE ACROSS REGIONS AND SUPPLY CHAINS PHASES

Analyzing and comparing assessments for the ease of integration of AI systems, and AI-supporting infrastructures, in developed and developing regions, we receive the opposite picture.

Over the next ten years, the receptiveness of supply chain phases to AI systems in developed countries is estimated to surpass significantly that in developing countries, not only in overall average aggregate score (63.26 versus 37.39, correspondingly) but for each supply chain phase in separate, standard errors considered.

The largest differences were recorded in the Retail, Agricultural Production, Production of Farming Inputs and Processing and Manufacturing phases (see figure 2).

FIGURE 2. THE AI DIVIDE IN AGRICULTURAL SUPPLY CHAINS, BY TYPE OF REGION.



Experts estimated that within the next ten years, Pre-Production of Farming Inputs ($\bar{x}$ =78.14, σ_{M}.=2.42), Agricultural Production ($\bar{x}$ =70.05, σ_{M}.=1.29), Trade and Market Intermediaries ($\bar{x}$ =55.58, σ_{M}.=2.19), National and International Transport and Storage ($\bar{x}$ =61.33, σ_{M}.=2), Processing and Manufacturing ($\bar{x}$ =62.83, σ_{M}.=2.08), and Retail ($\bar{x}$ =72.83, σ_{M}.=2.52) in developed countries will become "Very receptive" to AI integration.

However, no supply chain phase in developing regions received a score in the "Very receptive" score band, and only two supply chain phases in developing regions received a score in the "Moderately receptive to AI integration" score band: Pre-Production of Farming Inputs ($\bar{x}$ =46.8, σ_{M}.=2.16) and National and International Transport and Storage ($\bar{x}$ =49.2, σ_{M}.=2.09).

The research findings are summarized in two integrated maps: Figure 3 refers to staple crops' producers, processors and providers in North America, and Figure 4 refers to staple crops' producers, processors and providers in South America and South East Asia.

FIGURE 3. INTEGRATED ASSESSMENTS OF SUPPLY CHAIN PHASES' VULNERABILITY TO RISK (X AXIS), AND EASE-OF-AI DEPLOYMENT (Y AXIS), IN DEVELOPED COUNTRIES.

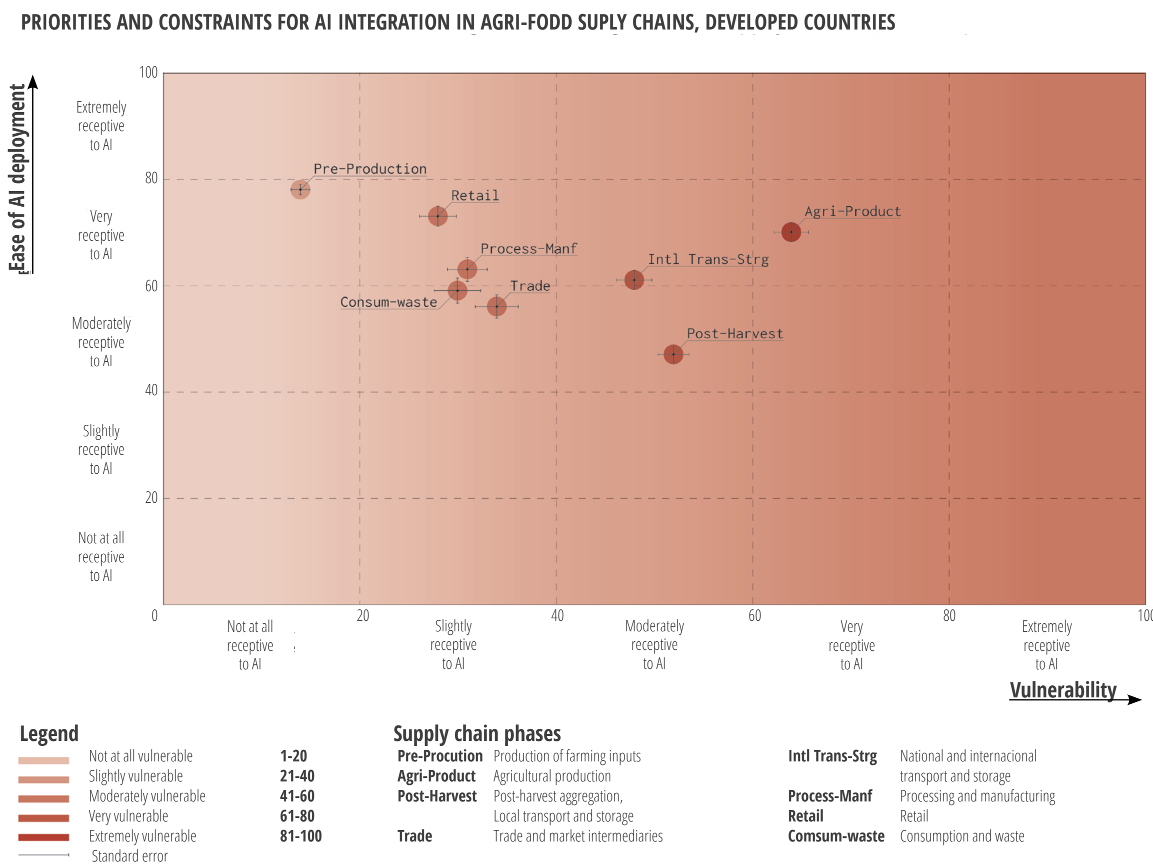
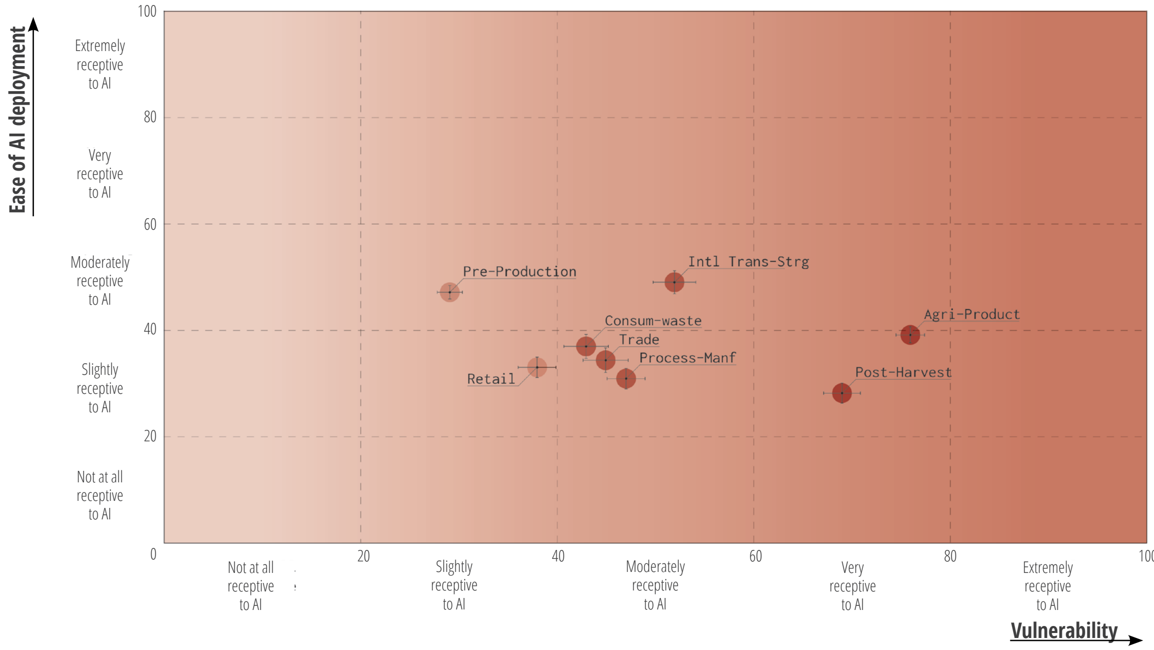


FIGURE 4. INTEGRATED ASSESSMENTS OF SUPPLY CHAIN PHASES' VULNERABILITY TO RISK (X AXIS), AND EASE-OF-AI DEPLOYMENT (Y AXIS), IN DEVELOPING COUNTRIES.

PRIORITIES AND CONSTRAINTS FOR AI INTEGRATION IN AGRI-FODD SUPLY CHAINS, DEVELOPING COUNTRIES



Legend

	Not at all vulnerable	**1-20**
	Slightly vulnerable	**21-40**
	Moderately vulnerable	**41-60**
	Very vulnerable	**61-80**
	Extremely vulnerable	**81-100**
	Standard error	

Supply chain phases

Pre-Procution	Production of farming inputs
Agri-Product	Agricultural production
Post-Harvest	Post-harvest aggregation, Local transport and storage
Trade	Trade and market intermediaries
Intl Trans-Strg	National and internacional transport and storage
Process-Manf	Processing and manufacturing
Retail	Retail
Comsum-waste	Consumption and waste

04 CONCLUSIONS

This research examined supply chains of staples for two distinct sets of socio-economic, socio-technical and environmental conditions: the first in developed regions, and the second in developing ones. Comparisons of rankings yield several conclusions.

First, although agricultural supply chain vulnerabilities in developing regions are projected to exacerbate, there are limits to the extent that AI can be applied as a way of mitigating vulnerabilities and improving food security.

In other words, where AI is needed the most according to experts, i.e. highly vulnerable phases, the prospects for AI integration are estimated to be most limited.

In contrast, while supply chains in developed countries are less vulnerable than those in developed countries, they were found significantly more receptive to AI technologies.

With regards to the prioritization of AI deployment in agri-food supply chains, one further observation is worth noting.

The phase of Pre-production of Farming Inputs, which refers to the research and development of seed varieties, plant breeding, seed production, inspection and distribution, was found to be highly suitable for AI integration while also being assessed as less vulnerable to risk.

Technological interventions in this earlier stage of the supply chain show considerable potential for improving food security; examples include the use of sophisticated bioinformatics and bioengineering methods to produce genetically modified, weather-resistant crops. The use of AI is likely to complement such approaches well. Hence the integration of AI in this phase warrants prioritizing, in spite of a low score on vulnerability to risk.

4.1. CAVEATS AND IMPLICATIONS FOR FUTURE RESEARCH

This research carried out an initial assessment of AI deployment potential and constraints across global supply chains. In exploring the potential for AI to aid in the mitigation of agricultural supply chain vulnerabilities, this study prioritized generalizability over specificity and nuance.

Consequently, this paper distinguished between two categories of staple crops producers, processors and providers: developing and developed countries. While this strategy allowed the elicitation of some general observations and identified priority intervention areas, it is well-acknowledged that socio-economic, socio-technical and environmental conditions vary vastly from country to country within each region.

Different social and geographical conditions will yield different risk environments, and this has further implication for the manner in which AI can and should be applied. The most valuable applications of AI are likely to mitigate specific risks (e.g. plant pests and diseases) rather than playing a role in reducing general vulnerability.

Future research should therefore analyze supply chains phase-by-phase if not function-by-function (e.g. diagnosing plant diseases, inspecting produce for defects), and should do so risk-by-risk and AI application-by-application.

It will also be necessary to perform analysis region-by-region and country-by-country. Such analysis would provide insights that would be more sensitive to specific risks and circumstances.

05 SUMMARY

This paper began from the view, generally accepted by the literature, that agricultural supply chain risk management – the implementation of measures to mitigate risks along the food supply chain – is essential for achieving and maintaining global food security.

Focusing on the supply chains of staple crops and on AI as a risk mitigation measure, this paper carried out an initial assessment of AI deployment options in both developed and developing countries, accounting for both comparative vulnerability of phases and comparative receptiveness to AI systems for the next ten years.

Some 72 global experts were surveyed for this purpose. Through the questionnaire, the anticipated vulnerability of supply chain phases was empirically analysed. This was followed by an assessment of ease-of-AI-deployment across supply chain phases in two categories of staple crops' "breadbaskets": a set of developed countries and a set of developing ones.

The results suggest that, for the next ten years (2020-2030), where AI will be needed the most, in highly vulnerable supply chain phases in developing regions and countries, its integration is estimated to be most restricted.

On the contrary, although agricultural supply chains in developed countries were estimated less vulnerable than those in developed countries, they were found significantly more receptive to AI experimentation and integration over the next ten years.

Only very cautious conclusions are possible, as distinguishing between two categories of global breadbaskets – developing and developed – may be too broad an approach to devise local interventions. Specifically, different local circumstances yield different risk environments, and this has further implication for the type of AI that can be employed.

DECLARATIONS

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CONFLICT OF INTEREST

The author declares no conflict of interest.

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