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# ARTIFICIAL INTELLIGENCE FOR AGRICULTURAL SUPPLY **CHAIN RISK MANAGEMENT**

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# ARTIFICIAL INTELLIGENCE FOR AGRICULTURAL SUPPLY CHAIN RISK MANAGEMENT

## PRELIMINARY PRIORITIZATIONS AND CONSTRAINTS FOR THE DEPLOYMENT OF AI IN FOOD CHAINS ASSESSED BY CGIAR SCIENTISTS

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CENTRE FOR THE STUDY OF EXISTENTIAL RISK


# ABSTRACT

**PURPOSE:** This paper seeks to propose priorities and support the integration of artificial intelligence (AI) in agricultural supply chains for the next ten years (2020-2030), with the aim of reducing supply chain vulnerabilities and to contributing to global food security.

**METHODOLOGY AND APPROACH:** Qualitative interviews with food chains and food security specialists from the FAO, the World Bank, CGIAR, WFP and the University of Cambridge, and an exploratory quantitative survey of 72 CGIAR scientists and researchers are used to derive integrated assessments of the vulnerability of different phases of supply chains and the ease of AI adoption and deployment in these phases. The integrated assessments are structured across food chains in developed and developing regions.

**FINDINGS:** The research shows 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 will be most desirable, in highly vulnerable supply chain phases in developing countries, the potential for AI integration is estimate to be limited.

**ORIGINALITY:** The methodical examination of AI through the prism of agricultural supply chain risk management (SCRM), drawing on insight from experts in food chains, food security, and big data and agriculture, has never to our knowledge been conducted. This paper carries out a first assessment of this kind and provides preliminary insights 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**

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# 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 (FAO, 1996[1]). This state can only be sustained by the continuous production, processing and provision of nutritionally adequate, safe and affordable agricultural commodities.

Food security , therefore, depends on effective, efficient, risk-resistant and risk-resilient agri-food supply chains (Douglas, 2009[2]; McGill, 2009[3]; Krejci and Beamon, 2010[4]; Mohan et al., 2013[5]; Garnett, 2014[6]; Grote, 2014[7]; Reardon and Timmer, 2014[8]; Soussana, 2014[9]; Macfadyen et al., 2015[10]; Paloviita and Järvelä, 2015[11]).

For example, Macfayden et al. (2015:1) argue that "We [...] need a resilient food supply sytem that is robust enough to absorb and recover quickly from shocks, and to continuously provide food in the face of significant threats."

That being so, agri-food supply chain risk management (SCRM) is crucial for achieving global food security (Jaffee et al., 2010[12]).

The crux of supply chain risk management is the acknowledgement and assessment of the risks that the supply chain may be exposed to, i.e. identifying supply chain vulnerabilities (see: Peck, 2006[13]; Wieland and Wallenburg, 2012[14]), and the actions prescribed to mitigate these impending risks and vulnerabilities – actions referred to as either *ex-ante* or *ex-post* risk management measures (Jüttner, 2003[15]; Jüttner, 2005[16]; Manuj and Mentzer, 2008a[17]; Tang and Musa, 2011[18]; Septiani et al., 2016[19]).

An extensive catalogue of *ex-ante* and *ex-post* measures is proposed in literature to manage and mitigate risks in agri-food supply chains (Ritchie and Brindley, 2007a[20]; Ritchie and Brindley, 2007b[21]; Manuj and Mentzer, 2008b[22]; Zsidisin and Ritchie, 2008[23]; Tummala and Schoenherr, 2011[24]; Ghadge et al., 2012[25]; Chopra and Sodhi, 2014[26]).

More recently, the scientific community has recognized that emerging technologies have the potential to 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. (2018:14) "to explore how innovations from [...] data science, robotics, artificial intelligence [...] impact on food security".[27]

Of these innovations, artificial intelligence (AI) is likely to have significant applications for supply chain risk management.

## 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, optimize resource allocation, navigate, predict failures, make personalized recommendations, and learn (Li and Du, 2017:1[28]). For certain cognitive functions (e.g. patterns and anomalies recognition), they can exceed human performance (Patterson, 1990[29]; Kurzweil, 2006[30]; Brundage et al., 2018[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 industries where manual work can be robotized, referred to as robotics process automation, or 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 (SDG2), AI systems are expected to have the potential to benefit the global agricultural system in a number of important ways; including contributing to the challenges of decoupling food production from environmental pressures, enhancing crop management, and identifying and responding to agricultural diseases more rapidly.

Several studies have discussed these options, and AI and robotics systems and networks are already being experimented with and integrated in various echelons of the food chain.†

Examples include detection and diagnostics of plant diseases and pests (Abu-Naser et al., 2010[32]; Patil and Kumar, 2011[33]; Hughes and Salathé, 2015[34]; Ferentinos, 2018[35]; Selvaraj, 2019[36]), protection of aquaculture from aquatic bacteria and viruses (Drillet, 2016[37]), modelling soil physicochemical properties and composition (Akbarzadeh et al., 2009[38]), simulating and evaluating future degradation of the biophysical environment emanating from deforestation for food production (Francesconi, 2015[39]), supporting farmers' choices in crop cultivation through the analysis of data collected and transmitted by sensors (Cosmin, 2011[40]), substituting

* As a label, AI covers 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 typically large quantities of data to carry out pattern identification and inference, producing predictions, decisions or actions for a particular task). Rule-based AI, machine learning, and other AI techniques are all used, sometimes in combination, in a wide range of contexts across industries. 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, 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 research, the concepts of "agricultural supply chain", "food supply chain", "agri-food supply chain" and "food chain" were used interchangeably.

animal pollination in farming with artificial pollinators (Chen and Li, 2019[41]), informing national agricultural policies through prediction of gaps between food production and consumption (Omran, 2010[42]), tracking and tracing agricultural commodities along shipping routes (Chen, 2005[43]), targeting food-insecure populations (Barbosa and Nelson, 2016[44]), detecting real-time outbreaks of food-borne diseases (Sadilek et al., 2016 [45]), 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 (Matthews et al., 2013[46]).

However, the methodical examination of the role of AI in mitigating agri-food supply chain vulnerabilities, has never, to our knowledge, been rigorously assessed.

There are several motivations for this systemic analysis of the potential applications of AI to agri-food supply chains for the purpose of improving global food security.

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 prospects and probabilities of occurrence, and an array of possible detrimental consequences (Waters, 2011[47]). An identification of areas of disproportionate vulnerability within the supply chain structure would inform priorities for the implementation of appropriate vulnerability mitigation measures (Chapman et al., 2002[48]; Wagner and Bode, 2006[49]; Wu and Blackhurst, 2009[50]).

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 examinations focused on supply chains in developing countries (e.g. Aruoma, 2006[51]; Sartorius and Kirsten, 2007[52]; Rich et al. 2009[53]; Henson and Humphrey, 2010[54]; Parfitt et al., 2010[55]; Rich et al., 2011[56]; Sodhi and Tang, 2014[57]).

Of course, not all agricultural activities are food-related, for example the cultivation of plants for fibers and fuels, and within the broad category of food and feed crops, a minority of just four cultivars -- wheat, maize, rice and soybean -- comprise approximately 50% of total croplands (FAOSTAT, 2017). Global food security is overwhelmingly dependent on those four crops, and as a result the experimentation and integration of AI in agriculture should be prioritized for these crops supply chains first from the perspective of mitigating major vulnerabilities.

In addition, not all supply chain phases present conducive environments for immediate AI integration and effective risk mitigation. The applicability of AI to these phases varies by location. Constraints such as insufficient, inadequate or otherwise scarce technological infrastructure, for example sensors and broadband internet, human capital, for instance skills and technological literacy, or operational standardizations – of processes, of data – will limit the opportunity for near-term application of AI and robotics.

As a result, the phases of supply chains for which application of AI is most readily applicable may not be the most desirable ones in terms of reducing vulnerability and enhancing food security: AI and robotics will have many applications within food chains, but not all will be equally impactful in mitigating vulnerabilities, and some of most vulnerable phases of particular supply chains may not be yet ready for the application of AI.

When the deployment of AI across the supply chains of staple crops is assessed, supply chain phases should be prioritized in two respects: (a) vulnerability to risks and (b) receptiveness to AI machines, systems and networks. Distinctions should be drawn in particular between the supply chains for staple crops in developed countries, and those in developing ones.

# 02 METHODS AND EMPIRICAL APPROACH

In this paper, we sought to prioritize agri-food supply chain phases for AI deployment in developing and in developed regions for the next ten years (2020-2030). For prioritization, a SCRM-focused approach was used.

## 2.1 QUALITATIVE COMPONENT: INTERVIEWS AND LITERATURE REVIEW TO ARTICULATE A SUPPLY CHAIN MODEL

First, we articulated a supply chain model based on a synthesis of secondary literary sources, by means of literature review, and interviews of five specialists, through which our model of the phases and functions of the supply chain for staple crops was refined.

A literature review of papers as well as manuals of institutions that the international community has established to address issues of food security and agri-food supply chain risk management (e.g. the World Bank Group, The FAO), was complemented with semi-structured in-depth interviews of two agri-food supply chain risk management specialists associated with the Institute for Manufacturing (IfM) at the University of Cambridge, one food chains and food security specialist from the Food and Agriculture Organization (FAO), one food security specialist associated with the Consultative Group for International Agricultural Research (CGIAR), and one food chains and food security specialist formerly with the World Bank and the UN World Food Program (WFP).

Each semi-structured in-depth interview referred to an initial supply chain model of 14 phases (i.e. echelons), and over the course of 60-90 minutes, each interviewee was asked to both abridge and refine the model in an attempt to achieve a degree of representativeness of the primary cereal and legume supply chains. ‡

Based on these five interviews, an eight-phase supply chain model was developed, and for each phase the critical functions, sites and stakeholders were identified.

‡ 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 (FAOSTAT, 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 prioritization sets clearer boundaries for the scope of the research.

The supply chain that was eventually modeled 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 (i.e. wheat, maize, rice and soybean), while also being suitable for representation of other cereal and legume supply chains.

## 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 managemente and forecastinga - food ordering from manufacturers - food receival at distribution centers - customer demand forecasting - food receival at storages 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 COMPONENT: SURVEYING 72 CGIAR EXPERTS

In the second stage of the research, and with the supply chain model as a shared point of reference (figure 1), we investigated how experts involved in scientific, technological and policy efforts relating to food security, agricultural SCRM and digital agriculture assess (a) the vulnerabilities of supply chains to risks and (b) the expected receptiveness of supply chain phases to AI systems, as means to mitigate vulnerabilities.

For the purpose of this research, we defined digital agriculture as an umbrella term that covers technologies for the entire agri-food value chain: on-farm technologies, like crop mapping, navigation systems, precision agriculture and ag-bots (i.e. agricultural automation including soil maintenance, weeding, irrigating, harvesting, picking, etc.), climate warning systems, digital extension services, machinery sharing and rental platforms, commodities e-trading and e-commerce platforms, warehouse/country elevators tracking and receipt systems, blockchain for food traceability, and consumer applications, among others.

The analysis in this paper was based on data collated from an anonymized survey of 72 food security, food supply chains, and digital agriculture researchers and scientists. Respondents were recruited from the 15 research centers of the Consultative Group for International Agricultural Research (CGIAR). All respondents were members of one of six Communities of Practice (CoP) of CGIAR's Platform for Big Data in Agriculture. Therefore, all respondents are involved in different capacities in initiatives to leverage technological systems and new data resources to create broader and deeper impact in agricultural-related programming, as well as to build capacity internally and externally on big data approaches in agriculture.

Specifically, respondents surveyed were engaged in data-driven agronomy, crop systems modelling, geospatial data and analysis, livestock and data modeling, socio-economic data, and data harmonization at the levels of collection and storage, and for data interoperability and data discovery.

Furthermore, 51 of the 72 respondents attended CGIAR Platform for Big Data in Agriculture's 2019 Convention in India, entitled *Trust: Humans, Machines & Ecosystems*, led by the International Center for Tropical Agriculture (CIAT), the International Food Policy Research Institute (IFPRI) and 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 had three days to complete the questionnaire.

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

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 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.[§]

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; US and Canada) within the next ten years (2020-2030). 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". Respondents used a scoring slider to set the numeric value for each supply chain phase.

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 different supply chain phases, and in different regions.

In the third question of the survey (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; 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".

Respondents again used a scoring slider to set the numeric value for each supply chain phase, 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".

§ These included: biological vulnerabilities and risks, including pests or plant diseases; environmental vulnerabilities and risks, including contamination or degradation of environmental resources, and biodiversity loss; weather-related vulnerabilities and risks, including climate change, droughts, floods and other extreme weather events; infrastructural vulnerabilities and risks, including destruction or degradation of energy, transport or communication infrastructures; operations-related vulnerabilities and risks, including use of spoiled seeds or phytosanitary conditions; economic risks, including supply and demand fluctuations, and prices volatility; institutional vulnerabilities and risks, including monetary, fiscal or tax policies changes; and social and political vulnerabilities and risks, including political instabilities, interruptions of trade.

** While considering standard AI (as in computer systems, or algorithms), respondents were prompted to consider the use of AI in combination with robotics (as in embedded systems). Along food chains, in farms, factories and food stores, AI and embedded systems enable each other.

Before respondents made assessments, they were asked to deliberate over the state of information and communication technology (ICT) infrastructures in developed countries today, and over the next ten years (2020-2030), 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 agricultural supply chains and AI supporting infrastructures, and ability of individuals to apply and make use of AI systems, machines and networks as well as their knowledge of such systems.

We provided a definition of artificial intelligence[††], followed with a short description of the infrastructure typically needed to support the use of AI systems.[‡‡]

For the fourth question, respondents scored each agri-food supply chain phase for ease of AI deployment in the previously-examined group of developing regions and countries: South East Asia (China, India, Bangladesh, Indonesia, Vietnam) and South America (Brazil and Argentina).

The third part of the survey contained questions about employment and educational background of participants, both verified via email addresses. We did not elicit additional personal characteristics of respondents (e.g. gender, nationality). We excluded questionnaire respondents who were not employed with CGIAR and did not meet the educational level criteria from our sample (postgraduate education), to reach a final sample of 72 complete entries.

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

The next section highlights some preliminary findings for the consideration and prioritization of artificial intelligence in agricultural SCRM, with a focus on prospects and limitations for deployment of AI in areas of heightened supply chain vulnerability.

†† Respondents were provided with a definition of Artificial Intelligence: Artificial Intelligence (AI) is a set of technologies that mimic cognitive functions. They are computer systems (i.e. machines, networks) that have some of the qualities that the human mind has, such the ability to identify objects, recognize patterns and anomalies, solve problems, optimize resources allocation, navigate, predict failures, make personalized recommendations, and learn. Furthermore, with robotics, AI could replace humans in routine work in industrial-scale production, in industries where manual work can be robotized (referred to as robotics process automation, or RPA)

‡‡ Respondents were provided with a short description of AI supporting infrastructure: AI performance depends on the accumulation and analysis of big data for decision making, and therefore on a supporting infrastructures – data collection, transmission, storage, processing, cleaning, and analysis apparatuses, for instance, sensor technology and the Internet of Things, broadband internet, satellite technology, mobile technology and global positions systems.

# 03 FINDINGS

Questionnaire results indicate that within the next ten years (2020-2030), experts anticipate that nearly all phases and functions, in all countries will become more vulnerable to an array of potential risks. With the sole exception of Pre-Production of Farming Inputs phase in developed countries ($x=14.19$, $\sigma M.=1.09$), no phase was found "not at all vulnerable" (i.e. average score in the 1-20 score band).[§§]

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

With comparatively high scores, Agricultural Production ($\bar{x}=64.15$, $\sigma M.=1.8$ in developed countries; $\bar{x}=75.75$, $\sigma M.=1.5$ in developing countries), Post-harvest Aggregation, Local Transport and Storage ($\bar{x}=52.06$, $\sigma M.=1.63$ in developed countries; $x=69.29$, $\sigma M.=1.93$ in developing countries), and National and International Transport and Storage ($\bar{x}=47.69$, $\sigma M.=1.86$ in developed countries; $\bar{x}=51.58$, $\sigma M.=2.23$ 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, with every single supply chain phase in developing countries receiving an average vulnerability score higher than the same phase in developed countries (standard errors taken into account).

Differences in vulnerability between regions are reflected in the gap between the total average vulnerability score – aggregating all 72 assessments for all the phases and functions – for supply chains in developed regions and for those in developing regions, 37.87 versus 49.8, respectively.

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 deployment of AI in developed countries is estimated to significantly surpass 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.

[§§] This research takes a narrow perspective of farming inputs, primarily focusing on seeds. It puts less emphasis on agrochemicals, herbicides, pesticides and chemical fertilizers.

[***] We assume the ease of integration of AI systems is, to some extent, a result of the supporting infrastructure that already exists.

The experts estimated that within the next ten years Pre-Production of Farming Inputs ($\bar{x}$ = 78.14, σM.=2.42), Agricultural Production ($\bar{x}$ =70.05, σM.=1.29), Trade and Market Intermediaries ($\bar{x}$ =55.58, σM.=2.19), National and International Transport and Storage ($\bar{x}$ =61.33, σM.=2), Processing and Manufacturing ($\bar{x}$ =62.83, σM.=2.08), and Retail ($\bar{x}$ =72.83, σM.=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, σM.=2.16) and National and International Transport and Storage ($\bar{x}$ =49.2, σM.=2.09).

Research findings are summarized in two integrated prioritization maps: Figure 2 shows staple crops producers, processors and providers in North America, and Figure 3 shows staple crops producers, processors and providers in South America and South East Asia.

## FIGURE 2. INTEGRATED ASSESSMENTS OF SUPPLY CHAIN PHASES' VULNERABILITY TO RISK (X AXIS), AND EASE-OF-AI DEPLOYMENT (Y AXIS), IN DEVELOPED COUNTRIES.

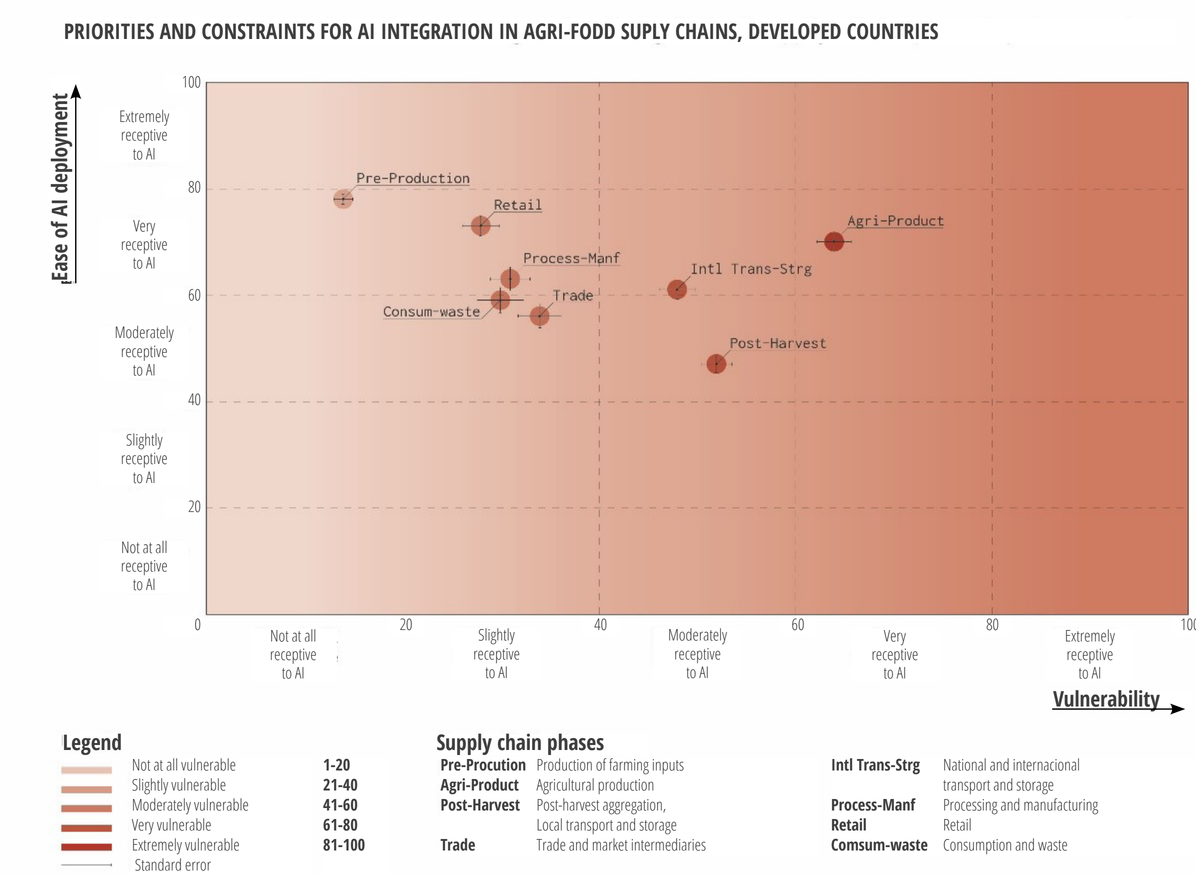
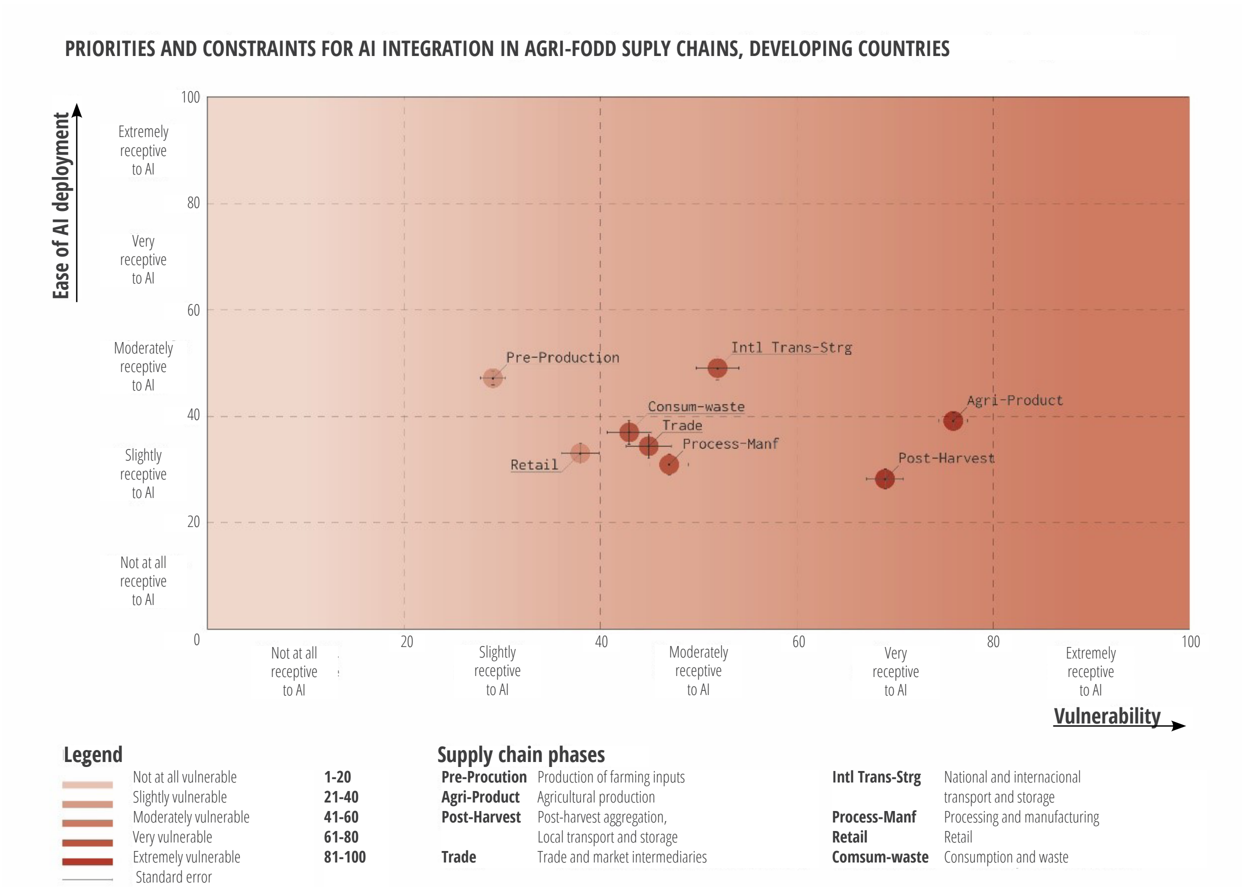


**FIGURE 3.** INTEGRATED ASSESSMENTS OF SUPPLY CHAIN PHASES' VULNERABILITY TO RISK (X AXIS), AND EASE-OF-AI DEPLOYMENT (Y AXIS), IN DEVELOPING COUNTRIES.



# 04 DISCUSSION: PRIORITIES AND CONSTRAINTS FOR AI INTEGRATION IN FOOD CHAINS

The survey examined supply chain phases 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 survey scores yield several conclusions.

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

Most supply chain echelons in these regions were ranked in the "slightly receptive to AI" score band, including several critical phases and function such as Agricultural Production (which covers soil testing, monitoring and preparation, applying farming inputs and seeds, cultivation and crops management, irrigation, harvest, initial handling and labeling) and Post-harvest Aggregation, Local Transport and Storage (which encompasses transportation of staple crops to post-harvest storage at country elevators, warehouses and silos near field, sampling and inspection for defects, ventilation and moisture management, fumigating, grading and classification).

In other words, where AI is needed the most (i.e. highly vulnerable areas) the prospects for AI integration are estimated to be most limited.

In contrast, while food chains in developed countries are less vulnerable than those in developed countries, they were found significantly more receptive to AI experimentation and integration.

This may relate to the state of AI-supporting ICT infrastructures in developed countries, as well as to projected investments in the devices, data and knowledge architecture allowing successful AI deployment. As respondents were not asked to provide these sorts of assessments this is a postulation on the part of the author. Nonetheless, this postulation may be pertinent for other advanced technologies requiring extensive physical and knowledge infrastructures for successful deployment.

With regards to the prioritization of AI deployment in agri-food supply chains, two further observations are worth noting.

First, the Retail phase and its functions – covering inventory management and forecasting, food ordering from manufacturers, food receival at distribution centers, customer demand forecasting, and food receival at stores and markets – is an echelon of the supply chain that attracts research, development and investments in AI systems (Doganis et al., 2006[58]; Li et al., 2006[59]; Tassou and Ge, 2008[60]; Chen and Ou, 2011[61];

Krüger et al., 2011[62]; Guo et al., 2013[63]; Mavromatidis et al., 2013[64]; Arsénio et al., 2014[65]; Pantano, 2014[66]; Birkin et al., 2017[67]; Brynjolfsson and Mcafee[68]; Weber and Schütte, 2019a[69]; Weber and Schütte, 2019b[70]). However, it has a lower score for vulnerability to risk compared to other phases. Consequently, through the prism of global food and nutritional security, Retail should be a phase of decreased immediacy and of a lesser priority.

Secondly, 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 (REFS). 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 CHAINSCAVEATS AND IMPLICATIONS FOR FUTURE RESEARCH

In exploring the potential for AI to aid in the mitigation of agri-food supply chain vulnerabilities, this studied prioritized generalizability over specificity and nuance.

Consequently, the paper distinguished between two categories of global breadbaskets: developing and developed. 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 region to region and from country to country within regions. 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 rather than playing a role in reducing general vulnerability.

Future research should therefore analyze supply chains phase-by-phase if not function-by-function, 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 begins from the view, generally accepted by experts, that agricultural supply chain risk management – the implementation of measures to mitigate risks along the food supply chain, based on periodic risk assessment, with the aim of reducing vulnerability – is essential for achieving and maintaining global food security.

Based on a survey of experts, we find that artificial intelligence has significant potential for reducing risks and vulnerabilities within agri-food supply chains. Accordingly, a more rigorous and systematic examination of AI through the prism of supply chain risk management is required. Proceeding on these assumptions, three basic conclusions can be derived.

First, since some phases of the supply chain are more vulnerable than others, an identification of areas of unproportional vulnerability within the food supply chain structure should set priorities in the implementation of appropriate vulnerability mitigation measures (i.e. AI systems).

Second, a distinction between agricultural supply chains in developing countries and developed ones is warranted, as well as a distinction between supply chain phases in terms of (a) vulnerabilities and (b) receptiveness to mitigation measures.

Third, within the broad category of food and feed crops, a minority of just four cultivars, wheat, maize, rice and soybean, comprise approximately 50% of total croplands. Global food security is dependent on those four items, and therefore, the integration of AI in agriculture, as a mitigation measure of vulnerabilities, should be favored for these crops' supply chains first.

In light of these, this paper sought to put forth a preliminary prioritization of staple crops' supply chain phases for AI experimentation and integration, in both developed and developing countries, accounting for both comparative vulnerability of phases and comparative receptiveness to AI systems for the next years.

For prioritization, a two stage Research was conducted. First, a supply chain model – based on a synthesis between secondary literary sources and primary specialists' interviews – was fashioned and refined. In the second stage of the research, and with the supply chain model as a shared point of reference, CGIAR scientists and researchers, members of one of six Communities of Practice of CGIAR's Platform for Big Data in Agriculture, were invited to take a comprehensive questionnaire. Seventy-two scientists and researchers eventually participated.

Through the questionnaire, the anticipated vulnerability of supply chain phases was empirically analyzed. This was followed by an assessment of ease of AI deployment across supply chain phases in two categories of staple crops' "breadbaskets": developed countries and developing ones.

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.

With regards to the prioritization of AI experimentation and deployment in agri-food supply chains, two more observations were worth mentioning. First, the Retail phase and its functions is an echelon of the supply chain that attracts research, development and investments in AI systems, yet, comparatively to other phases, it is a phase with a lower vulnerability score. So, in the prism of global food security, it should be a phase of decreased immediacy and of a lesser priority. Second, the phase of Pre-production of Farming Inputs, specifically the research and development of seed varieties, was found highly receptive to AI integration, although less vulnerable to risks. To the extent that the risk of staple crop losses in the Agricultural production phase could be mitigated by interventions in an earlier stage of the supply chain, for example, by applying AI to bioengineering of genetically modified, weather-resistant and resilient crops, the integration of AI in this phase warrants prioritizing.

Finally, only very cautious conclusions are possible, as the socio-economic and ecological circumstances vary vastly from country to country and, distinguishing between two categories of global breadbaskets – developing and developed – may be too broad to device local interventions. Specifically, different local circumstanced yield different risk environments, and this has further implication for the type of AI that is employed: the most desirable AI applications should mitigate particular risks and not general vulnerabilities.

## DECLARATIONS

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## CONFLICT OF INTEREST

The author declares no conflict of interest.

# REFERENCES


1 Food and Agriculture Organization (1996). Rome Declaration on Food Security and World Food Summit Plan of Action. Retrieved 18 December 2019.

2 Douglas, I. (2009). Climate change, flooding and food security in south Asia. *Food Security*, 1(2), 127-136.

3 McGill, A. E. (2009). The potential effects of demands for natural and safe foods on global food security. *Trends in Food Science & Technology*, 20(9), 402-406.

4 Krejci, C. C., & Beamon, B. M. (2010). Environmentally-conscious supply chain design in support of food security. *Operations and Supply Chain Management*, 3(1), 14-29.

5 Mohan, S., Gopalakrishnan, M., & Mizzi, P. J. (2013). Improving the efficiency of a non-profit supply chain for the food insecure. *International Journal of Production Economics*, 143(2), 248-255.

6 Garnett, T. (2014). Three perspectives on sustainable food security: efficiency, demand restraint, food system transformation. What role for life cycle assessment?. *Journal of Cleaner Production*, 73, 10-18.

7 Grote, U. (2014). Can we improve global food security? A socio-economic and political perspective. *Food Security*, 6(2), 187-200.

8 Reardon, T., & Timmer, C. P. (2014). Five inter-linked transformations in the Asian agrifood economy: Food security implications. *Global Food Security,* 3(2), 108-117.

9 Soussana, J. F. (2014). Research priorities for sustainable agri-food systems and life cycle assessment. *Journal of cleaner production*, 73, 19-23.

10 Macfadyen, S., Tylianakis, J. M., Letourneau, D. K., Benton, T. G., Tittonell, P., Perring, M. P., ... & Okabe, K. (2015). The role of food retailers in improving resilience in global food supply. *Global Food Security*, 7, 1-8.

11 Paloviita, A., & Järvelä, M. (2015). Climate change adaptation and food supply chain management: an overview. In Climate Change Adaptation and Food Supply Chain Management (pp. 19-32). Routledge.

12 Jaffee, S., Siegel, P., & Andrews, C. (2010). Rapid agricultural supply chain risk assessment: A conceptual framework. *Agriculture and rural development discussion paper*, 47(1), 1-64.

13 Peck, H. (2006). Reconciling supply chain vulnerability, risk and supply chain management. *International Journal of Logistics: Research and Applications,* 9(2), 127-142.

14 Wieland, A., & Wallenburg, C. M. (2012). Dealing with supply chain risks. *International Journal of Physical Distribution & Logistics Management.*

15 Jüttner, U., Peck, H., & Christopher, M. (2003). Supply chain risk management: outlining an agenda for future research. *International Journal of Logistics: Research and Applications*, 6(4), 197-210.

16 Jüttner, U. (2005). Supply chain risk management: Understanding the business requirements from a practitioner perspective. *The international journal of logistics managemen*t, 16(1), 120-141.

17 Manuj, I., & Mentzer, J. T. (2008). Global supply chain risk management. *Journal of business logistics*, 29(1),] 133-155.

18 Tang, O., & Musa, S. N. (2011). Identifying risk issues and research advancements in supply chain risk management. *International journal of production economics*, 133(1), 25-34.

19 Septiani, W., Marimin, M., Herdiyeni, Y., & Haditjaroko, L. (2016). Method and approach mapping for agri-food supply chain risk management: A literature review. *International Journal of Supply Chain Management,* 5(2), 51-64.

20 Ritchie, B., & Brindley, C. (2007). An emergent framework for supply chain risk management and performance measurement. *Journal of the Operational Research Society,* 58(11), 1398-1411.

21 Ritchie, B., & Brindley, C. (2007). Supply chain risk management and performance: a guiding framework for future development. *International Journal of Operations & Production Management*, 27(3), 303-322.

22 Manuj, I., & Mentzer, J. T. (2008). Global supply chain risk management strategies. *International Journal of Physical Distribution & Logistics Management,* 38(3), 192-223.

23 Zsidisin, G. A., & Ritchie, B. (Eds.). (2008). *Supply chain risk: a handbook of assessment, management, and performance* (Vol. 124). Springer Science & Business Media.

24 Tummala, R., & Schoenherr, T. (2011). Assessing and managing risks using the supply chain risk management process (SCRMP). *Supply Chain Management: An International Journal*, 16(6), 474-483.

25 Ghadge, A., Dani, S., & Kalawsky, R. (2012). Supply chain risk management: present and future scope. *The international journal of logistics management*, 23(3), 313-339.

26 Chopra, S., & Sodhi, M. (2014). Reducing the risk of supply chain disruptions. *MIT Sloan management review,* 55(3), 72-80.

27 Cole, M. B., Augustin, M. A., Robertson, M. J., & Manners, J. M. (2018). The science of food security. npj Science of Food, 2(1), 1-8.

28 Li, D., & Du, Y. (2017). Artificial intelligence with uncertainty. CRC press.

29 Patterson, D. W. (1990). *Introduction to artificial intelligence and expert systems.* Prentice-hall of India.

30 Kurzweil, R. (2006). Reinventing humanity: the future of machine-human intelligence. *The Futurist*, 40(2), 39.

31 Brundage, M., Avin, S., Clark, J., Toner, H., Eckersley, P., Garfinkel, B., ... & Anderson, H. (2018). The malicious use of artificial intelligence: Forecasting, prevention, and mitigation. *arXiv preprint arXiv:1802.07228*.

32 Abu-Naser, S. S., Kashkash, K. A., & Fayyad, M. (2010). Developing an expert system for plant disease diagnosis. *Journal of Artificial Intelligence,* 3(4), 269-276.

33 Patil, J. K., & Kumar, R. (2011). Advances in image processing for detection of plant diseases. *Journal of Advanced Bioinformatics Applications and Research*, 2(2), 135-141.

34 Hughes, D., & Salathé, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics. *arXiv preprint arXiv:1511.08060.*

35 Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145, 311-318.

36 Selvaraj, M. G., Vergara, A., Ruiz, H., Safari, N., Elayabalan, S., Ocimati, W., & Blomme, G. (2019). AI-powered banana diseases and pest detection. Plant Methods, 15(1), 92.

37 Drillet, G. (2016). Food security: Protect aquaculture from ship pathogens. *Nature*, 539(7627), 31.

38 Akbarzadeh, A., Mehrjardi, R. T., Lake, H. R., & Ramezanpour, H. (2009). Application of artificial intelligence in modeling of soil properties (case study: Roodbar region, north of Iran). *Environmental Research Journal*, 3(2), 19-24.

39 Francesconi, W., Miñana, E. P., Willcock, S., Villa, F., & Quintero, M. (2015). Linking ecosystem services to food security in a changing planet: Assessing Peruvian Amazon deforestation using the artificial intelligence for ecosystem services (ARIES) framework. In *ASABE 1st Climate Change Symposium: Adaptation and Mitigation Conference Proceedings* (pp. 1-3). American Society of Agricultural and Biological Engineers.

40 Cosmin, P. O. P. A. (2011). Adoption of artificial intelligence in agriculture. *Bulletin of University of Agricultural Sciences and Veterinary Medicine Cluj-Napoca. Agriculture*, 68(1).

41 Chen, Y., & Li, Y. (2019). Intelligent autonomous pollination for future farming-a micro air vehicle conceptual framework with artificial intelligence and human-in-the-loop. *IEEE Access,* 7, 119706-119717.

42 Omran, A., Khorshid, M., & Saleh, M. (2010, November). Intelligent decision support system for the Egyptian food security. In 2010 10th International Conference on Intelligent Systems Design and Applications (pp. 557-562). IEEE.

43 Chen, T. C. (2005, May). RFID and sensor-based container content visibility and seaport security monitoring system. In Sensors, and Command, Control, Communications, and Intelligence (C3I) Technologies for Homeland Security and Homeland Defense IV (Vol. 5778, pp. 151-159). International Society for Optics and Photonics.

44 Barbosa, R. M., & Nelson, D. R. (2016). The use of support vector machine to analyze food security in a region of brazil. *Applied Artificial Intelligence,* 30(4), 318-330.

45 Sadilek, A., Kautz, H., DiPrete, L., Labus, B., Portman, E., Teitel, J., & Silenzio, V. (2016, March). Deploying nEmesis: Preventing foodborne illness by data mining social media. *In Twenty-Eighth IAAI Conference.*

46 Matthews, R. B., Rivington, M., Muhammed, S., Newton, A. C., & Hallett, P. D. (2013). Adapting crops and cropping systems to future climates to ensure food security: The role of crop modelling. *Global Food Security,* 2(1), 24-28.

47 Waters, D. (2011). *Supply chain risk management: vulnerability and resilience in logistics.* Kogan Page Publishers.

48 Chapman, P., Christopher, M., Jüttner, U., Peck, H., & Wilding, R. (2002). Identifying and managing supply chain vulnerability. *Logistics & Transport Focus*, 4(4), 59-70.

49 Wagner, S. M., & Bode, C. (2006). An empirical investigation into supply chain vulnerability. *Journal of purchasing and supply management*, 12(6), 301-312.

50 Wu, T., & Blackhurst, J. V. (Eds.). (2009). *Managing supply chain risk and vulnerability: tools and methods for supply chain decision makers.* Springer Science & Business Media.

51 Aruoma, O. I. (2006). The impact of food regulation on the food supply chain. *Toxicology*, 221(1), 119-127.

52 Sartorius, K., & Kirsten, J. (2007). A framework to facilitate institutional arrangements for smallholder supply in developing countries: An agribusiness perspective. *Food Policy*, 32(5-6), 640-655.

53 Rich, K. M., Baker, D., Negassa, A., & Ross, R. B. (2009). *Concepts, applications, and extensions of value chain analysis to livestock systems in developing countries* (No. 1005-2016-79380).

54 Henson, S., & Humphrey, J. (2010). Understanding the complexities of private standards in global agri food chains as they impact developing countries. *The journal of development studies,* 46(9), 1628-1646.

55 Parfitt, J., Barthel, M., & Macnaughton, S. (2010). Food waste within food supply chains: quantification and potential for change to 2050. *Philosophical transactions of the royal society B: biological sciences*, 365(1554), 3065-3081.

56 Rich, K. M., Ross, R. B., Baker, A. D., & Negassa, A. (2011). Quantifying value chain analysis in the context of livestock systems in developing countries. *Food Policy,* 36(2), 214-222.

57 Sodhi, M. S., & Tang, C. S. (2014). Supply-chain research opportunities with the poor as suppliers or distributors in developing countries. *Production and operations management*, 23(9), 1483-1494.

58 Doganis, P., Alexandridis, A., Patrinos, P., & Sarimveis, H. (2006). Time series sales forecasting for short shelf-life food products based on artificial neural networks and evolutionary computing. Journal of Food Engineering, 75(2), 196-204.

59 Li, D., Tang, O., O'Brien, C., & Wang, X. (2006). Improve food retail supply chain operations with dynamic pricing and product tracing. International Journal of Services Operations and Informatics, 1(4), 347-362.

60 Tassou, S., & Ge, Y. (2008). Reduction of refrigeration energy consumption and environmental impacts in food retailing. In Handbook of Water and Energy Management in Food Processing (pp. 585-611). Woodhead Publishing.

61 Chen, F. L., & Ou, T. Y. (2011). Sales forecasting system based on Gray extreme learning machine with Taguchi method in retail industry. Expert Systems with Applications, 38(3), 1336-1345.

62 Krüger, A., Schöning, J., & Olivier, P. (2011). How computing will change the face of retail. Computer, 44(4), 84-87.

63 Guo, Z. X., Wong, W. K., & Li, M. (2013). A multivariate intelligent decision-making model for retail sales forecasting. Decision Support Systems, 55(1), 247-255.

64 Mavromatidis, G., Acha, S., & Shah, N. (2013). Diagnostic tools of energy performance for supermarkets using Artificial Neural Network algorithms. Energy and Buildings, 62, 304-314.

65 Arsénio, A., Serra, H., Francisco, R., Nabais, F., Andrade, J., & Serrano, E. (2014). Internet of intelligent things: Bringing artificial intelligence into things and communication networks. In Inter-cooperative collective intelligence: Techniques and applications (pp. 1-37). Springer, Berlin, Heidelberg.

66 Pantano, E. (2014). Innovation drivers in retail industry. International Journal of Information Management, 34(3), 344-350.

67 Birkin, M., Clarke, G., & Clarke, M. (2017). Retail location planning in an era of multi-channel growth. Routledge.

68 Brynjolfsson, E., & Mcafee, A. N. D. R. E. W. (2017). The business of artificial intelligence. Harvard Business Review, 1-20.

69 Weber, F. D., & Schütte, R. (2019a). State-of-the-art and adoption of artificial intelligence in retailing. Digital Policy, Regulation and Governance.

70 Weber, F., & Schütte, R. (2019b). A domain-oriented analysis of the impact of machine learning—the case of retailing. Big Data and Cognitive Computing, 3(1), 11.

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