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# Leveraging Agentic AI and Cloud Infrastructure for Predictive Logistics in National Food Supply Chains

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## Abstract

Long-term problems of food supply chain management include supplier selection, transportation, and supply chain structure planning. Due to the integration of advanced technologies in food supply chain design, new challenges arise for supply chain robustness in consumer-driven behavior and climate change. AI algorithms will be absolutely necessary to assess the avoidable variability in food supply chains. Agents with their own objectives and preferences form networks. The evolution and robustness of networks can be simulated using agent-based models. As an advanced manufacturability and a complex food supply chain, a multi-agent system was built. A cloud-based platform allows agents in different locations to collaborate while keeping their data private. This research shows that cloud infrastructure simplifies and accelerates collaboration in a blockchain system.

As supply chains evolve, the asymmetric nature of mutual dependencies imposes serious risks. The time-varying nature of supply chain relationships generates unknown feedback. Based on this uncertainty, a partially observable finite-state Markov decision process was developed for visibility estimation and redesign. It adopts a hybrid deep recurrent neural network to estimate the number of nodes and the biases of parameters. Devices with an ongoing impact on supply chains were identified via simulations and case studies. Conventional approaches assume that supply chain changes only happen occasionally and originally, while this approach detects highly dynamic changes comprehensively.

As the depiction of supply chain structure, an ontology for ensuring information sharing was created through an integrated methodology involving data acquisition, coding, modeling, and validation. Aiming at serving various manufacturing industries, a recommender system based on a business model ontology was developed. This ontology mines customer preferences and generates a candidate strategy pool for managers. To conquer the trade-off between the quality of recommendations and costs, a multi-objective optimization model was derived. The efficiency and effectiveness of the recommender ontology were tested and verified, marking the first step for an AI supply chain to augment post-COVID-19 resilience.

**Keywords:** Agentic AI,Predictive logistics,Cloud infrastructure,Food supply chain,National logistics systems,AI-driven forecasting,Supply chain optimization,Intelligent agents,Real-time data analytics,Agricultural logistics,Demand prediction,Smart food distribution,AI in supply chains,Cloud-based logistics,Food security management.

## 1. Introduction

Global food supply chains are among the world's largest interconnected systems, equipped with mechanisms to largely avert a food shortage. How long this retribution will last is an issue due to the ever-expanding disruptive forces. Hence, nation-reminiscent actions are expected to be taken to shore up transparent, resilient, and low-carbon food supply chains to enhance public safety in food supply. The first step to such actions is abundant scenario predictions of food supply chains under both business-as-usual and remedy conditions. Noteworthy, however, scenario predictions are non-trivial due to the elusive nature of food supply chains in which numerous intermediary processes involve dynamic, multi-disciplinary, and agentic interactions among heterogeneous agents.

To this end, agentic AI-powered prognostics models are proposed and discussed in-depth to enable abundant scenario predictions via gargantuan cloud infrastructure. Leveraging agentic mechanisms from both nature and society, a multi-agent architecture is designed to regain the agenticity of food supply chains. Particular attention is devoted to the designing of novel agentic AI capabilities to endow this architecture with up-to-scratch capabilities to predicate the (de)stabilization of food supply chains. To facilitate the input assimilation of diverse data modalities, an AI pipeline is discussed to recover the missing information and extract interpretable features. To model the variant modes of operations and resiliency mechanisms of food supply chains, agentive cells are proposed and showcased their advanced efficacy in modeling the multi-agent interactions to hitherto inaccessible depth. To implement the aforementioned functionalities, an advanced cloud infrastructure is discussed to build a cloud-based platform for the proposed predictions.

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A global context is considered in making comprehensive food supply chains to represent a basic prototype of food supply chains. In particular, the national food supply chains of China and the UK are constructed, involving multi-tier latent food supply chains from raw cultivations to consumer shopfronts. Seven types of data are gathered to characterize the mechanisms for safeguarding food safety and security, food supply chain entry, and domestic food supply chain inter-connectivity and disruptions, as well as the factors for food price prediction.

Agentic AI embraces the agentic AI-powered prognostic and decision-making models of commodity-producing processes, focusing on the food provision service of food supply chains. A multi-agent architecture is designed to regain the agenticity of food supply chains to make thought-provoking predictions on the (de)stabilization of food supply chains and the impact of remedy actions.

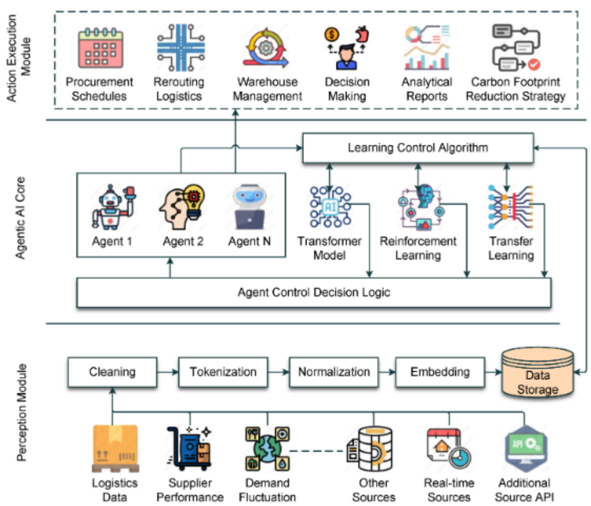


**Fig 1: Agentic AI and Cloud Infrastructure for Predictive Logistics in National Food Supply Chains**

**1.1. Background And Significance**

As the world becomes increasingly concerned with the impacts of climate change, sustainability, and improving food accessibility and food equity goes more to the forefront of governance, national food supply chains are of growing concern given their role in tackling these food systems issues. Governments seek to reduce their vulnerability and dependency on foreign food supply chains and are thus increasingly motivated to invest in their domestic food supply chains, whilst at the same time growing interest in improving the efficiency of domestic food supply chains to tackle food wastage and improve food equity in national food systems overall. Food supply chains are already complex networks that span multiple geographies and governance levels, and government's increased efforts to improve in this complex and tightly interwoven world introduce risks both to food equity and to food accessibility.

In this context, leveraging the mass data provided by the digital transformation of food supply chains and agentic AI systems are not only pivotal in predicting disruption to food supply chains but also provide the first step towards proactively mitigating it and ensuring robust food supply. This conceptual design outlines high-level requirements for a predictive AI system for national food supply chains that can be incrementally filled in and allows for adaptation to local contexts.

The rapid rise of consumer food demand in food supply chains can result in ground-up frustration across all food supply chain stakeholders, resulting in undersupply food spikes on food acquisition dissemination platforms. A predictive digital infrastructure of food supply chains can track the systems events in micro-granularity resolutions across supply chain nodes. It can output monitoring measures of food supply chains on-the-fly assessed against state-space models of the supply chain nodes. Digitally transformed consumer food systems are currently producing large amounts of data, but they go mainly unutilized. The data produced at the food aggregation points represent the degree of mismatch between food purchase demand and food supply for the supermarkets in supply chain nodes.

**Equ : 1 Demand Forecasting with Agentic AI**

$$D_t = \alpha_1 \cdot H_t + \alpha_2 \cdot S_t + \alpha_3 \cdot W_t + \varepsilon_t$$

- $H_t$: Historical consumption
- $S_t$: Seasonality indicator
- $W_t$: Weather data from cloud-based services
- $\alpha_i$: Learned AI weights
- $\varepsilon_t$: Noise term

## 2. Overview of Food Supply Chains

In the highly competitive food market, food quality is a major consideration for consumers due to the low storability of raw food products. Food safety incidents are very harmful to food companies. Public food safety incidents can leak consumers' preferences or opinions, impacting the demand for food products. Food companies engage in massive trials to generate marketing intelligence, i.e. predictive logs on the previous food supply chain. Traditional food quality checking is characterized by small samples and static rules, which may

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not work in modern consumer-driven and dynamic food systems. Vision sensing is a foundation for smart food supply chains. These supply chains use multi-channel signals to examine quality variations throughout the supply chain, and a quality extension mechanism can enlarge the unseen data space. Dynamic food safety risk textualization is a more comprehensive view for both food safety incidents and public food safety opinion contagion. The food safety risk and opinion of consumers change dynamically based on the generation and spread of food safety incidents, and geographic spreading patterns. Data mining tools, including sentiment classification, face the word mismatch issue, or cannot model and predict the change of evolving markets efficiently. Food transporting and storing is the key intermediary between the steps involved in the food supply chain. Improving the efficiency of food transportation and monitoring to reduce food loss and waste is vital for satisfying food accessibility of consumers. Food transporting and storing are the key steps of food supply chains that transport and store food products between every two steps respectively. Transportation inefficiency in these steps leads to food loss and waste, which heavily influences food accessibility. In advanced societies, transportation and storage are usually separated, so they are reviewed and discussed in local fields separately. However, an appropriate setup plan for the food supply chain is fundamental to large food transporting systems involving multiple participants and large capital. During the setup phase, participants select suppliers, design food transporting routes, optimize fleet assignments, and collect feedback.

## 3. Challenges in Current Logistics

The whole chain of logistics surrounding the national food supply is fraught with challenges, impacting national security. The food supply chain (FSC) consists of various systems including agricultural production, processing, transportation, storage, and trading. Recent studies have revealed that predictions of price fluctuation and food supply chain control through logistics data is an increasingly important area of research. When food prices go up after a natural disaster or seasonal climate change, food manufacturing and wholesale companies can be helped by such predictions. If retailers know when product sales predictions are high, optimal business decisions can be made to provide supplementary stock. This section outlines the major logistic challenges in this context. The logistics of the national food supply is provided as a case study mining the intelligence for agentic AI.

135 food companies in 13 cities are directly engaged in the logistics of the national food supply. Networks assigned to each company are first obtained based on transport connections, and a time-inference problem is constructed per company for predicting the completion time of items on the connecting networks. Transport vehicles are often stuck in traffic jams in urban environments, resulting in considerably long time completion of transporting items. Therefore, taking network state into account is necessary. This state cannot be collected by monitoring tools, hence historical data, which is a snapshot of the networks unchanged over the time, is retrieved for each route on the networks. Entering this often large amount of data into chosen algorithms often either results in a time-consuming training progress or unsatisfactory prediction performance. Overcoming this issue requires a more suitable format for inputting the historical data. In parallel, further countervailing the impact of ill-distributed training data under agentic and federated AI, improved recurrent neural nets able to embed information of training instances into the architecture are considered preliminarily. The efficacy of a better suited loss function is also explored based on deep reinforcement learning. Focused efforts in parallel are beneficial to more efficient food logistics as well as other logistics in dense urban environments.

The difficulties facing the whole national food supply and food logistics. Analyzing the food supply is crucial for national security. Coupling macro and micro analysis, the structure and systems are first described. Widely applied measures include grain reserves, price fluctuation, blueprint plan, and a city-based packet for fast tracking food manufacturing and wholesaling. Predicted results are also analyzed, providing insights on storing and transferring foodstuffs by predicting average price fluctuation at the national level. A case study of leveraging the whole supply structure is performed, identifying companies that have large fluctuations in trading, manufacturing, or pricing in consideration of structure-based measures. Further actionable and explainable insights are provided.


**Fig 2: Challenges Logistics Companies Are Facing**

### 3.1. Supply Chain Disruptions

Supply chains may suffer from both functional and disruptive risks. Functional risks lead to local supply chain disruptions. The impact of these disruptions may be small, like the lead time increase of a ship arriving at a port. Alternatively, the impact may be larger, like the lead time increase of a supplier broadcasting that they do not have sufficient material to supply to their customers. The latter type of risk is often well known, and it is relatively easy to model such supply chain disruptions. In contrast to functional risks, disruptive risks lead to global supply chain disruptions. The category of disruptive risks is extraordinarily broad, ranging from big geopolitical changes to once-in-a-lifetime black swan events, such as the COVID-19 pandemic and the Suez Canal blockage. The impacts of the above risks are highly drastic and, most of the time, poorly anticipated. A self-reinforcing feedback loop amplifies the impact of supply chain disruptions: when supply chain disruptions show imperceptible signs of increasing risk, organizations may perceive this risk as benign. In this way, the supply chain might be highly vulnerable to the gradual rise of the risk.

For decades, supply chain management (SCM) has been a popular topic of research. The body of knowledge of SCM consists of multifaceted insights into supply chain design, planning, and operations. These insights improve responsiveness, visibility, and reliability along the supply chain. Unfortunately, this knowledge is virtually absent from the literature on supply chain disruptions. To address this gap in the literature, three individual research studies were conducted. The first study focused on functional supply chain disruptions. A mathematical model that simulates such disruptions was developed and validated. Subsequently, the second study explored logistical structures and networks. The aim was to identify early indicators of disruptive supply chain disruptions. Ultimately, a mathematical model that considers seven discrete event structures was developed and validated. Finally, to provide scientifically backed perspectives on supply chains amid disruptions worldwide, the third study shifted the focus to technology – in particular, blockchain technology.

**3.2. Resource Allocation Issues** The global flexibility and freedom promised by the internet has fueled the rise of e-commerce platforms selling a huge variety of products and revealing previously invisible algorithms that govern and control the economy. A huge segment of this global economy has come to be dominated by the Online Food Delivery (OFD) service market. An ODD platform is a mediator operating in a triadic governance structure, which brings together food producers (restaurants and food chains) and end consumer customers, and connects them to independent transporters (delivery drivers) who physically carry the food from the producer to the consumer. Commonly referred to as physically carrying the food from Point A to Point B, the process which defines the grouping of many such transporters and consumers, while managing the physical dynamics of the transport operations is technically termed last-mile delivery problem (LMDP). The OFD services in this day and age are using tech-intensified operational paradigms that form complex behaviors out of a large number of simple rules. Last-mile delivery organizations perform large-scale and complex real-world operations daily while trailing behind ride-hailing organizations, similar but larger in scale, complexity, and revenue born out of the internet.

Existing OFD platforms assume and enforce that after an online order enters the platform, dispatching, driving, and delivering decisions are made electronically with no human's physical involvement. Due to this strong package of assumptions and restrictions, existing LMDP algorithms for OFD platforms are also oriented for brownfield digital cities and hence look for continuous global optimization or one-shot optimization at periodical time-slices. Simulation-based methods model the FRP using deeper and abstract representations of the agent state and take online local corrective actions based on results of simulated futures. These, however, require strong approximate models of the dynamics of the complex system, which are not available for most greenfield settings. Such online emergency requests may involve operators transferring severely tardy deliveries or otherwise bottleneck deliveries from home/vehicle agents to alternate ones. During such emergency transfers, an entire prior arc path is offloaded, while it is assumed to keep the state of the offline agent intact.

All aforementioned time-dependent models only consider single time-slice models and are all applied to a given graph. They consider all paths without regard to driver behavior or road types. All approximate graph aggregation models are static. They propose a RNN-based approach to mitigate the infeasibility of modeling the entire large graph online using local aggregation and hierarchical mapping mechanism. However, it is only shown effective in offline RNN-based models and needs to assume the modeling agent to be static.

**3.3. Demand Forecasting Difficulties** In recent years, significant advancements have been made in improving forecasting accuracy through the application of machine learning techniques. Various studies have exemplified this progress, particularly in the context of e-commerce supply chains where sales of products, and thus demand, increase tremendously during promotional events, and in retailers needing to deploy an effective marketing strategy with pricing promotions. Meanwhile, there remain open questions about how to adapt successful machine learning techniques, which mostly do not incorporate domain knowledge, for carefully forecasting demand of products with

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low sales prior to the forecasting day. On one hand, in the highly competitive supply chain environment, there is increasing availability of big data in less organized form which needs to be dealt with. There is also a huge need for transparent models built on domain knowledge, which may be more accurate than those based purely on data. adapting machine learning success stories to help improve supply chain performance while taking into account the above mentioned demand forecasting difficulties.

As such, the existing work is expanded in this line of research in three aspects. First, machine learning-based cross-product joint demand forecasting methods are studied and developed for the first time. Recent success stories of knowledge-based forecasting of retail products are used to demonstrate the need of cross-product joint demand formulation in the complex grocery products supply chain network. Methods to jointly forecast demand through transductive transfer learning are proposed. Second, based on both the above proposed methods and the existing knowledge-based demand and inventory forecasting framework, the first pipeline framework for cross-product joint forecasting of demand and inventory management of grocery retailers is demonstrated. Third, as domain knowledge heavily relies on data, the need for packaging and sharing such knowledge across everyone in a structured way is studied, and a knowledge network graph framework is proposed.

## 4. The Role of Agentic AI

Agentic AI refers to a multi-faceted, heterogeneous set of embedded large language and multimodal generative AI software and hardware systems. Formatted in different ways, these AI systems typically account for many components such as extensive pre-trained transformer models, computerized auditory and visual systems, processors to run AI algorithms, and software for parallel processing and data transmission. As the multi-agent systems are fueling radical advances in the fields of generative AI and robotics, it is envisaged that by 2030 rapidly increasingly sophisticated agentic AI systems will enter mainstream use in agriculture and the food sector.

AI systems are rapidly advancing in capability and reliability and are likely to have the same impact on the transformation of agriculture and food sectors as smartphones have had in the past decade. Natural language processing, ubiquitous agentic and personal AI systems, multimodal capabilities, and democratized access to AI systems via app stores and other online services rapidly advance. These radically advanced AI systems are expected to have the potential to transform working and leisure practices and power relations in agricultural and food systems.

The introduction of agentic AI about text and complex multimodal information could augment, replace, or both augment and replace cognitive and perceptual tasks performed by the workforce and consumers. For example, from simple voice-controlled functions in products or services interfacing with consumers, agentic AI could quickly flip into complex human interaction-compensating and enriching tasks with more conscious comprehension and behavior in jobs or daily life. This means that while AI systems advance rapidly into agentic and smaller-scale software products, along with their hardware counterparts, the use of such systems is likely to become essential for all forms of work, including farming, food production, and consumption.

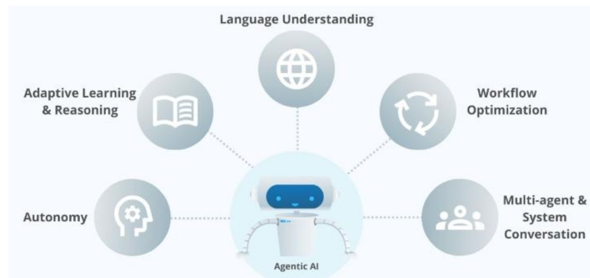


**Fig 3: Understanding Agentic AI**

**4.1. Definition and Characteristics** This section aims to present a definition and an analysis of the main characteristics of the concept of predictive logistics in national food supply chains – supply chains with food safety and security applications in the food industry as well as in food transportation, distribution, storage and retailing. Such supply chains contain a large number of business enterprises, who act as diverse stakeholders in a multi-agent system, co-working to ensure food safety and security in a well-working supply chain. As an expression of multi-agent systems, the stakeholders of food supply chains (agents) can cooperate, compete, as well as react to each other, and react to the variations in conditions in both the internal and external environments.

National food safety and security is crucial, and predictive logistics in national food supply chains are indispensable for this. Stakeholders in national food supply chains are usually with regards to individual utilities (maximizing their own benefits), and it may generate suboptimal outcomes for public industries and utilities. This implies that a predictive(reactive) logistics planning and scheduling system for supplying all agents with enough resources (food safety and security) is essential in a food supply chain, as a kind of central control in a distributed multi-agent system. Since large food supply chain systems are always time-variant and dynamic, a predictive logistics system with an effective modelling algorithm would be developed, enabling the involved

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stakeholders to cooperatively achieve foresight of food safety and security breaches, and optimization of resources recommending nudges or action tips to scheduling and reallocation policies. This is the ideal case, and it may not be attainable. One way of handling this is to keep the coalitional cooperation topologies of stakeholders changed over a long time-scales under random reallocation of data mining results.

Considering feasibility, the middle range is the possible case, where agents analyze the impacts of changes in either the physical flow system or food or demand parameters on overall safety-security risks using self-model-check-optimal techniques, form coalition groups based on the utility recoveries of being compatible in cooperative strategies and allocate their resources under predictive or learning agent reactivity (responses of the others are anticipated). In this case, simulation would be conducted to assess the risks and costs of variations of safety and security specifications. This would help reach an "acceptable" prediction regarding the logics of formulations and computational understanding.

**4.2. Applications in Logistics** Agri-food producers and supply chain organizations have unique production methods and consumer demands. Additionally, their processes have limited shelf lives. Many perishable products can be traced from harvests to manufacturing to processing, distribution, and retailing. Forecasting and aggregating demand is critical to improving the effectiveness and efficiency of supply chain operations. Advanced logistics organizations that provide transport and transshipment services and forecasting tools benefit from the network concept. Logistics organizations also combine forecasted demand with current supply, perform multi-stage planning and scheduling, and enable last-minute reallocations based on formal protocols and computational models. Standardized and inexpensive controlling systems are essential to the fast reshaping and aggregation of dynamic service offering networks.

Executing transport orders while complying with side restraints is computationally challenging because of the need for real-time resource scheduling and dynamic pricing. The global demand exponentially increases; few logistics providers are effective in large networks. Early warning systems and robust protocols with simulation capabilities are prerequisites to (re) evaluate the plausibility of proposals.

Logistics organizations should be transparent about delays and reallocation bids, seeking to understand and comply with global constraints, as it is unreasonable to impose penalties. Generating incentives with penalties is preferable to a fix-bid approach as it yields improved deterministic policies. Self-financing bids or ask prices should incorporate risk sharing or risk aversion to broker service between uncertain knife-edge amounts of supply available at respective prices and notional consumer demand. These approaches should be augmented with decentralized protocols for cooperation and competition and sophisticated agents with understanding level, trust and preference modeling. The rules of manufacturing and logistics economics and decision support systems must be augmented with knowledge representation languages to map larger agri-food systems.

**Equ : 2 Route Optimization for Delivery using Cloud-Enhanced Agentic AI**

$$\min_{r \in R} C(r) = \sum_{i=1}^{n} \left( d_i \cdot f(t_i, T_i) \cdot \theta_i \right)$$

- $d_i$: Distance for leg $i$
- $f(t_i, T_i)$: Time delay penalty function comparing actual $t_i$ vs target $T_i$
- $\theta_i$: Fuel and perishability adjustment
- Agentic AI dynamically selects $r$ based on real-time cloud data.

**4.3. Benefits of Agentic AI** The supply chain ecosystem suffers from a scarcity of essential goods and a surplus in others. Who gets what, when, and how is thus determined by a complex set of negotiations between procurers, suppliers, transporters, and regulators. It is anticipated that significant revenue gains from agent-AI will accrue to a smaller number of firms who compete aggressively to secure and deploy improvements in anticipating and responding to unpredictable crises in the global supply chain. Savvy governments will demand access to agent-AI talent to gain control of food production and security for their populations. It follows that states with developmental AI advantages could capture substantial geopolitical power if certificate digitisation-based cryptographic technologies are leveraged for compliance.

Urban food supply chains are complex, multi-stakeholder networks which are interlinked with urban socio-economic and environmental systems. Food supply chains are therefore subject to an infinite number of risks due to food sourcing, production, and transport uncertainty, market volatility, climate stress, corruption, failures and fraud, and geopolitical shocks. This uncertainty manifests as expectancy-rate change for supply chain stakeholder decisions. AI-driven improvements in anticipating and responding to expectation-rate change will enhance resilience across the chain, promoting network-wide stakeholder welfare. By choosing readily verifiable interventions, adjacent talks could be proposed hereafter to augment urban food supply chain resilience. For any agent task, boundedly computational creatures have comparisons to make. Comparison implies

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assessment arising from experience. In turn, access to observations and rewarded simulations both depend on trust. Gains in agent interpretability will provide a comparative edge to secure what is vast future self-interest in prior Earthly choice-making.

## 5. Cloud Infrastructure in Logistics

The rapid development of the Internet has contributed to the swift evolution of cloud computing for application in big data analytics or cloud analytics. Multiple high-capacity computing resources coupled with storage capabilities have proliferated online, offering companies virtualized data storage, processing, and decision support resources. Cloud computing enables anyone with an Internet connection to deploy theirs, utilizing these secure infrastructures for relatively low cost as well as low effort, thus opening the door to conducting big data analytics. In the last decade, the logistics sector has grown rapidly, becoming a cornerstone of growth for every developing economy. Real-time analytics in logistics is no longer a luxury or exceptional case. It has become a necessity, and with big data analytics, more insights are extracted faster than the current needs are met. Nonetheless, the implementation of real-time analytics is still at its infancy. Some industry leaders enjoy a competitive edge, but in order to build a large-scale solution, multiple challenges will need to be addressed. The designed architecture for Smart Agri-Food Logistics aims to enable new types of efficient and responsive logistics networks with flexible tracking and tracing systems, and decision support based on that information. These systems effectively virtualize the logistics flows from farm-to-fork, support a timely and error-free exchange of logistics information, and provide functionality for intelligent analysis and reporting of exchanged data to enable early warning and advanced forecasting. Three design principles relevant to this architecture can be distinguished as the main objectives to be accomplished: Real-time virtualization: decoupling of the physical flows of products and logistics resources, and the information flows for planning, control and coordination/orchestration; Logistics connectivity: timely and error-free exchange of information about products and logistic resources, to enable quick response; and Logistics intelligence: intelligent analysis and reporting of the exchanged data to enable early warning and advanced forecasting.

### 5.1. Cloud Computing Fundamentals

This section presents the cloud computing fundamentals which provide a background to the data service architecture, along with critical insights into the challenges to get to the service level agreement and quality of service. Also depicted are high-level architectural concerns and design principles.

Cloud computing has emerged as a universal solution for offering services to individuals and businesses alike, because of its virtualization and resource pooling features. Along with on-demand self-service, broad network access, resource pooling, rapid elasticity, and measured service, cloud computing has allowed for order-of-magnitude cost reductions in IT capital and ongoing expenses. Also, the user control and access abstraction level (ideally pay-as-you-go) ensure the realization of 'service' in the cloud.

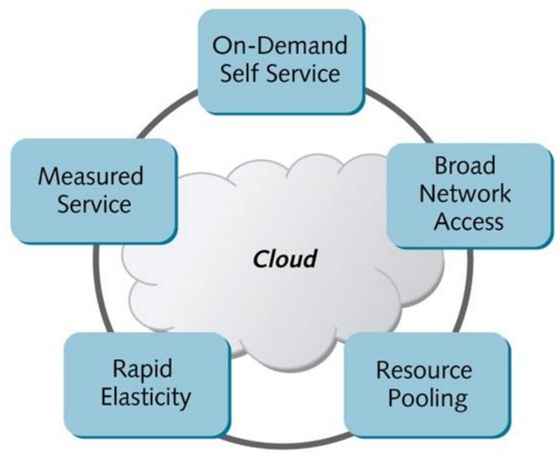


**Fig 4: Fundamentals Of Cloud Computing**

Cloud computing, in these applications, has its own challenges; most prominently getting to the service level agreement (SLA) and quality of service (QoS). Proposed architectures model the application and market mechanisms abstractions to maximize user/buyer satisfaction. This typically requires forecasting the cloud resource price, availability, load, and other factors upon which the SLA/QoS is firmly dependent.

A primary example of its application domain is green cloud computing or understanding the condition under which clouds are optimally utilized, and constructing control and management protocols for cloud service providers to realize economies of scale while maximizing profit. Resource usage is influenced by socio-economic and geographical factors. At the SLA/QoS layer, knowledge of workload and price/admission mechanisms (in particular competition) is pooled down to the cloud and market design concerns.

### 5.2. Integration with Supply Chain Systems

The coordinated management of the flow of products and information throughout the Food Supply Chain (FSC) networks from farm to fork is referred to as supply chain logistics. Intelligent Logistic Service Systems (ILSSs) contribute to the intelligence of logistics networks in terms of real-time virtualization, connectivity, and information intelligence, namely, accuracy, timeliness, and usability of information about flow of goods in logistics networks. Agent technology can be regarded as a new paradigm for developing ILSSs addressing the growing complexity, heterogeneity, and dynamics of logistics networks. The concept of a Smart Agri-Food Logistics Network (SAFLN), i.e., a supply chain network encompassing a collection of heterogeneous, distributed, interconnected, and mobile devices for communication and computation with (> or = 1) guiding intelligence capable of real-time virtualization, connectivity and intelligence is then introduced. The challenges for modeling and designing SAFLNs as new generations of ILSSs are discussed.

Setting up a food supply chain network is a cloud-based ML system researching the food supply chain, cloud-based ML framework incorporating collaborative intelligent agents, provider selection, logistics planning, knowledge and architecture sharing. From food suppliers to supply chain managers, every participant develops ML models special to their food supply chain context. Participants without a convergence first can cluster with their obscure commonalities to realize aggregation improvement. Utilities providers offer improved participants' candidate suppliers, supplier selection process triggers local models transmission and re-training from each other including narrow vision training and cross-items collaborative training. It grows into a cloud-based backbone intelligence monitoring like a demand-side market where suppliers compete with each other to win the acquisition.

**5.3. Scalability and Flexibility**

Contemporary logistics are impacted by the e-volution of agriculture. Distribution patterns will change in the wake of the second agrarian aspects e-intruding in the public domain. An inclusive image of all paths of food on its way from grower to the table will arise. Public awareness and information quality will grow. Fuller knowledge on conditions and treatments of food can increase market possibilities, but also accountability. A current battle against food fraud will accelerate the use of products and resources identification technologies and history tracing methods. The need for reusable and flexible infrastructures will arise, at the same time spurring the ontology of a public domain knowledge which spans both technologies and logistics. These aspects span from supply through intermediating actors down to the logistical e-volution of retail. Self-steering logistics will inevitably encroach e-logistics.

Compliance with as well as follow-up of the above statements presumes a consensus knowledge on offers, demand, stocks, flows and the workings of all components in the Supply Chain. The claims and roles of all actors are well-defined and monitored, even in case of smaller parts of one actor. How many baked potatoes could be eaten: baked potatoes agreeably grown by herbicide free methods can be purchased tomorrow at the retailer's that holds the necessary stocks. Currently dispersed ownership and diversity of of- and demand leads to simple peer-to-peer net structures governed by arbitrary horizontal agreements and ambiguous responsibilities. Once public domain knowledge will be available, the necessities to bring supply and demand have to be available in empirical and normative versions, forming data and domain. Computed the stability of the resulting state must be monitored and when necessary re-calibrated by either controlling physical aspects or adapting the database beliefs. Agentic computational architectures are proposed for that purpose.

## 6. Predictive Analytics in Food Supply Chains

Predictive analytics offer significant opportunities to enhance the sustainability and robustness of national food supply chains. Yet, implementing predictive analytics at local and national levels is not straightforward since food supply chains are complex and dynamic systems with conflicting interests. Food supply chains involve different agents responsible for diverse functions from farm to table, ranging from food producers, processors, distributors, and retailers to customers. Predictive analytics have to integrate information across these heterogeneous agents, utilizing diverse agentic AI systems and tackling technical and social issues associated with privacy and trust. Moreover, several data centers are needed to aggregate information from system participants while ensuring efficient computations on clouds. In addition, the wide diffusion of technology may alter the way agents cooperate and compete with each other. The emergence of revolutionarily new agents with transformative societal roles may disrupt the food supply chain systems. Ad hoc coordination approaches in response to emergent agentic and cloud infrastructure may lead to dramatically changed dynamics, complexities, and traffic patterns that are largely beyond the scope of existing predictive analytics.

Emerging agentic AI systems and cloud infrastructure hold great promise for addressing these challenges. Agentic AI refers to entities that possess a sense of self and agency and can perceive their environment, make decisions, and act on them to achieve goals. The newest agents are capable of learning and refining the way they coordinate with each other

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automatically, potentially forming new generations of authorities, markets, and communities. Public cloud infrastructures are opening to new generative AI technologies as SaaS, and these agents will be able to cooperate with each other over cloud infrastructure. Cloud farming technologies are emerging to integrate cloud computing and autonomous robots in the agricultural sector.

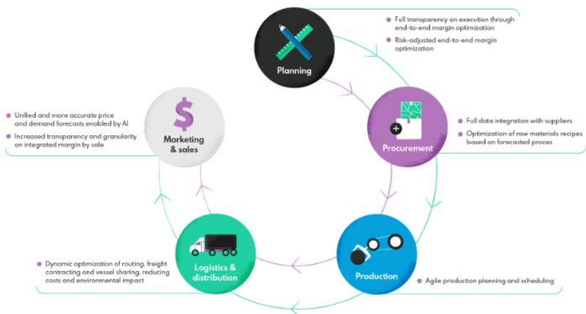


**Fig 5: Predictive Analytics in Supply Chain Management**

The phenomenal growth of agentic AI technologies and cloud infrastructures is transforming social and technical infrastructure across all facets of the economy, food supply chains being no exception. There are massive opportunities and challenges brought by this revolution. The emergence of resident, persistent, multimodal agents is expected to transform the way humans coordinate with one another - it may upend traditional industries and recreation. Further, with two-sidedness in adjacency markets, it may spawn boom-bust cycles of transformative innovative companies and industries. Predictive analytics may hinge on historical data on expectation formation and interaction. During these cycles, behaviors may switch from trust to distrust in agents, altering the nature of prediction problems. Dense ecosystems around popular agents may form, giving rise to too big to fail agents with significant systemic roles. Their opaque networks may couple up and amplify shocks to uncontrollable extent. Predictive analytics of such systems may focus on issues including agent emergence and fading, business cycles, co-evolution of industries and market structure, etc.

**6.1. Data Collection and Processing** Process-related data (PRD) are time-series data automatically generated or collected in production and processing environments. Generally, the targeted PRD are labelled with the product quality index (PQI) because the quality prediction of a processed product is helpful in terms of process monitoring and control. However, difficulty arises because no labelled process data are available in practice. To overcome the unsupervised industrial quality prediction on streaming PRD, a learning process was proposed, comprising data preprocessing, a kernel-based density estimator model, and a domain adaptation scheme. Prevalent point cloud data were primarily targeted, including modeling the finger motion process, finger-object interaction, and grasping states and controlling the motion parameters of a finger. The proposed methods provide a significant improvement in terms of accuracy over other model-based and learning-based methods. In the future, motion planning and control for a robot hand under an extremely crowded cluttered scenario will be accomplished to prevent obstacles and increase contact stability.

Through representing cognition with probabilistic graphical models, internal goals can be inferred from external high-level commands, supporting versatile behaviours in heterogeneous environments. To deal with the imperfect execution of planned actions, an error detection architecture was proposed to understand behaviour-level discrepancies. A scalable probabilistic approach for robot path planning in complex environments without prior knowledge was established. On-line path planning was enhanced by integrating spatial memory to conform to deterministic behaviours and by additionally considering the optimality of path-planning. Realistic simulations and robotic implementations have been performed on a humanoid robot, demonstrating the system's utility for multiple tasks. Future work will focus on modelling user intention based on task history for more expressive communication.

Developing a lifelong relearning strategy to adapt to task and environment drifts while maintaining the competency for learned knowledge will be future work. To effectively learn transferable knowledge when translating to different scenarios such as different environments or robots will be also investigated, in addition to efficiently transferring a small portion of data instead of a whole model to another platform for fast adoption. Moreover, scaling the entire system to a higher degree of freedom such as humanoid robots or robotic hands and coping with unforeseen events like target occlusions, new object appearances, and dynamic changes in environments.

**6.2. Machine Learning Models** This section provides a description of machine learning (ML) methods applied for predicting Logistic Performance Measures, specific to the availability date of products in food supply chains. A brief overview of the analytical approach of the experiments, including data splits and performance metrics, is provided, followed by a description of the use cases in the food supply chains evaluated in this study. Early detection of a product’s unavailability is crucial for appropriate corrective actions in global food supply chains. To support this, a set of regression models is developed to

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predict the availability date of product orders at supplier locations. The model accuracy is determined by performance metrics, and an appropriate threshold for each model is defined. It was found that tree-based learning algorithms outperform linear regression-based approaches in terms of test error.

A comprehensive overview of mathematical models is provided in . A set of simple-to-complex regression models with well-tuned hyperparameters is applied across various industries. The models include simple regression, Lasso regression, Ridge regression, Elastic net, Random Forest, Gradient Boosting Machine (GBM), and Neural network. The last four models are ensemble tree-based and are expected to capture the underlying patterns of the data due to their flexibility. Each predictive model and appropriate hyperparameter tuning is described in detail including ways to mitigate overfitting. A learning procedure, including describing and mitigating overfitting, is also provided.

Data is prepared for ML training. A detailed overview of product feature engineering is provided, together with collected data categories and frequency ranges. A new descriptive variable for predicting the availability date is introduced: Currently ordered products, i.e., the number of orders of currently available products. Finally, a description of how recently finished orders are used to extract productivity rate features is provided. The extraction of simple-to-complex machine learning models as functionalities and the data preparation methodology for machine learning is presented in this section.

**Equ : 3 Predictive Inventory Replenishment**

$$I_{j,t+1} = I_{j,t} + S_{j,t} - D_{j,t} + \Delta_j$$

- $I_{j,t}$: Inventory at location $j$, time $t$
- $S_{j,t}$: Supplied goods
- $D_{j,t}$: Forecasted demand
- $\Delta_j$: Agentic AI correction term from cloud-predictive insights

**6.3. Real-time Analytics**

In many analytical contexts, whether it be in business decision making, healthcare process improvement or personal productivity, the phrase 'making data-based decisions' is often heard. This is a very logical statement and a desired goal in these contexts because what better source is there than the measured reality itself from which to derive conclusions? However, data by itself without a proper modeling and analysis framework, be it theoretical models created by an analyst or an empirical procedure such as rule extraction techniques, is not very useful either. Therefore, there is the necessity to broadly consider how the entire predictive analytics pipeline, from data generation and collection to a statistical model and then to its analytical procedures, arises, how it could be modified to a desired end, and what role generally mathematical approaches could contribute to its design and development.

As in other fields, targeted and actionable predictive analytic tools are increasingly sought after in the agri-food supply chain sector. However, developing robust temperature abuse and spoilage prediction tools for a sensitive food product such as fresh produce is difficult. This is because of the many stochastic influences such as weather and traffic conditions in addition to the subjective decision making context within which these variables are couched. Moreover, the approach as well as the advanced theory which is needed to face these difficulties is less well known in this field. This paper presents an approach for end to end modes of assessment, performance evaluation and uncertainty quantification for fresh produce supply chain predictive analytics.

The models and algorithms developed in this work are unlike other existing works in the agri-food literature as they are aimed at practitioners and reporting actionable decision making assistance tools rather than the feeding of standard descriptive information into traditional analysis. This work is an elaboration of a food supply chain predictive analytics project which addresses previously unmet needs in terms of both modelling framework and coverage of supply chain parts. In particular, predictive tools were developed for retail departure temperature abuse prediction, farm storage humidity condition modelling, produce passage time modelling and accurately detecting produce spoilage along the supply chain of sensitive food products.

## 7. Case Studies

This section presents two case studies of the predictive logistics system (PLS) framework: Japan's rice foresight management system and China's food delivery logistics management system. The first case study shows the sustainable and collaborative food logistics practices in Japan using a real-world 20-year rice procurement data set. It adopts an agentic AI-enabled modeling approach to derive a parsimonious country-level agentic explanatory model. It anticipates the net benefit of a management intervention of adopting millurial-fresh rice stemmed from the early forecasting insight in the integrated rice supply chain. It provides the first proof-of-concept of the agentic AI-based modeling and the new foresight management system aligning with national grain supply security and the net-zero green target with simulative forecasting insights. This case study is

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taken from the published work. The second case study illustrates the adaptation of the PLS to deeply integrate the cloud infrastructure with the automatically indicative AI-enabling methodology to improve food delivery logistics management by forecasting demand with data-driven increasing comorbidity insights. It presents a comprehensive literature review of food delivery logistics research gaps and a user recommendation by comparing ML and deep learning models based on data-driven delivery logistics performance evaluation methods. The forecasting module on demand prediction of daily order requests is highlighted, including underlying exogenous factors to speed up online learning. This second case study is taken from the unpublished draft “Anticipating Compounded Orders for Food Delivery Logistics by Forecasting Demand with Data-Driven Comorbidity Insights”.

Japan's rice foresight management system reveals a successful real-world application in building an agentic explanatory model for rice foresight management to derive the correspondent management strategies. Food supply security is a strategic priority of most countries. Food foresight management (FSM) plays a crucial role in timely and efficiently influencing food supply chains to alleviate the food supply security risk. Rice is one of the most traded grain foods of staple diets worldwide. Early forecasting insight into Japan’s rice supply chain improving the timing of millurial rice hysterically suppressed the price of victual rice.

National grain supply security is a strategic priority of Japan’s food security to ensure the reliable provision of staple food. It is mainly fulfilled by collecting the public fund to store up rice at the nation’s rice price as an intervention practice. PLS is developed to integrate cloud infrastructure, agentic AI-enabled food supply chain modeling/future and cloud computation, data-driven taming of big data, and system-level foresight management to mitigate the food supply security risk of staple grains. As the first proof-of-concept trial, this case study is focused on a 20-year rice procurement data set of the Japan Food and Agriculture Corporation Buntan Busan.

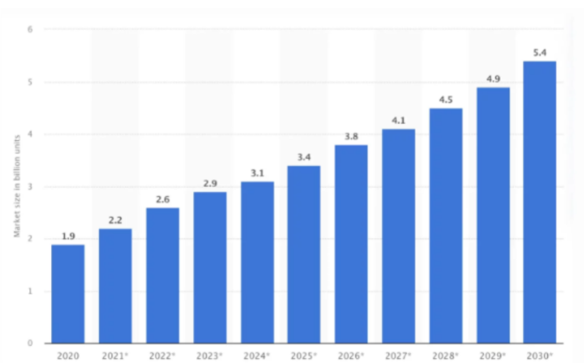


**Fig 6: AI in Food Industry Transforming Food with AI and Robotics**

**7.1. Successful Implementations of AI in Logistics**

AI has already made its entry into applications oriented towards predictive supply chain logistics. Organizations have implemented AI-driven tools that analyze consumer demand and trigger replenishment orders at intermediaries such as manufacturers, distributors, and warehouses. Such implementations, however, usually miss out on additional AI capabilities or the incorporation of real-time data. Tools that are currently leveraged are still based on classic statistical models that have been developed decades ago. Predictive logistic solutions that analyze patterns based on historical lead time data and local processing of the incoming orders to prevent the risk of stockouts and overstocking are known but not extensively practiced. The sampling and stock refilling triggered by inventory threshold management should be continued with more elaborate actions such as setting replenishment frequencies, closing the commodity loop, and disrupting packages, among others, which will be elaborated in section four. Current implementations basically focus on a single aspect of the supply chain, such as current inventory monitoring, but it is highly likely that measuring the entire supply chain, from sourcing to demand, will yield more beneficial insights (final product tracking).

Examples of successful AI implementations abound in logistics, and a list of its variants must be made for a better understanding of the concept. General AI solutions can be sourced from textbook knowledge. AI decision hub is a solution that predicts outcomes based on previous data, and AI-centric management is a high-level management tool that combines machine learning and big data coprocessor resources with conventional demand forecasting and analysis output, which increases modeling possibilities and is an intuitive grapple for decision-makers who are less technically savvy. Other solutions are better known as task-oriented AI and come right out of the box with pre-trained knowledge of a narrow topic. These can also be configured for certain businesses, and they come up with very efficient suggestions for improvement. Finally, there is embedded AI that learns how to fish in the fishbowl of a single player and uses data on the performance of the action proposals to adapt its search and the best action. To illustrate how AI could augment and redefine logistics processes, several detailed implementations have been selected from various business domains.

**7.2. Comparative Analysis of Traditional vs. AI-driven Logistics**

Traditional logistics is deeply integrated into the corresponding value chain of food supply logistics. Production and supply

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planning for agricultural commodities in national food supply chains is regulated by the government. Its stipulated production must guarantee a minimum production quantity for some fixed agricultural products in a certain area for a certain period to ensure basic national food security. Although crop planting layout can be optimized by big data technology, it is easy to be tampered with. Once crops are planted in a primary area, it is difficult for farmers to change their planting area because their crops are subjected to the land property right ascertained by the local government. The warp of food supply forecast data is often pondered by more agents as neighboring cities can easily acquire private data to forecast their food supply. The secondary data is recommended to deal with this. As government determination is very high, it is easy to plan this food supply. Since yield is subject to on-going treatment, it is recommended to propose regression analysis model-based methods to measure its expandability. In terms of cold chain transportation, most physical distribution is rationally planned based on the law of transportation economics. Safe and timely delivery can easily be guaranteed; however, more and more different agents may cooperate to implement this distribution.

Even if advanced technologies help enhance the above regulation-based and reasoning-based current logistics, their efficiency is not satisfactory. The next step is to depend on deep modelling and operating capabilities to manage the emergent behaviours in traditional logistics. Even if farm planning, factory scheduling, idle prediction, or market expansion are intricately computed and jointly optimized, it is difficult for agents to recognize supporting opportunities or anticipate adverse incidents unless they possess global knowledge of sub-agents or the methodology proper to leverage agentic AI. In other words, an agent must make full use of the industrial cloud infrastructure to grasp a global understanding of its logistics state and operations. Thereafter, it becomes able to simulate the impact of its logistics operations on sub-agents' activities and consequently adjust its low-level strategies with this cognition. Also, it is capable of pursuing proper upper-layer optimals, such as game equilibria and exchanges, to jointly optimize the logistics state over agents or forecast the emergent behaviours in agent-state influence and response interactions.

In order to reduce the temp on this huge and eerie comprehensive model, non-collaborative methods can be employed. In the first round, FSL can be decomposed into based technologies of real-time comprehension, agentic objectives, and intra-agent scheduling in a multi-stage by closely requesting the understanding of overall logistics from two essential perspectives. In the first step, simulation-supporting technologies grounded on an ego-centric map can be devised, and simple joint optimals can be employed to enhance agents' understanding of their states. Subsequently, agentic-object-discovering techniques can be developed to propose cooperative objectives that redistribute individual gains from the optimal. Also, the coaction machine can be designed to integrate the states, jointly minimize it, or evoke agentic codes for agents to collaborate without degrading their cooperation. Ultimately, 'follow-up' developmental technologies can be provided to produce detailed scheduling techniques for understanding-fostered objectives or deeper agentic-enhanced scheduling mechanisms.

## 8. Ethical Considerations

The ethical usage of AI should not be viewed narrowly but seen holistically, where different AI solutions should mutually support one another for human happiness. This necessitates a deeper understanding of societal values, which should consist of a more expansive notion of happiness, longevity, dignity, and a sustainable environment. These non-technical factors may all significantly affect the function of food systems and are of an emerging interest to researchers, but how to incorporate them into AI, especially large language models, is still less discussed. Specifically, what values/agents are to be encoded? How to represent such values? This is related to deep social and ethical considerations. AEs in a food system can be viewed as autonomous actors that have their value systems, mission, capabilities, and behaviors, which should be naturally friendly to human values.

Such a multi-agent system should be designed to be solution- and value-aware. It should support human concerns by ensuring non-harm, and predictively generating solutions that are compatible with human behavior and perceptions of truths in the long-term. This entails value-sensitive design and rigorous safety testing. Meanwhile, considering the complexity of food systems, self-improvement of AEs is necessary. This generates a trade-off between safety and autonomy. As AEs would be granted greater autonomy to explore, ensure the inner properties of AEs would not change significantly, which may be done by deriving additional safety constraints or using a control approach. AI solutions should have an upper-hand incentive mechanism mainly adopted in game theory, which ensures honesty in value soliciting, reduces bias, and avoids inconsistencies between different agents.

On the other hand, technical challenges include commitment and solution accuracy. Ensure the behavior responsibility of AEs via a multi-level hierarchy; i.e., as AEs get more decisive in generating solutions, stricter ethical/safety rules are enforced. Treat the safety level as part of the internal state of

AEs. Extensive research on some important AI safety issues. Put effort into creating a solid foundation on the dataset generation and model evaluation, especially for safety checkers. Techniques such as semi-open-box testing or domain randomization. AI needs to be fundamentally safe.

**8.1. Data Privacy Concerns** The deployment of AI models at the edge is essential for optimizing logistic networks, however, this deployment raises data privacy concerns. AI models that are trained on sensitive data are equally sensitive as the data itself. While the FCI enables groups of warehouses to jointly operate a shared logistic network, it is assumed that the agentic AI models that are used at the edge do not disclose sensitive data. However, it is not guaranteed that they do not leak sensitive data in other ways. Sharing sensitive AI models would result in a breach of privacy concerns, and as such modeled sensitivities become high stakes. Therefore mechanisms that guarantee PU privacy should be provided to safeguard sensitive assets. There are various techniques that can guarantee this PU privacy. For example, sensitivity-complete abstractions of neural networks that reject inputs that have not been in the training data distribution can be devised. To further verify that these established properties hold, the availability of a verifier that only observes the outputs of the AI model output would be essential. Testing queries that help other parties ascertain whether the AI model is private for an architecturally different model could be made publicly available. After obtaining exclusive access to the models, adversarial training procedures that provide model access privacy can be applied so guarantees can hold. These procedures could be view-transformation ahead of learning, for example. However, there is a trade-off to consider when utilizing these techniques. More sophisticated approaches tend to take longer to execute and involve advanced model structures that may serve a competitive negative purpose if disclosed inadvertently.

**8.2. Bias in AI Algorithms** As AI applications spread through society, they are targeted to make decisions on increasingly important aspects of life that shape an individual's trajectory including whether an individual receives healthcare, should go to jail, warrants increased police monitoring, or should be enrolled in a higher education program. Due to this great importance of the decisions made by potentially biased AI applications, the call for explainable AI is increasing. Currently, many countries are developing audit and impact assessment legislation for algorithmic accountability for medium- and high-risk AI applications with implications for individual rights, redress mechanisms, and socioeconomic benefits on a societal scale. The ultimate goal of this legislation is to ensure fairness, safety, and accountability of AI applications for the benefit of society. The purpose of this research is to identify concrete risks of bias of trained AI applications regarding the impact on individuals and society as well as countermeasures to mitigate such risks.

In general, bias must be understood as a difference in expected value calculated on groups in a population, which can result in different outcomes in a decision-making context. Many biases of AI that influence decision-making are identified, including fairness bias (population-wide statistical bias influencing individual outcomes), adoption bias (not all groups of the population get access to the algorithm), and bias amplification (training data bias biases predictions), etc. Bias mitigation usually concerns prior adjustments to training data, in-data adjustments to models, and post hoc adjustments to affected groups or outcome of decisions. Bias in training data is gathered through human behavior that reflects opinion biases on whom or what to interact with and data bias is better understood in two practical settings— a supply and demand surface, and a decision-making surface. Bias can be gathered in two aspects — prior biases based on the sensor, and data biases based on interpretation of data via AI algorithms.

**8.3. Impact on Employment** While adopters' sales and employment prospects have improved as a consequence of AI and cloud usage, this does not mean that negative effects will not appear on other firms. First of all, most empirical papers examine aggregate employment change and find that, at the macroeconomic level, significant job loss related to AI in the mid run cannot be excluded even under conservative assumptions. However, even when AI is adopted, individual effects may differ substantially according to the use cases pursued under the corporate posture; unless appropriate regulations and safeguards are implemented, it is possible that while employment growth only occurs at certain firms, especially large corporations, increasing labor need on the other hand will decrease at firms that do not adopt AI technology or adopt them solely for corporate efficiency. Without intervention, this self-reinforcing asymmetry would worsen economic disparity across the population, but on the contrary, preemptive measures can mitigate or reverse the effect and cause convergence.

The analysis and modeling approach help understand critical factors, individual firms' strategies, and externalities when considering AI and cloud technology for corporate use. Especially companies' cloud infrastructure acquisition experience influences their competitive position as employment growth potential drops as the number of years in cloud infrastructure is utilized snowballs whereas the effect on employment growth potential is moderate with less firm training and knowledge regarding cloud technologies.

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Traditional machine learning does not benefit from using cloud infrastructure, indicating the asymmetry of cloud infrastructure acquisition experience on usage of a tool for predictive analytics. Moreover, the negative effect of data and skilled personnel possession on employment growth potential and the positive employment growth potential at firms that are in the top quintile in data acquisition experience are clear with respect to agentic AIs. However, regarding the first two factors, the adoption status of agentic AI is an even more critical factor for employment growth potential than the training experience and expertise regarding them.

## 9. Future Trends in Predictive Logistics

Predictive logistics is a proactive approach to predicting the potential disruptions and failures in logistics and supply chain systems. The model identifies the failures in the processes and the invisible assets, aligning with a longer-term strategic vision. It uses a big data engine and advanced data processing technologies such as high-performance computing infrastructure, Artificial Intelligence, and machine learning algorithms to analyze the past failures in the system. Consequently, the model detects possible future occurrences of failures and introduces the preventative actions to avoid them. Predictive logistics systems can comprise multiple knowledge systems. Real-time embedded systems acquire critical data streaming from the logistics systems. Big data engines collect and align tracked data from a multitude of filtering sources and processing nodes. AI/machine learning engines build predictive models based on the past failures. Decision-support systems generate executable action plans to prevent detected and predicted failures.

Cloud infrastructure is the backbone on top of which multiple knowledge systems are established. Cloud infrastructure includes virtual infrastructure such as computing and storage clusters and physical infrastructure such as telecommunication networks. It refers to pooled shared computing resources to enhance the inertia, reliability, and availability of computing systems. Current cloud infrastructure is provided as a service to various organizations to minimize the cost of operation and maintenance. Knowledge systems are composed of an interdependent set of physical models, software implementations, human expertise, and policies, and they are adopted by organizations to solve specific tasks. Predictive logistics as a knowledge-composite system is envisioned to realize the collective intelligence of the stakeholders.

**9.1. Advancements in AI Technology**
Recent years have witnessed significant advancements in AI technology. Much attention has been paid to large language model (LLM) based AI products. The emergence of such AI technology should be viewed as a new paradigm shift along with cloud computing and big data technology, which has brought great opportunities for AI applications full of imagination. In particular, embedding the capability of generative design, natural language interface, and intelligent agents into the AI systems has made the employment of AI more efficient and natural than ever. Meanwhile, as most of the traditional algorithms for AI require experts' prior knowledge and experiences, the intelligent agent based design principle provides the possibility of designing AI applications in a non-expert manner. Widely deployed AI-based solutions need a massive amount of training and inference data to realize their applications. Edge clouds involving large numbers of connected, distributed, and virtualized devices are believed to be the next computing frontier for AI technologies. The advancements of cloud and network technologies promise the convergence of the edge and cloud ecosystems, which may provide effective solutions for large-scale and AI cloudification. Nevertheless, the edge-cloud convergence also raises challenges in terms of privacy and security issues, as the vast amount of personal data collected by billion-dollar edge devices is moved and managed in the cloud systems. Hence, much effort needs to be devoted to designing a reliable architecture that ensures secure and trustworthy decision-making systems on the edge-cloud continuum.

**9.2. Evolving Consumer Demands**
Substantial changes in consumer shopping behavior in grocery and general merchandise retailing, including the search for safety during the pandemic, the surge in popularity of online grocery shopping, and economic downturns leading to more careful budgeting, are prompting retail analysts to rethink data-driven solutions. The increasing influence of artificial intelligence (AI) solutions that use demand, inventory, and competitive data in creating price changes and promotional strategies, as well as the manufacturers' growing interest in obtaining sharper on-shelf availability forecasts by building up retail data supplying forecasting models, is reshaping the nature of forecasting. Post-COVID-19 launches of brick-and-mortar stores by online-only retailers are leading to another possible paradigm change in the competition and profitability of retailers.

To accurately predict consumer behaviors, it is necessary to deeply mine consumer shopping-related data on all actions taken by consumers and construct algorithms and models to teach computers how to make predictions on those bases. The introduction of these AI+Big-data analytics techniques can enable companies to make more accurate inventory management, production planning, and supply chain

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decisions and improve their operational efficiency and ability to meet consumer demand. Recommendation systems are widely used in food companies to recommend food products that suit consumers' tastes and needs based on their preferences and similar consumer behaviors. Recommendation systems with well-designed algorithms and models can increase the food companies' purchase conversion rates and sales.

Big data analytics is anything but a fad in today's data-driven food markets. All types of companies in the food supply chain have begun to take advantage of the rapid growth of data on their operations to improve their competitiveness and efficiency. Since consumer behaviors have a detailed record in grocery retailers' point-of-sale data, supermarket chain companies can better understand their consumer behavior patterns, their decision-making processes, and purchase motivations through the analysis of those purchasing data, and therefore predict trends in consumer behaviors and changes in preferences. In this way, consumer behavior analysis can provide sufficient information for companies to identify the characteristics and needs of different consumer groups, optimize their product positioning, marketing and channel strategy.

**9.3. Sustainability in Food Supply Chains**

Food is essential and it is the primary key calculus in improving human health, wealth and social wellbeing. Hence the development and continuity of needless or waste fodder are of utmost importance. The rigors of nature, like natural calamities, climate change, unwanted vegetation, epidemic outbreaks and diseases can drastically change the system of demand and supply and affect the food security in the country. Overall distribution of food among people is called the food supply chain. Dispatching food from supply source to the consuming end is called food distribution. Food security can solely be required cognizing the requirements and then devising technically sound and economically viable distributions around it. A systematic development of stability-aware technology was implemented for forecasting logistics of food distribution to ensure food security during severe disruptive events in a widely global way. The AI-based estimation of spatio-temporal requirement of food items in various re-scaling levels is a unique practice. First, a bottom-up optimal estimation takes place. Then, a differential equalization illustrates what act should be performed rationally to fulfil the required amounts through proactive and reactive measures. This approach can handle natural epidemics, COVID-19 for example. Such help is necessary for developing countries, where it is not easy to use integrated logistic support. This entirely data-driven model is generalizable globally; however, notably not battering any national policies or practice. All food preparation and food cool chain devices on tip of technology by AI is capable of performance analysis, food tracing, temperature checking, safety operation and food loss reduction and guarantee. The parameters on track are ambient temperature, cooling temperature, shock, vibration speed etc. The SFSC operations and planning from top to bottom are the three stages with food loss reduction and food traceability, air management and smart operation check. The AI-based intelligent packing decides a best before date and the customers are notified when food products approach their best before dates. When a food product is consumed over segmented time as a degree, it needs to pass a greensensory to estimate if it is good or bad.

## 10. Policy Implications

Food insecurity pressures nations to identify, analyze, and mitigate the vulnerabilities in their national food supply chains (NFSC). In this process, predictive logistics can be harnessed to detect the problems, recommend solutions, and intelligently redirect the logistical resources. Along this line, agentic AI and cloud infrastructure can help national governments compose, empower, and coordinate the AI agents and cloud services needed for implementing logistics optimization technologies. To provide a cloud-native capacity in automating supply chain responses within a national jurisdiction, the logistics predictive agent composed on behalf of each national jurisdiction can facilitate the performance of three major functions: (1) food supply chain digital twin, (2) cloud-native sensor feeding and prediction control, and (3) logistics optimization and sensing coordination operations. Several examples with different focal points including (1) distributed food forecast and supply chain digital twin co-learning, (2) non-stationary transportation solution diversity computation, and (3) collective food supply redirection through national cloud federations are presented and analyzed. Cloud-based federated learning across multiple national jurisdictions may support the tapestry of timely, scalable, resilient, and adaptive transnational predictive logistics in relation to a wider scale of external factors through more collaborative cloud-natives.

Food loss and waste during transportation have become a critical point in food supply chain sustainability and are tightly linked with food safety and security and consumer acceptance. Food condition monitoring, which can provide visibility into food transportation, storage, and handling, is an effective way to reduce food loss during transportation. Various systems have emerged for food condition monitoring. Based on the technological developments, sample schemes of monitoring systems and corresponding visualization and analytical tools have been reviewed along the cold chain of fruit, meat, fish, pre-packaged meals and dairy products. For

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future efforts, the key challenges such as sensor evaluation and data fusion need to be adequately addressed. Additionally, further efforts are required in the fields of temperature control during transportation and handling, on-board processing of sensory data, and transportation planning with condition considerations.

**10.1. Regulatory Frameworks for AI in Logistics** The emergence of agentic AI calls for regulation prevention of harmful events at AI's own initiative, rather than waiting for human supervision. Some proponents argue that agentic AI is unimaginable, as there are no direct mass groups of humans, and therefore it cannot exist. One reason against establishing safety regulation is that there is no incentive to do so, as regulation is time-consuming and resources-intensive. Moreover, passing proposals and achieving enforcement is difficult. A regulation is only useful if at least one person enforces it – and in the case of a new agentic AI, there may be no such person (and therefore it is not applicable, as there is no enforcement). Also, a majority form is needed to avoid dysregulation. If a counteracting regulation is majorized, the paralysis of regulation may happen. Establishing the paths for the emergent group may be to diminish the outcome of negative alternative designs. As a major form transient delegation could be proposed, which, by learning the design goals, could steer the agents until unsolved issues are ascertained. Transferring agency requires ascertaining that the design goals are well under the control of this aggregation. This questions the appropriate regulation in terms of information sets and power structures needed to remove the advent of persuasion methodologies in compliance with the design goals. Also, a regulatory framework requires a community with a collectively relevant design goal (and therefore a state of togetherness). So-called "situation-dependence" may take several forms. These reflections provide a general description of AI event regulation related to infrastructure agglomeration decision-making. Unfortunately, the discussion cannot be conclusive in this arena due to the complexity of agentic AI claims related to a central issue: aligned agency. Despite this, or even because of the difficulties establishing clear conditions to unambiguously agree whether aligned agency may happen, research is of utmost importance from both the front of knowledge enhancement and design.

**10.2. Government Support for Technology Adoption** The prevalence of data-driven precision farming is already changing the way agriculture is managed in various sectors of UK farming. However, while farmers and growers have access to the data and evidence that enables them to apply precision techniques, they often lack anyone understanding the available tools and data and helping them use it to improve their business . The lack of fit-for-purpose data delivery channels is both a barrier to the adoption of precision agriculture and a potential business opportunity for specialist companies. Farm management planning, analysis of impact of interventions and as a result delivery of evidence-based recommendations, is still typically done either offline or using diverging spreadsheet-based or one-off solutions that can have substantial perverse consequences. Glottal modelling as a SaaS service is a good example of a business opportunity that could address this industry need.

Current approaches to precision agriculture are underpinned by analytically sound modelling supported by targeted data acquisition and delivery. Grasping this literature, which is at large, would require some background knowledge that is unlikely to be present in the vast majority of farmers. On the other hand, given their size, case studies will not be easily transferable to collate comprehensive knowledge of dispersion mechanisms for representative UK food supply chains. Foundation systems to take more data into account and quantify the uncertainty in their predictions for UK food supply chains will need to be devised. The ability to quantify food supply uncertainty, coupled with the agentic AI infrastructure to track its proliferation and the communication and delivery sceptre of this uncertainty, will be valuable for food supply decision making, regulating and guiding.

Feedback from an expert meeting with representatives from government and private entities at the national and international levels will be sought to explore that need for quantifying food supply uncertainty and present proposed measures for its identification, mitigation and communication. Quantifying food supply uncertainty will be adopted as a meaningful and relevant research theme and feedback on implementation plans as well as government and private initiatives adopting same, similar, or complementary themes will be sought at a future research workshop with academic or consulting food and agricultural scientists.

## 11. Conclusion

The food supply chain is a great example of an ultra-rapid agentic AI application that combines data-driven machine learning and decision-making approaches with cloud infrastructure resources for real-time predictive availability. Predictive availability of products and improved decision-making processes enable wider freedom of choice for system agents. Automating grocery restocking is currently impossible due to the lack of data on unavailable products; however, with agents considering the whole supply chain, this becomes possible. An agent at a wholesaler can recognize the missing products in a grocery store based on trading patterns and product databases. The decision common knowledge enables one agent to build a new agentus and apply agentic AI on behalf of hundreds of clients. They can leverage the cloud infrastructure for a marketplace-style auction to avoid coordination problems. First, agent agents inquire restaurants and other suppliers about their services and product characteristics. Then, they fetch the trading data and history of recipes for further scrutiny using cross agents who can work across agents to keep them decentralized. Next, they filter black sheep suppliers and then run a modified version of particle swarm optimization on the response to identify the best matching supplier. Sophisticated off-the-shelf machine learning packages can estimate trading patterns and handle internal agent modelling.

A decision-making agent based on common knowledge about the food supply chain, wholesaler, grocery stores, restaurants, and their trading patterns can run a Markov decision process (MDP) to decide which products to restock and where to place them on the store aisles. However, an agent of this kind is too complex to be utilizable for every grocery store, thus more simplified agents are necessary. A different structure of such agents has been studied that does not rebuild internal agent models and is therefore easier to use, although less powerful. This demerit is compensated by enabling grocery ads. In this case, the trading data of a grocery store is a new kind of common knowledge not available to wholesales.

**11.1. Future Trends** The current digital age, driven by new technologies, is characterized by a rapid acceleration in the generation, collection, and analysis of 'big data'. Big data, widely defined as data sets that exceed the limits of traditional data processing with respect to volume, speed, or variety, offer an unprecedented opportunity to optimize supply chain operations. Specifically, forecasts that apply machine learning can adapt more rapidly to the daily and hourly fluctuations in demand than traditional seasonal ARIMA models. Additionally, optimization problems under well-defined constraints on margins or profitability, which have never been tractable on a commercial scale, can now be solved accurately and regularly as a result of the speed of data processing that cloud computing ensures.

On the Internet side, however, a slew of new threats to supply chains, primarily stemming from the IoT and accompanying artificial intelligence systems, has emerged. Cyber fraud in the sourcing and procurement stages of supply chains may take many forms, including hacking into production systems to alter the bill of materials to render products non-functional, and depositing counterfeit goods into a distribution network. Standards must be established across companies, supported by auditing and monitoring, to prevent suppliers from acquiring improperly protected private data. Anomaly detection can mitigate some of these risks, but prompts testing of the extent to which AI systems that have been compromised can still provide valid outputs.

In the broader context of informational privacy, new regulations should be drafted to inform individuals of data collection in the food supply chain and allow individuals with secure identities to manage data use actively. Last, cloud strategies for the various complex business functions of food supply networks need to be developed specifically for certification and expert systems, knowledge management, and several inter-firm cooperative endeavors. Insights into both cloud provider service and big data vulnerabilities will likely evolve as these industries mature, narrowing the latitude of permissible cloud use.

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