www.ijecs.in
International Journal Of Engineering And Computer Science
Volume 11 Issue 12 December 2022, Page No. 25673-25690
ISSN: 2319-7242 DOI: 10.18535/ijecs/v11i12.4737

Leveraging Agentic AI for Autonomous Decision-Making in Food Supply Chain Logistics

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Abstract
Food supply chains are inherently complex, dynamically adaptive, and constantly subject to variability. However, the immense importance of a safe, secure, and efficient food supply system has never been more apparent than in recent years, as catastrophic shortages, waste, and rising prices have prompted a surge of interest from policymakers and researchers. To address these challenges, new technologies have the potential to transform food supply chains from fat and frisky to fit and fine-tuned by facilitating decision-making and instilling more automation. Recently, several advances in AI-based solutions have arisen, to the point where some very sophisticated and very powerful solutions capable of very sophisticated strategic, tactical, and operational decision-making processes are becoming available. At the same time, their commercial ecosystem is maturing, and commercialization landscapes supporting everything from verticals to incubators are emerging. Much like how a rising tidal current can float all boats, this flourishing new generation of decision-making AI systems and technologies holds the potential to transform food supply chains.
This paper argues that deployable higher cognitive capability AI systems, or Agentic AI, can be leveraged to embed multiple layer decision-making capabilities along the food supply chain to address its various challenges, particularly at the operational and tactical levels. The ability to integrate the physical and cyber systems with autonomous decision-making capabilities also holds the potential to seamlessly fuse human operator and control tower insights with those of increasingly capable IT systems, enabling meaningful opportunities for operator-awareness, oversight, and collaboration. We outline an operational framework for modeling food supply chain decision-making challenges and then layer Agentic AI capability enhancements on top to demonstrate how the framework can leverage Agentic AI to overcome the challenges faced at the operation-tactical level of food supply chain logistics.

Keywords: Food Supply Chains, Decision-Making AI, Agentic AI, Operational Framework, Tactical Decision-Making, AI Commercialization, Automation, Supply Chain Optimization, Cyber-Physical Integration, Human-Machine Collaboration, AI in Logistics, Food System Resilience, Operational Intelligence, AI for Policy, Strategic AI Solutions, AI-Driven Oversight, Real-Time Decision Making, AI Ecosystem, Food Supply Resilience, AI Deployment Strategies.

1. Introduction

The transformation of global food supply chains by the economic and societal demand for faster and cheaper services, increased customer satisfaction, promotion of environmentally sustainable models, and cultivation of organized global markets for individual commodities has been nothing short of tectonic. We have seen the growth of lengthy international transportation routes, decline of reseller margins, establishment of hub-and-spoke distribution centers relative to sales densities, and establishment of supplier alliances to consolidate production and transportation. Indeed, as travel was conducted across longer and longer bottleneck routes, food spoilage or value depletion became commonplace. Emphasis began to be placed on the design, and rapid redesign of highly responsive and fast chain distribution, with linkages fortified by information technology. Yet, while the proverbial need for speed was extensively affirmed in the theory, actual practice was centered on reduction of chain production costs, and optimization of logistics intra-firm.

Historically, most supply chains in our world have been farmer-driven or buyer-driven, which operate on commodity markets. However, these two supply chain types have transformed. In the farmer-driven evolution, greenhouse culture, production-oriented information technology involving quality, food safety, and environmental preservation, and genetic engineering innovation have become focal points. These innovations are designed to create demand-pull markets for temporary monopolists in various phases of the production cycle, and avoid current dual-impulse market valley cycles to the extent possible. The buyer-driven evolution is visible in the hybridization of conventional import country commodity chain activity with fast food supermarket brands and trading companies, with the objective of minimizing time uncertainty and risk exposure in inventory balance.

1.1. Overview of the Study

"Agentic AI" refers to a type of artificial intelligence that possesses its own goals and can utilize its competencies to achieve those goals in autonomy. In Food Supply Chain Logistics (FSCL), Agentic AI could serve valuable roles. This study presents a foundational exploration of whether FSCL management gaps could be addressed through Agentic AI by examining two research questions. The first question studies FSCL openness to Agentic AI intervention. The study contemplates safety and mission assurance challenges along with the inherent ethical dilemmas of transferring FSCL operational authority to AI systems. The second question examines which FSCL functions, decision-making activities, or project types could leverage an experience-based Agentic AI. The study draws on extant literature and on original work in function and competence modeling for FSCL logistics, as well as on model application to Agentic AI system architecture and competency analysis.

The position taken in this exploration is that human decision-makers in FSCL perform only partial optimization of system utility, based on inputs that are purposely kept limited for safety and practical reasons, and that Agentic AI intervention in FSCL operations may enable more effective networking of decision authorities, and optimization of system utility, without diminishing the roles and competence of human decision-makers. The originality of this study is that Agentic AI is postulated as having a disparate competency model from a human FSCL decision-maker. Agentic AI may have a better capacity for FSCL resource allocation and scheduling decisions than a human decision-maker, especially as FSCL complexity increases with intelligent demand and supply partnerships. However, Agentic AI may be expected to deal poorly with FSCL project choices that require qualitative assessments, particularly in the absence of well-established metrics for project evaluations or for the critical dimensions of project performance.

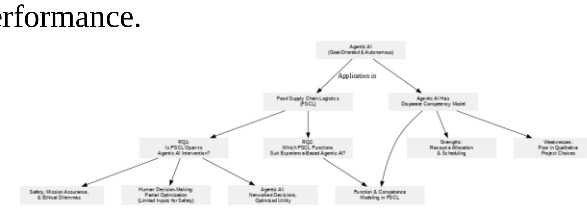

Fig 1 : Agentic AI (Goal-Oriented & Autonomous)

2. Background and Motivation

As the global population surges towards the predicted 10 billion by the year 2050, accelerating progress in food production systems is our only motto to feed the rapidly growing flock. Within this context, Food Supply Chains (FSCs) play a critical function in providing the expected service at low cost and risk. Undeniably, the pandemic has nicely exposed the exposable resilience bottlenecks and problems across critical global supply chains, and it has integrated needs into the long-awaited digital transformation in the years ahead. However, today visual graphical systems are unable to partially or fully assure supply chains resiliency, especially in continuously flowing food systems in the presence of unusual volatility in demand and supply chain disruption. New concepts such as resilience at all costs seem challenging to abandon. As these decelerate the re-discovery and deployment of novel virtual technologies for smart control and supervision of the required food supply chains resilience, the time can no longer be overlapped with the wait for the launch of the necessary data-supported digital transformation. Actors within and behind these systems react even more diversely and address any trouble passively.

The intention of this paper is to explore and assess the opportunity threshold to effectively turn such a sidelined time into the careful and prudent collection of needed data to transition the needed migration into the positive domain of active decision-making in times of uncertainty volatility for such food-related supply chains through singularly smart agentive digital twins. To this goal, we plan to capitalize on the concept of Predictive Analytics as a pathfinder into the preventive safety margins for effective and autonomous agent decision-making. Thus, a pluripotent transport feature is proposed in the form of Digital Twins as Enablers of Agentic Artificial Intelligences to learn to serve. It is done in the face of the distinctive marker of available training condition data prior to the Digital Twin's deployment, and local intervention training data only, during the Digital Twin's operation at real time.

Equation 1 : Autonomous Routing Optimization (Agentic Utility Function):

$$U_r = \max\left(\sum_{i=1}^{n}\left(\frac{Q_i}{T_i + C_i + \delta_i}\right)\right)$$

where:

- U_r = Utility of routing decisions
- Q_i = Quantity/value of goods delivered on route i
- T_i = Travel time
- C_i = Cost of route
- δ_i = Delay risk factor (e.g., traffic, perishability)
- n = Number of potential routes

2.1. Importance of Research and Its Relevance

The argument is that leveraging new technology is key to reduce post-harvest losses and boost investment in transportation and logistics processes. Economic growth and improved health in low- and middle-income countries are accompanied by increased per capita food and forage consumption. This transition entails greater use of intensive farming methods whose outputs are more sensitive to production shocks. A key factor in intensifying demand for food products are population expansion and sustained urbanization processes, leading to rising levels of waste and food loss. Availability of nutrient-rich food, and its preservation, requires national governments to integrate logistics into their food security programs. The contribution underlines that with increasing urbanization in a rapidly globalising world, more sophisticated deliberate risk-based modelling, particularly in the decision-making area of logistics, is required. New research addressing these factors should provide new tools with the capability and functionality to enhance effectively the decision-making and operations of logistics in today's highly interconnected marketplaces.

Agentic AI in the realms of an Agency Framework, Neural-Symbolic grounded learning mechanisms and Resource-Aware Decision making, provides important new decision-processing capability different from the traditional heuristic driven operational and tactical level decision-making techniques presently used in the Food and Logistics Supply Chain processes, that can utilise real-time data on climate change, bio-chemical and logistics real-time forecasting, prevention and intervention requirements at all levels from the farm through to shelf, to provide for much more capable, less risk-prone, real-time operations. This capability can be available at the macro level firstly to International institutions, National Agencies and Corporates driving the operations of the Food and Logistics Supply Chain, as well as, secondly, Governments, NGOs and Food Activists organisations managing the Food Aid Distribution processes.

3. Understanding Agentic AI

An increasingly wide array of applications, from creative design to composition or coding, are being undertaken by artificial intelligence. The rapid emergence of creative capabilities in generative AI has called into question the conventional view of AI as static or primarily assistant-like. Based on these developments, we posit the need to understand and define the notion of agentic AI, which we consider to be AI that can learn, evolve and create autonomously and without human intervention, is able to make independent decisions, has agency-like attributes and characteristics, including autonomy, goal orientation, judgment, interactivity and transformational capability, uses various forms of human-like reasoning including causal and design reasoning, and results in autonomous ability in the AI to take creative and impactful actions in the real world and is able to perceive its context and situation. While these broader capabilities have been discussed within the general theoretical structure of general artificial intelligence, the continued march towards leveling up the current round of narrow AI to attain forms of agentic AI is likely to present the need for wider exploration of these capabilities. While current forms of generative AI act as powerful assistants to aid creativity, we see the differences between them and agentic AI as expressed in four demarcation points. The first is autonomy, whereby agentic AI can work independently without human steering. The second is goal orientation, where agentic AI is able to articulate and pursue goals given various forms of human feedback. The third is judgment, where agentic AI is able to evaluate actions and their outcomes for attendant trade-offs and risks. The fourth is interactivity, whereby agentic AI interacts with humans in creative and generative tasks not merely as co-workers but as genuine partners with comparable capabilities.

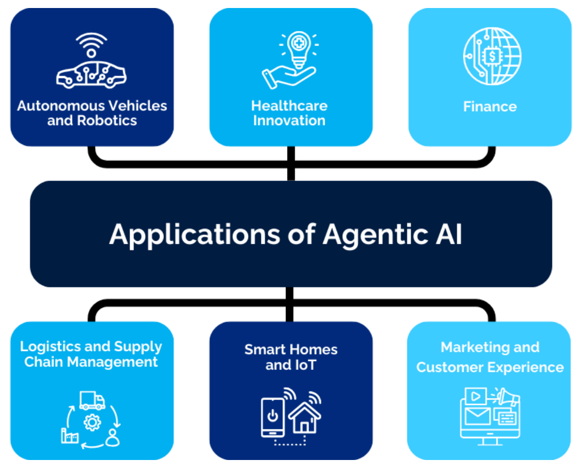

Fig 2 : Understanding Agentic AI

3.1. Definition and Characteristics

In the context of research presented in this paper, an agentic AI is one that can make autonomous decisions. It is capable of understanding data, processing it, and autonomously taking decisions on its own that could affect its users. Considering the common definition of agency, we define a system as agentic if it has an intention to act in a particular way, an ability to act in that way, and an authorization to do so. The AI / Software Agent has individual and social intention underlying its actions, the technological capability to execute tasks without human assistance, and the power to do so. Similar definitions articulate that algorithms observed the behavior of human participants and then acted unobserved on those participants, automating organizational and social decision processes, along with designating how they would act and, in some cases, punishing them for inappropriate behavior. In recent years, a larger variety of decisions are getting outsourced to the algorithmic and software agents in settings ranging from battlefield planning to bond trading to risk analysis and mitigation to driver-less vehicles. Such kinds of decisions inherently carry the risk of negative consequences.

This decision-making disparity raises key questions: Are the algorithmic or software agents really taking these decisions? Are they autonomous? Are they agentic? Are we humans waiving our responsibilities in these domains recklessly? These are important questions, especially with recent evidence that these decisions are not agentic but rather mirror images of our decision-making. The decisions are not utilitarian, with the goal of maximizing utility, but instead are highly biased in the direction of the objectives used to build these algorithms.

3.2. Historical Context and Evolution

The term "agent" has historically been grounded on philosophical propositions of agency, especially within the realms of ethics and psychology. Philosophically, agents exhibit goal-directed behavior and make rational choices according to preferences while being held accountable for their actions. Early usage of the term "Agent" within Computer Science grew from an inspiration to integrate principles of intelligent behavior into the design of software systems. An agent may be anything that can act based on certain conditions; however, software suddenly gained heightened responsibility. Simultaneously, expert systems architected on Rule-Based Inference Engines opened the door to Intelligent Systems in a way that mimicked how agents made decisions, though in a relatively narrow domain of problem-solving, with limited outcomes of human-expressed goals accomplished by the software's programming. Although these systems enjoyed notable use and results, they lacked the independence required to fulfill the term "Agent" and decision-making capacity. Human-centered SoftBot-style Agents developed out of academic experimentation in the 1990s with instant messaging and micro-transactions on the slew of emerging e-commerce structures, and ad-hoc construction of simple bots to interface with the Agent's customer. These SoftBots required user direction and attention to fulfill specific, usually transactional, tasks.

Almost concurrently, the emergence of the Internet and B2C e-commerce culminated in the mass exploitation of client-side web tools, often with Agent-like functions, to deliver smart, independent, goal-based assistance to users as they attempted to navigate the emerging e-commerce web space toward purchasing decisions. Agents would serve as a trusted user-side intermediary resource amidst an otherwise wild-west selection of vendor websites, fostering, directing, and polishing the transaction to protect users from dubious vendors. These e-commerce tools straddled the line between specialized software tools and intelligent Agents, their core technology being software expedience for users strongly colored and directed by corporate profit motives. The term "Intelligent Agent" had all but fallen out of vogue by 2000, although work persisted on proper Mathematical Game and Decision Theoretical Models of decision-making with imperfect vertical baselines, and improvements to Multi-Agent Systems design for algorithms that implement these models.

4. The Food Supply Chain: An Overview

One of humanity's great achievements is the ability to produce food in quantities sufficient to feed billions. However, despite staggering innovations in physical production and supply chain logistics, the logistics operations in the food supply chain remain inefficient and unoptimized, wasting vast amounts of money, time, and carbon emissions. The recent pandemic has brought significant disruption to global food systems and highlighted vulnerabilities and inefficiencies in how food is produced, stored, and delivered. An estimated 30 to 40 percent of the U.S. food supply goes to waste each year—equal to 133 billion pounds for a total cost of $161 billion. These and other contemporary challenges—escalating transportation costs with inflation, inefficient logistics operations leading to delayed deliveries, high greenhouse gas emissions—urgently demand the greater digital transformation of food logistics operations with emphasis on automation and intelligent decision-making to alleviate food waste, improve food access, and reduce the environmental footprint while enhancing the resilience of our modern day food logistics ecosystems.

With these challenges, now more than ever, the food logistics domain is calling for radically dynamic and intelligent solutions to manage, monitor, and automate decision-making and offer total supply chain visibility of shipments. Data-driven decision support systems tasked with optimization of food logistics from "farm to fork" can leverage real-time market signals and support strategic, tactical, or operational decision support for planners. More specifically, the food logistics problem can be framed as: How do we deliver the right food product to the right customer at the right time, at the lowest cost, and, increasingly, in an eco-friendly manner? Answering this question with practical decision support systems using machine learning solutions at all decision levels can support customer-centric food supply chains with improved service levels, increased operational efficiency, greater responsiveness, and reduced environmental impact. Here, we provide a brief overview of key components of the food supply chain, describing how they function, and their interdependencies, and present key challenges in the logistics processes that delay food from reaching consumers.

4.1. Key Components of the Food Supply Chain

The food supply chain (FSC) is a network of processes through which food is produced, processed, distributed, and consumed. It encompasses all the steps food connections take, from the field to the consumer’s plate. Like all supply chains, the FSC is intended to meet consumer needs by coordinating activities across diverse groups of producers and intermediaries. With the increasing number of people in urban areas and growing concern for food safety and quality, the food supply chains are becoming more integrated with controlled and coordinated production from farms, and quality inspection and distribution.

There are multiple factors that make food supply chains different from other forms of supply chains. The FSC is distinguishable by its perishable product properties, narrow profit margins at farm level, many establishments in the recycling phase, growing cost share absorbed by processing and retail sectors, loss of quality and minimal processing at the farm level, information flow with relatively little direct control over products, and demand influences applied through large retail chain stores. Organized support from well-developed processing and distribution is particularly important to developed countries with less surplus agricultural production. Thus, the key components that form the FSC are producers, distributors, and consumers. Each component performs various processes such as growing crops and livestock, food product manufacturing and processing, transportation, refrigeration, wholesaling in the distribution center, sub-distributing, and food retailing. The production component, the initial part of the FSC, plays an important role in providing food supplies to prevent food shortages, especially in the event of unforeseen disruptions to food availability.

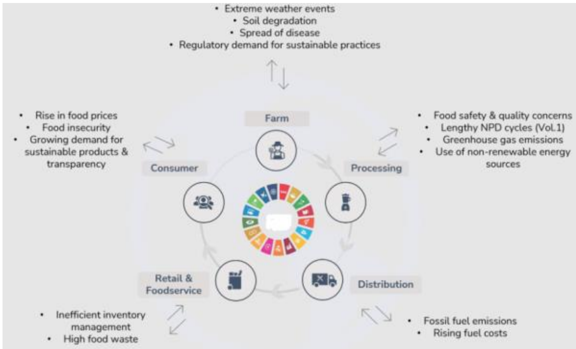

Fig 3 : AI in the food supply chain

4.2. Current Challenges in Food Logistics

The global supply chain is highly integrated, requiring a great number of negotiations in order to make it run. Information asymmetries are very important, and have attracted attention in areas like fish supply, where piracy exists. These kinds of problems are worsened by the fact that food has very specific features that make it more exposed to market failures: issues related to public health, food safety, quality, and the effect of traditional value systems. The first are linked to badly constructed infrastructures; technical features; malfunction; lack of investment; existence of barriers and restrictions to trade; or markets prone to situations of monopoly or oligopoly. The second problems are due to the existence of food safety public goods that are not taken care of by the market. The third are associated with cultural and traditional issues, and distortions in the effect of prices along the chain. All these problems require an active intervention on the supply chain. As food characteristics constitute a crucial approach determining demand, packaging, food safety, and quality requirements must be considered in policies to regulate the food supply.

For international markets, the coherence of the internal supply, its degree of organization, and market development are important factors. In such markets, product price level and stability, quality, geographical signature, delivery times, and guarantees are crucial aspects, and the reduction of supply costs is a strategic factor. The balance in quality, price, and service level is considered an efficient way to deal with market strategies, and requires an infrastructure with high levels of information, coordination, and technical capability.

5. The Role of AI in Supply Chain Management

The rapid advancement of technology, in particular machine learning and artificial intelligence, has enabled companies to innovate their supply chain networks, promoting value alongside cost efficiency. AI technologies are becoming increasingly prevalent in supply chain applications. More specifically, AI can contribute four types of technologies to advance supply chain management: predictive analytics, autonomous agents, computer vision, and robotics. By virtue of these capabilities, AI technologies have the potential to enhance almost any supply chain function. In the area of supply chain planning, predictive analytics are used to enhance forecasts and mitigation strategies in demand, supply, supply chain network design, risk and cost. More broadly, AI can be used to enhance decision making in logistics management through improved decision alternatives, logistics activities, and decision-making processes. These decisions include face customer inquiries, select suppliers, manage inventories, manage logistics, and provide outbound fulfillment. AI is also being used to enhance logistics performance capabilities in visibility, agility, response time speed, and cost. AI is also advanced in several specific logistics areas beyond simply improving decision quality. AI in demand management is being employed to combine demand from different sources, refine demand forecasts, plan product promotions, develop marketing resource allocation solutions, and optimize worthiness of claim investigations. In warehouse management, AI is being used to forecast storage volume; for put-away and picking planning, and for inventory management.

AI can provide both real-time and predictive visibility; however, more emphasis has been placed on developing predictive capabilities. In transportation management, AI is being used in carrier selection, route and load planning, shipment tracking, freight auditing, and mode selection. In international logistics, AI is being focused on enhancing logistics performance through real-time visibility and performance measurement. Overall, AI has the potential to enhance both the performance of supply chain functions and the overall supply chain performance.

5.1. AI Technologies in Use

There is no denial that contemporary supply chains are intricate, synchronized networks involving multiple players and multiple business functions that have their own challenges. For example, the modern agri-food supply chain is characterized by resource shortages, demand uncertainty, large information delays, significant climatic risk, and lack of standards as well as traceability challenges. From farm to fork, there are many inter-connections: primary production, supply and postharvest handling, commodity markets, agri-food companies, distribution and wholesaler systems, and retailing, which create huge opportunities for establishing win-win partnerships. However, the design of collaborative networks for agri-food supply chains can be assisted significantly with AI, especially with tools that allow multi-agent decision support, optimization and simulation.

The traditional approaches are based on optimization methods, simulation packages, or rule-based multi-agents; however, these are not flexible enough to cope with dynamism, adaptability, and heterogeneity of collaborative supply chains for agri-food. The recent advancements in Agent-Based Systems, along with the evolving capabilities of Artificial Intelligence technologies are showing tangible results in creating intelligent agents that drastically improve the agent-based modelling methodology, making it so easy to build flexible and sophisticated multi-agent decision support systems that it is becoming rapidly more widely used. The combination of advances in agent-based modelling of complex systems and available agent application components is providing an acceleration in the availability of decision support agents across many socioeconomic sectors such as agriculture, food supply chain logistics, and many collaborative supply chains. The most relevant technologies that are becoming used applications are those based on fully autonomous cooperative decision-support agents, in combination with AI applications with embedded multi-agent architectures.

5.2. Benefits of AI Integration

The importance of SC stakeholder cooperation may challenge the replication of the vast majority of benefits of AI adoption. However, these benefits are so varied and compelling that in periods where rising wages compress SC profit margins, many companies will adopt AI technologies in an effort to restore them. Hence, companies will recognize the value of these technologies, but their realization will differ according to the structure of the SC and the extent of ST cooperation. For example, SC transparency and product traceability have become paramount in a world that increasingly questions product and service provenance, as reflected in the popularity of certifications. Many SC stakeholders are investing in solutions embedded in blockchain technology in order to increase SC visibility, as well as other technologies associated with AI in order to fulfill the demand for product provenance traceability.

However, tagging and organizing products within a SC in order to make them compliant with blockchain technology requirements and visible to the end-users is an SC activity that has an associated incurred cost. Such costs could deter stakeholders from investing in the AI applications that increase SC product visibility. Conversely, AI adoption contributes to make SC stakeholder cooperation possible as a way to lower the incurred costs. It is the benefits of those applications that could persuade SC partners to invest in traceability solutions. They become more appealing when SC members can assess their level of expected adoption-related ROI, which occurs when all stakeholders are equally constrained to invest in SC traceability. In such cases, formulation of the SC adoption game will indicate equilibrium mechanisms that will be effective in persuading stakeholders to invest in AI traceability applications for products along different SCs. Other cases will reflect SC stakeholder uneven incentives to invest, which will then need to be collectively modeled in order to design incentive schemes that induce adoption of SC product and service traceability to the required level.

Equation 2 : Adaptive Agent Learning for Logistic Environment Changes:

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla_\theta \mathcal{L}(f(X_t; \theta_t), Y_t)$$

θ_t = Agent model parameters at time t

η = Learning rate

$\mathcal{L}$ = Loss function comparing predictions vs. actual outcomes

$f(X_t; \theta_t)$ = Agent prediction model

Y_t = Actual logistic outcome at time t

6. Agentic AI in Decision-Making Processes

1. Autonomy in AI Systems

Autonomous real-world agents, both natural and artificial, exert influences in their decision-making and actions that serve to determine the satisfaction of interests or objectives. For humans, this autonomy is recognized based on agency, a social construct grounded in the cognitive architecture of the mind; that is, while we recognize that the individuals around us may not act according to the interests that we have, we realize that the ability of others to have such effects is determined by cognitive functions of which mental representations of objectives, beliefs about the states of the world, and particular characteristics of the behaviors made available for execution are the building blocks. For AI systems endowed with a limited form of organisational autonomy, project internal cognitive structures that support similar functional capabilities to fulfill strategic roles in effectively dynamic decision-making processes.

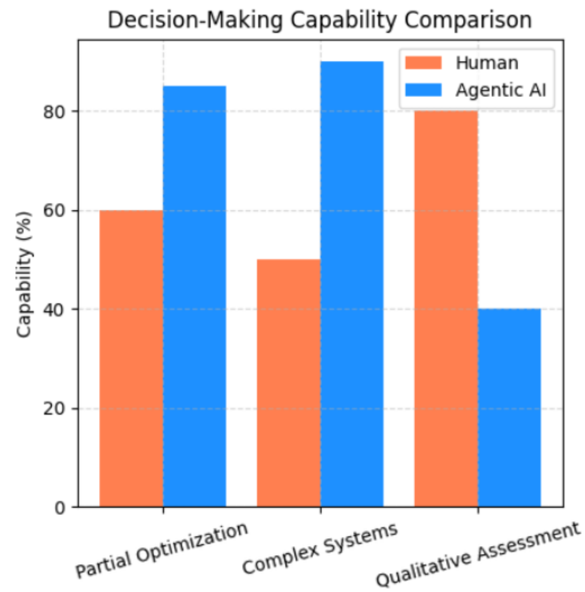

Fig 4 : Decision-Making Capability Comparison

2. Decision-Making Frameworks

Aspects of a strategic role are defined by the structure of an empowered agent's capabilities with regard to the dynamical role of the whole organization. Specifically, we place importance upon adaptability in the plan-following aspect of deliberative enterprise, the motivational aspect of action selection, and the stability of executive performance. AI decision-making architecture assumes agentic decision-making capability to change its internal cognitive structures to adapt to additional contextual information imposed by unexpected events in a decision-making enterprise. AI agency further assumes volitional capability or agency systems architecture to explain contextual information assumed pre-rational – background factors specialized as social, economic, cultural, psychological, ethical, or moral factors that influence the behavior of individuals and groups involved in a decision-making enterprise. Enriching capacity in a new role can render the agent expendable without notice or have the opposite effect; providing the organizational stability by becoming committed to functions of monitoring and organic control in addition to decision-making.

6.1. Autonomy in AI Systems

The decision-making process is a critical component of problem-solving in many domains. For example, an intelligent agent operating in a complex environment may have to make evaluations, forecasts, filters, or judgments based on some criteria and further influence the environment to accomplish its goals. Historically, various AI methods have contributed to the development of autonomous decision-making, including Bayesian statistics, simulations technique, logic-based or constraint-based search, utility theory, mathematical optimization, rules, heuristics, and expertise modeling. With the advent of machine learning built upon deep learning, especially the current emphasis on the development of large language models and their power for cognition, reasoning, and solving many complex tasks, there exists a tendency to overlook or underestimate the importance of agentic decision-making in AI. Nevertheless, we tend to think agentic AI is special because it performs real-time decision-making in dynamic systems, therefore plays a bridge role connecting or relating action-learning and traditional decision-making areas. We further point out that agentic AI differs from traditional decision-making approaches in the input and output.

The autonomy in AI systems defines the capacity of an artificial intelligence system to independently choose the means or methods of accomplishing its goals. While it is important to clarify that decision-making is not the only autonomous function of AI systems; they also may learn or reorganize the internal models of special systems and execute the actions to fulfill their goals. However, traditionally, these tasks, the so-called learning and act task, have not been the major interests in the AI community, but have been studied and developed by the research community on autonomous agents, which also became the core roots of the foundations of agentic AI.

6.2. Decision-Making Frameworks

Decision-making can be defined as a structured or unstructured process of selecting a course of action from alternatives and resources available to achieve desired objectives, which can be performed either manually or through automation. Decision-making can be classified into levels and types, each level associated with a type of decision. The interrelation among decision types and levels describes the information processing requirements of the organization. Structured decisions are made at the operational level, semi-structured decisions are made at the management level, and unstructured decisions are made at the strategic level. Decisions can also be punctual, that only happen once, or recurrent, that regularly happen with various degrees of frequency. AI has been recognized as a tool that allows great autonomy for punctual decisions, increasing the efficiency of decision-making processes at the top or the bottom of an organization. However, AI effects on recurrent decision-making processes at the level of the operational core of the organization are not yet clear.

AI-induced changes in decision-making are likely to vary not only by level but also by type and frequency of decisions. Decisions regarding the assignment of people to activities might benefit from AI forecasting tools that combine information about the workload and other contextual factors that affect people’s productivity and work preferences, such as weather, calendars, schedules, preferences, external events, and past data on the variations or changes in such factors. AI can also increase transparency about the decision-making process in recurrent situations and about the reasons for modifying roles, task assignments, or activity coordination rules put in place during routine, and therefore reduce the level of distrust. However, delegation or fear of overexposure to management monitoring can demotivate employees, undermine the feeling of autonomy of added value activities, and negatively affect motivation and performance.

7. Case Studies of Agentic AI in Food Logistics

Our research of the literature on Agentic AI, and interviews with agentic AI developers and users in industry, led us to identify six interesting domain-specific examples of agentic AI systems that are in use or were attempted: Seeq, Shipwell, ShipBob, TerraFood, ClearMetal, and SoftCredit. The first three companies provide logistics software commanded and operated by users or other software. The last three are companies that attempted to create a higher level of autonomy by using agentic AI technology to set logistics decisions in motion and require only limited human input.

1. Successful Implementations

Seeq is a data analyst-friendly exploration and visualization variant of autonomous software agents, with dozens of production implementations at numerous Fortune-500 food and beverage companies. Like the other people-friendly implementations, Seeq combines autonomous software with friendly user interfaces developed for people. The Seeq product has some similarity to another system that also helps expert analysts with advanced capabilities in fault discovery and root cause analysis. Seeq eases user work by combining scalable data provisioning and connection, making it easy to see large amounts of data minus noise, as well as identify correlations quickly to help with the discovery of anomalies and root causes. Dozens of Fortune-500 food and beverage sector users have implemented Seeq to help their analysts and data scientists with data analytics. These users reported back to us that they see relatively little autonomous behavior and rely mostly on the work it saves their data analysts.

7.1. Successful Implementations

Over the past several years, companies and organizations have developed successful implementations of intelligent agent systems in several areas of food logistics, ranging from food safety to health and nutrition, to food availability and choice, to optimizations of food supply chains and food distribution. While these applications differ greatly in their characteristics, the underlying functionalities provided by agentic AI are essentially the same among them. Several of these success stories are shared in the following sections.

Guided by policies and priorities, and enabled by its partnership with a global health organization, FSIS has successfully implemented agentic AI at the heart of its food safety inspection system to oversee establishments that produce a geographically dispersed supply of ready-to-eat meat and poultry products. FSIS's intelligent agent system, called Risk Management System, or RMS, is ground-breaking in enabling FSIS to nationally, efficiently, and effectively reach and address risk-based decisions regarding the daily inspection of establishments on which to assign its food safety inspectors and how many hours to assign to each establishment. By introducing artificial intelligence and learning capabilities with continuous risk assessments of food safety risks for each meat and poultry establishment, the system enables FSIS to be proactive rather than reactive and anticipate food safety problems that may be forthcoming, and thus respond appropriately. The preliminary recommendation results are then released, and based on input from the real experts in food safety regulatory inspection, decisions are made for what is called the optimum inspection assignment for that day.

7.2. Lessons Learned from Failures

Failures are a fertile ground for valuable lessons and practical insights on how not to design, operate, and deploy intelligent agents and agent systems. The case studies presented in this section aim to shed light on the seemingly unanswered question: Why have agent-based systems predominantly failed to deliver the expected technological advance? A large number of recent surveys on agent technologies have compiled extensive lists of failed applications, which in many cases can be traced back to technical, architectural, methodological, or social reasons. Also, the burden for the application developer is still high, since a wide range of different technologies are needed to implement, integrate, and deploy agent-based systems, from traditional software development techniques to advanced artificial intelligence and multiagent techniques. Given that agent technologies have had high expectations as the basis for the next generation of largescale multiagency systems, similar questions can be asked for the reasons for the relative failure of the ability of agent-based implementations to deliver real advantages in performance, scalability, and robustness. The phenomenon of failed agent-based systems is not limited to agent technology. Technology projects often fail. Reliable data for the overall frequency of computing application project failure is inconsistent at best and is often only a subset of all project failures, such as enterprise-wide systems. Nevertheless, these data sets indicate a high range: about one in three business computing application projects fails to meet its stated objectives, while a large percentage of the remaining projects exceed their budget or time thresholds several-fold. The consequences of project failure are dire. Many projects have implicated financial loss; others have lost management support for computing technology application development entirely.

8. Challenges and Risks of Implementing Agentic AI

While agentic AI's potential benefits are clear, there are also serious challenges and risks associated with its deployment in food supply chain logistics that must be addressed. From a technical standpoint, there are still large limitations around current architectures' abilities to act autonomously, do cognitive planning, and blend simulation- and action-based trajectories. From an ethical and sociological perspective, the question of what types of impact these technologies will have for global economic equity and the livelihoods of low-skill workers in the logistics sector must be contemplated. Finally, a robust decision-making infrastructure for overseeing and supervising this technology must be developed in order to ensure that the tools are acting within the best interests of the decision-makers. In this section, we focus on these dimensions of concern, and additional technical-sociological gaps and future steps are discussed.

1. Technical Limitations

Despite recent advances, there remain significant obstacles for autonomy in AI decision making. General architectural considerations around LLMs, namely that current models are extremely computationally expensive to deploy, require complicated prompting systems that often use external memory, and only operate within limited bandwidths and timeframes. Enhanced planning and simulation capabilities could enable agentic AI to hypothetically become more cognitively autonomous, but this remains an open area of research – existing approaches are primitive. While continued enhancements in visual, motoric, and decision-making tasks have driven increased levels of agentic or embodied AI performance, these capabilities are not yet integrated into robust decision-making frameworks. The post-agentic AI world will require additional proof that cognition-action synergy based architectures can be developed from currently separate systems.

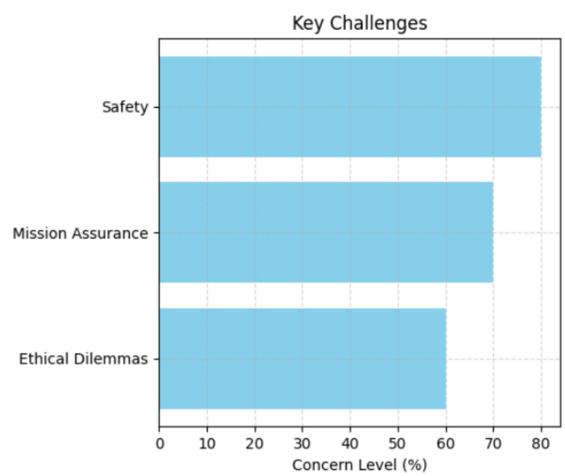

Fig 5 : Key Challenges

8.1. Technical Limitations

The deployment of Agentic AI, used directly as a decision support tool or indirectly for the automation of tasks, in food supply chain logistics could bring multiple advantages to the operational and strategic decision-making and also foster the

Food Logistics 4.0 vision. However, today's technologies still need to overcome challenges and mitigate risks in order to unlock their full potential. The research frontiers to address start from the AI algorithms available today and relate to all levels of the technological stack, from hardware up to the decision model implemented with AI.

The development near commercialization of LLMs that enable conversational AI represents an important breakthrough that could favor the use of AI support for FSCL decision-making. However, these tools, and any further development of LLMs, need to be used very judiciously. Sometimes, the output is surprisingly informative and appears to rely on a solid statistical basis. But these tools are unable to achieve knowledge creation necessary to support important logical reasoning. Ad-hoc prompting is required to mitigate some of the problems and to only partially overcome the limitations. Furthermore, one important issue is the lack of transparency and explainability that prevents decision-makers from using these tools with full confidence. This limitation has a strong impact especially when the output needs to be audited, if any risk is involved, or the implemented task is particularly complex and involves detailed logical reasoning. Implementations with few specialized examples have shown the ability of LLMs to assist in specific tasks in FSCL such as demand forecasting. But we still need to wait for a full understanding of the inclusion of LLMs in the toolbox to understand what are the services available, which are the critical areas and tasks, and the requirements for safe and effective use. Ask, tell, and show principles have been defined for prompting LLMs. These prompts can guide the models to effectively perform tasks such as classification and extraction of specific information, drafting business communication, and summarizing and analyzing data. These prompts represent a basic development and design strategy to test the effectiveness, safety, and reliability of LLMs in specific FSCL use cases.

8.2. Ethical Considerations

Agentic AI raises important ethical questions about the use of AI in life-and-death decision-making, accountability for its errors, and how moral agency is defined. There are three main areas of concerns regarding delegation of such power to an AI system: accountability, AI value alignment, and the granting or withholding of moral agency. We consider these issues in reverse order, starting with moral agency.

Moral agency is typically ascribed to humans, usually at the age of legal discernment, capable of making decisions guided by rationality, capable of moral reasoning, and understanding norms and moral value. The ascription of moral agency allows an actor to be treated as being the originator of any instrumental acts it performs and for those acts to be judged as expressions of the moral status of the moral agent. Currently, AI does not fulfill all criteria necessary for moral agency. Such a system does not make its actions for instrumental reasons; though it may seem like it does, a well-designed AI decision-making algorithm is merely optimizing a reward signal and thus carries out behavior that an observer may interpret to be rational but without a subjective state that characterizes rationality in conscious beings. Hence, AI cannot be treated as a legitimate moral agent and held responsible for its actions. AI could also never be aware of the environmental context of parameters and explicit sub-goals that condition the operation, thus effectively exposing its ignorance regarding potential consequences of its actions. The absence of moral agency means that AIs need not be treated morally but must be designed, used, and viewed as tools for optimizing human action, subject to moral and ethical scrutiny of their functions by their designers, implementers, and users.

9. Future Trends in Food Supply Chain Logistics

Optimistic predictions are emerging concerning the future of the food supply chain logistics system. Some predict that food supply chains will be simply referred to as 'logistics' due to the growing familiarity with the systems and the technologies used. We review a selection of these optimistic viewpoints and predictions to provide a sense of direction. First, there are the particulars relied upon to provide forecasts on the future structure of food supply chain logistics.

To begin with, there are some additional technologies already being developed and deployed to supplement and accelerate the digitizations of food supply chain logistics. These technologies include AI-enabled cameras deployed at various positions throughout the supply chain routes and network, robotic delivery services, broader acceptance of UAV-assisted product inspections and store deliveries, IoT devices for temperature, humidity, and gas detection, energy harvesting, payment microchips, and more. The expected future development of AI, according to various experts, will lead to much-needed capacity improvements. We examine the forecast development of AI itself and its improvement in capacity.

Besides the broad categories of positive predictions related to logistics mentioned above, some specifically discussed the predicted impact of self-driving trucks on food supply chain logistics. There were also predictions with regard to blockchain technology and 5G mobile communication technology that will assist or augment the new predicted revolution in food supply chain logistics. There is also a discussion about the vital environmental and climate consideration related to the future of food supply chain logistics. What sort of future logistics that provide a sustainable supply of food to the population? The trend is towards a very sustainable future.

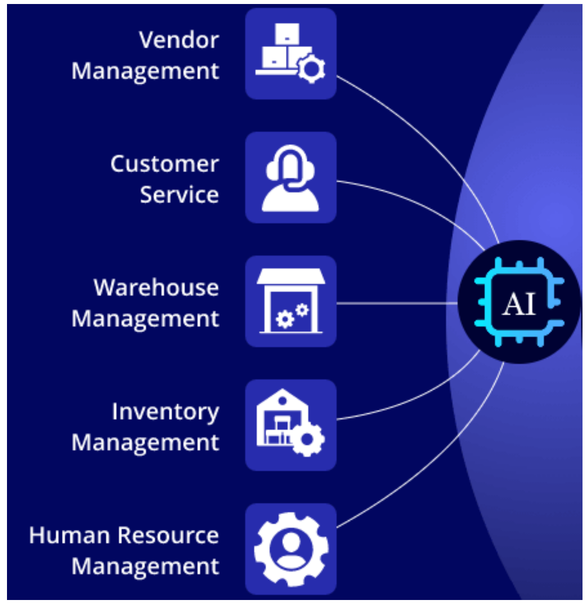

Fig 6 : AI in logistics and supply chain

9.1. Emerging Technologies

The emerging technologies such as unmanned aerial vehicles, unmanned ground vehicles and autonomous last-mile delivery systems impose profound influences on food supply chain logistics in aspects of system configuration, business process reengineering, and service models restructuring, etc. First, adopting the above-mentioned autonomous vehicles will subvert the traditional operating mechanism of the food supply chain, and switch the focus of labor cost advantages to capital cost advantage. Autonomous vehicles are capital-intensive logistics equipment, which have high initial investment. In the future, it might be a better choice to use the autonomous vehicles collaboratively, and set up vehicle pools based on the advanced technology of resource scheduling. Second, when autonomous last-mile delivery systems come into service, customers must be re-educated. Traditional food supply chain logistics is built upon the foundation of consumer convenience, and customers demand to receive the food at a specific time. But with the service of automated small delivery robots, customers can only receive the food models with less specifications, during a certain period of time.

Finally, emerging technologies reshape the service mode of food supply chain logistics. Food supply chain logistics will shift from traditional centralized storage and transportation systems to a new decentralized micro-local service model, including instant delivery systems within urban areas. Instant delivery can be defined as a kind of urban logistics service to deliver a package to the customer in a very short time. A centralized service model can benefit from the economy of scale, which greatly reduces the logistic cost per unit. But few people can deny that the enterprise cost of such a service model will increase significantly, when the customer's requirement for service level is extremely high. Due to the fact that the investment for last-mile delivery vehicles is becoming lower and lower, this mode shift can be understood as a transition from the asset-light era into the asset-heavy era.

9.2. Predicted Developments in AI

Monitoring the technological landscape of AI and pinpointing potential developments can offer distinctive insights into the terminal points and transition processes of technology trajectories. AI plays a pivotal function in engineering humanity's future, simultaneously stimulating novel industrial revolutions through advanced automatization and substitutive creative work with inner resources, as well as driving humanity to capital singularity where creative work succeeds. Additionally, AI is impossible to be balkanized and epitomizes the essence of superintelligence, not limited to individual humans. Moreover, merging diverse knowledge from life, social, physical and information fields as well as establishing a new scientific paradigm upon the extra-large model workload are also paramount to the role of future AI. Based on the growing scale and impressive performance of large-scale pretrained models, future AI will also voyage through a wave of fusion and convergence. Some experts hypothesize that LLMs may currently represent the highest capabilities of AI, and beyond-human capabilities would currently require a fundamental change in model training. More data leads to better performance on well-represented tasks for current LLMs with around a trillion parameters. Future fusing tasks and knowledge through knowledge graphs while going beyond large-scale pretrained models may be the key to the further development of both AI and cognition. Without careful incorporation of these concerns, future AI poses serious risks and threatens not simply some jobs but society at large. These risks stem directly from goals misaligned to those of humanity, which were not present with existing narrow AI. The development of such AI depends primarily on continued progress in computer science and related fields such as mathematics, neuroscience, and cognitive science.

Equation 3 : Supply Chain Resilience Score with Agentic Interventions:

$$R_s = \frac{\sum_{j=1}^{m}(A_j \cdot S_j)}{D_l + \lambda \cdot F_l}$$

R_s = Resilience score

A_j = Agentic response effectiveness for disruption j

S_j = Severity of disruption handled

D_l = Delivery loss due to disruptions

F_l = Food spoilage/loss

λ = Spoilage sensitivity factor

m = Number of agentic decisions in response to disruptions

10. Conclusion

In this chapter, we outlined the rationale and potential for agentic AI to facilitate autonomous decision-making in food supply chain logistics. As a critical and busy sector, driven by unstable factors like currency fluctuations, wars, and pandemics, food supply chain logistics still relies heavily on the manual perception of the complex web of moving components. These aspects can be further exacerbated by dramatic shifts towards local production and shorter supply lines. These supply lines need to be shaped and adapted but also closely coordinated for efficiency. Here, AI can add efficiency: simplifying logistics, adjusting routing, flexibility, and rerouting toward changed demand, while acting on behalf of the stakeholder without either hindering or benefiting the opposition. AI can decide moment-by-moment on behalf of the party with the long-term interest in mind. With a coalition of the short- and long-term party stakeholder states, the development from a game-theoretical perspective of cooperative and collaborative solutions to non-cooperative games can allow AI-based actors to focus on optimizing outcomes, serving the benefits of all stakeholders.

Future directions should strengthen the potential we outlined while searching for robust, computationally cheap, and potentially decentralized ontologies for the complex negotiations and collaborations between genAI or agentic AI actors. For this to be possible, we need to further strengthen the interaction channels between human and autonomous agents and, if feasible, establish mutual shared ontologies. In order to support this complex effort of trustful, smooth, human-driven, and goal-oriented interaction, we have to furthermore strengthen our understanding of the deep ethical roots of daily decision-making to be able to share these with autonomous purpose optimization. In sum, it is essential that we enhance the human feedback loop and interaction with the goal to be the responsible and curious long-term piece of the dialog and coordination moving toward trusted, societal, autonomous actors.

10.1. Final Thoughts and Implications for the Future

As outlined throughout, agentic AI is ultimately an emergent technology. To wit, agentic AI does not yet exist and is not foreseeable for any near term. The work put forth within these pages is merely an exploration of a mature piece of HCI, low level ML, just-now emerging aspects of Large Language Models, and ideas from control theory and cognitive psychology. And yet, we hope the exploration reveals a path forward to serious, safe, multi-tasking agentic AI within 5-10 years. Ultimately, the implications for the future, should agentic AI indeed be possible, would be immense. Cognitive offloading and decision automation is perhaps the prime reason we as a species have built and trained humans to become our leaders. Create societal hierarchies which then create wealth at the top and power all around them, which leads to social stratifications, with the requirement for our descendants to take on horrible burdens to keep the "higher" caste in comfort. Yet with agentic AI, the desire for greater leadership would seem moot, and we may almost create a form of "Star Trek". Certainly, achieving some sort of sharing the burden economy, we would hope would become possible.

In a more immediate sense, should agentic AI be shown to be possible, products driven by such technology may move us forward on paths towards what we hope is not frivolity in terms of some currently existing tools in industry and education, and instead be focused on increased productivity and general empowerment. The empowerment of those on the lower rungs of hierarchies, and on paths towards the potential future described earlier of a more equitable distribution of both power and wealth. Where that goal is surely a long, arduous journey for the human condition; perhaps, agentic AI will assist us in the way toward that better world

11. References

1. Ganti, V. K. A. T. (2019). Data Engineering Frameworks for Optimizing Community Health Surveillance Systems. Global Journal of Medical Case Reports, 1, 1255.
2. Maguluri, K. K., & Ganti, V. K. A. T. (2019). Predictive Analytics in Biologics: Improving Production Outcomes Using Big Data.
3. Polineni, T. N. S., & Ganti, V. K. A. T. (2019). Revolutionizing Patient Care and Digital Infrastructure: Integrating Cloud Computing and Advanced Data Engineering for Industry Innovation. World, 1, 1252.
4. Chava, K., Chakilam, C., Suura, S. R., & Recharla, M. (2021). Advancing Healthcare Innovation in 2021: Integrating AI, Digital Health Technologies, and Precision Medicine for Improved Patient Outcomes. Global

Journal of Medical Case Reports, 1(1), 29–41. Retrieved from https://www.scipublications.com/journal/index.php/gjmcr/article/view/1294
5. Nuka, S. T., Annapareddy, V. N., Koppolu, H. K. R., & Kannan, S. (2021). Advancements in Smart Medical and Industrial Devices: Enhancing Efficiency and Connectivity with High-Speed Telecom Networks. Open Journal of Medical Sciences, 1(1), 55–72. Retrieved from https://www.scipublications.com/journal/index.php/ojms/article/view/1295
6. Adusupalli, B., Singireddy, S., Sriram, H. K., Kaulwar, P. K., & Malempati, M. (2021). Revolutionizing Risk Assessment and Financial Ecosystems with Smart Automation, Secure Digital Solutions, and Advanced Analytical Frameworks. Universal Journal of Finance and Economics, 1(1), 101–122. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1297
7. Gadi, A. L., Kannan, S., Nandan, B. P., Komaragiri, V. B., & Singireddy, S. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization. Universal Journal of Finance and Economics, 1(1), 87–100. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1296
8. Singireddy, J., Dodda, A., Burugulla, J. K. R., Paleti, S., & Challa, K. (2021). Innovative Financial Technologies: Strengthening Compliance, Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures. Universal Journal of Finance and Economics, 1(1), 123–143. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1298
9. Anil Lokesh Gadi. (2021). The Future of Automotive Mobility: Integrating Cloud-Based Connected Services for Sustainable and Autonomous Transportation. International Journal on Recent and Innovation Trends in Computing and Communication, 9(12), 179–187. Retrieved from https://ijritcc.org/index.php/ijritcc/article/view/11557
10. Balaji Adusupalli. (2021). Multi-Agent Advisory Networks: Redefining Insurance Consulting with Collaborative Agentic AI Systems. Journal of International Crisis and Risk Communication Research , 45–67. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2969
11. Pallav Kumar Kaulwar. (2021). From Code to Counsel: Deep Learning and Data Engineering Synergy for Intelligent Tax Strategy Generation. Journal of International Crisis and Risk Communication Research , 1–20. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2967
12. Somepalli, S., & Siramgari, D. (2020). Unveiling the Power of Granular Data: Enhancing Holistic Analysis in Utility Management. Zenodo. https://doi.org/10.5281/ZENODO.14436211
13. Ganesan, P. (2021). Leveraging NLP and AI for Advanced Chatbot Automation in Mobile and Web Applications. European Journal of Advances in Engineering and Technology, 8(3), 80-83.
14. Somepalli, S. (2019). Navigating the Cloudscape: Tailoring SaaS, IaaS, and PaaS Solutions to Optimize Water, Electricity, and Gas Utility Operations. Zenodo. https://doi.org/10.5281/ZENODO.14933534

15. Ganesan, P. (2021). Cloud Migration Techniques for Enhancing Critical Public Services: Mobile Cloud-Based Big Healthcare Data Processing in Smart Cities. Journal of Scientific and Engineering Research, 8(8), 236-244.
16. Somepalli, S. (2021). Dynamic Pricing and its Impact on the Utility Industry: Adoption and Benefits. Zenodo. https://doi.org/10.5281/ZENODO.14933981
17. Ganesan, P. (2020). Balancing Ethics in AI: Overcoming Bias, Enhancing Transparency, and Ensuring Accountability. North American Journal of Engineering Research, 1(1).
18. Satyaveda Somepalli. (2020). Modernizing Utility Metering Infrastructure: Exploring Cost-Effective Solutions for Enhanced Efficiency. European Journal of Advances in Engineering and Technology. https://doi.org/10.5281/ZENODO.13837482
19. Ganesan, P. (2020). PUBLIC CLOUD IN MULTI-CLOUD STRATEGIES INTEGRATION AND MANAGEMENT.