

An Artificial Intelligence Framework for Food Supply Chain Management: Policy Implications for UAE Public-Sector Agricultural Authorities

Yaser Abdulla Yousef Hasan Alfarsi

Faculty of Technology Management and Business

Universiti Tun Hussein Onn Malaysia, Malaysia

Roshartini Omar (Corresponding author)

Faculty of Technology Management and Business

Universiti Tun Hussein Onn Malaysia, Malaysia

E-mail: shartini@uthm.edu.my

Received: July 10, 2026 Accepted: September 30, 2026 Published: October 12, 2026

doi:10.5296/ijssr.v14i3.24090 URL: <https://doi.org/10.5296/ijssr.v14i3.24090>

Abstract

Artificial intelligence offers significant potential to strengthen food supply chain management in countries facing resource constraints and food security pressures. This study develops and empirically evaluates an AI framework within the Abu Dhabi Agriculture and Food Safety Authority and derives policy implications for UAE public-sector agricultural authorities. A quantitative cross-sectional survey was administered to operational employees. Of 500 questionnaires distributed from a population of 1,506 employees, 402 valid responses were retained after data screening. The data were analysed using SPSS and Partial Least Squares Structural Equation Modelling. The model examined four AI capabilities, namely Expert System, Machine Learning, Agent-Based System, and Artificial Neural Network, in relation to three food supply chain outcomes: Production and Sourcing, Logistics and Distribution Efficiency, and Safety and Quality Control. Six of the twelve hypothesized relationships were supported. Artificial Neural Network was significantly associated with all three outcomes, Expert System with Production and Sourcing and Safety and Quality Control, and Agent-Based System with Logistics and Distribution Efficiency. Machine Learning showed no significant direct effects. Although the structural model demonstrated predictive relevance, several constructs recorded average variance extracted values below 0.50; therefore, the

findings should be interpreted with caution. The study proposes a capability-based policy framework emphasizing AI governance, data infrastructure, workforce readiness, institutional coordination, and phased implementation. Sustainability is treated as a broader policy objective supported through improved operational resilience, efficiency, and safety rather than as a directly measured outcome.

Keywords: artificial intelligence, food supply chain management, food security, public-sector agriculture, AI governance, UAE, PLS-SEM

1. Introduction

Food security has become a strategic policy priority as governments respond to population growth, climate change, resource scarcity, changing consumption patterns, and increasingly frequent supply chain disruptions. These pressures are especially significant in countries with constrained agricultural environments, where domestic food production is limited and national food systems depend heavily on international supply networks. In the United Arab Emirates (UAE), limited arable land, water scarcity, and harsh climatic conditions intensify the need for resilient, and efficient agri-food supply chains. Strengthening forecasting, sourcing, logistics, food safety, and risk-management capabilities has therefore become central to the country's long-term food security agenda (Manikas et al., 2022).

Recent disruptions have further demonstrated that food security depends not only on access to supply but also on the resilience, visibility, coordination, and adaptability of the entire agri-food system. Digitalization can strengthen these capabilities by improving forecasting, information sharing, and decision-making across supply chain activities. Evidence from the UAE suggests that supply chain digitalization and enhanced forecasting capabilities can contribute to food security and sustainability by enabling more timely and coordinated responses to operational uncertainty (Aldhaheri et al., 2023). Accordingly, public-sector agricultural authorities are increasingly expected to combine regulatory oversight with technological innovation, data-driven governance, and cross-institutional coordination.

Within this context, the Abu Dhabi Agriculture and Food Safety Authority (ADAFSA) occupies a strategically important position in the UAE's agricultural and food governance system. Its responsibilities include agricultural development, food safety regulation, biosecurity, risk monitoring, and coordination across different stages of the food supply chain. The importance of public-sector coordination in food safety was also reinforced by the FAO/WHO International Food Safety Authorities Network meeting held in Abu Dhabi, which highlighted the need for stronger collaboration, information exchange, and institutional preparedness in responding to food safety risks (World Health Organization, 2020). The operational complexity of these responsibilities requires public authorities to move beyond fragmented and predominantly reactive management practices toward integrated systems capable of supporting forecasting, traceability, monitoring, and evidence-based decision-making.

Artificial Intelligence (AI) has emerged as a potentially transformative capability for addressing these requirements. In supply chain management, AI can improve forecasting, risk assessment, inventory planning, logistics coordination, and decision support by processing large and complex datasets more rapidly than conventional approaches (Baryannis et al., 2019; Pournader et al., 2021). AI applications can also help organizations move from descriptive and reactive management toward predictive and prescriptive decision-making, thereby improving their capacity to anticipate disruptions and allocate resources more effectively (Duan et al., 2019).

The relevance of AI is particularly pronounced in food and agricultural supply chains. AI-enabled tools can support production planning, demand forecasting, food safety

monitoring, traceability, resource optimization, and early risk identification. Deep learning and neural-network applications have already demonstrated potential in agricultural monitoring, prediction, and classification tasks (Kamilaris et al., 2017), while AI-based systems have been applied to the detection and regulation of food contamination risks (Li et al., 2019). More recent evidence also indicates that AI, big data, and Internet of Things technologies can strengthen food safety early-warning systems and improve the resilience of food systems to emerging risks (Mu et al., 2024). These applications illustrate the potential of AI to support operational dimensions that are closely associated with food supply chain management, including production efficiency, logistics performance, traceability, safety, and quality assurance.

However, the value of AI does not arise automatically from technology acquisition. Successful implementation depends on the alignment of AI capabilities with organizational resources, institutional priorities, data readiness, and workforce competence. Research on AI adoption in food supply chains identifies factors such as data availability, technological infrastructure, employee skills, implementation cost, organizational readiness, and managerial support as critical conditions for successful adoption (Dora et al., 2021). From a resource-based perspective, AI can create strategic value when technological resources are combined with complementary organizational capabilities that are valuable, difficult to replicate, and effectively deployed (Barney, 1991). Similarly, dynamic capability theory suggests that organizations must be able to sense technological opportunities, seize them through investment and coordination, and continuously reconfigure processes and skills as conditions change (Teece et al., 1997).

These challenges are particularly important in public-sector contexts. Government organizations must consider not only performance and efficiency but also transparency, accountability, cybersecurity, fairness, and public trust. Responsible AI therefore requires governance arrangements that clarify decision rights, establish oversight mechanisms, protect data, and support explainability. The importance of transparency and interpretability has been emphasized in the explainable AI literature, particularly where automated systems influence high-stakes decisions (Arrieta et al., 2020). International policy frameworks have similarly stressed that AI systems should be robust, transparent, accountable, and aligned with human and societal values (Organisation for Economic Co-operation and Development, 2019; European Commission, 2020). In the Abu Dhabi context, these governance requirements are consistent with broader public-sector ambitions for strategic AI adoption and digital transformation (Abu Dhabi Digital Authority, 2021).

Despite the growing body of research on AI in supply chain management, much of the literature focuses on private-sector organizations, manufacturing systems, logistics firms, or individual technological applications. Empirical evidence from public-sector agricultural authorities remains comparatively limited. In particular, insufficient attention has been given to how distinct AI capabilities such as Expert Systems, Machine Learning, Agent-Based Systems, and Artificial Neural Networks that relate to different food supply chain outcomes within a government-operated agricultural system. This gap is important because AI technologies are not functionally interchangeable. Their effectiveness may vary depending on

whether the organizational objective concerns production and sourcing, logistics and distribution, or safety and quality control.

This paper addresses this gap by developing and empirically validating an Artificial Intelligence Framework for Food Supply Chain Management based on evidence from a UAE public-sector agricultural authority. The framework examines the relationships between four AI capabilities [Expert System, Machine Learning, Agent-Based System, and Artificial Neural Network] and three food supply chain management dimensions: Production and Sourcing, Logistics and Distribution Efficiency, and Safety and Quality Control. In doing so, the study responds to calls for more context-sensitive research on AI-enabled supply chain transformation and extends earlier work on AI applications in supply chain management (Min, 2010; Pournader et al., 2021).

2. Literature Review

2.1 Artificial Intelligence and Public-Sector Transformation

Artificial Intelligence (AI) has become a central driver of digital transformation by enabling organizations to perform advanced data analysis, prediction, automation, and intelligent decision support. Unlike traditional information systems that primarily focus on data storage, retrieval, and transaction processing, AI systems are capable of identifying complex patterns, learning from historical information, and generating recommendations to support decision-making under uncertainty (Duan et al., 2019; Jordan & Mitchell, 2015). These capabilities have positioned AI as an important strategic resource for organizations seeking to improve operational efficiency, resilience, and innovation.

The development of big data analytics, cloud computing, Internet of Things (IoT) technologies, and advanced computational methods has accelerated AI adoption across organizational environments. In supply chain management, AI enables organizations to integrate large volumes of operational data generated from production, inventory, logistics, transportation, and quality-control activities. This integration improves supply chain visibility, enhances forecasting accuracy, supports risk identification, and enables a transition from reactive management toward predictive and proactive decision-making (Baryannis et al., 2019; Pournader et al., 2021).

AI has become particularly relevant for public-sector transformation because government organizations manage complex systems where efficiency must be balanced with transparency, accountability, and public value creation. Unlike private organizations, public institutions must consider regulatory responsibilities, ethical requirements, stakeholder trust, and long-term societal outcomes when implementing emerging technologies. Therefore, AI adoption in government environments requires not only technological investment but also governance frameworks, institutional capabilities, data management strategies, and workforce readiness (Organisation for Economic Co-operation and Development [OECD], 2019; European Commission, 2020).

For agricultural and food safety authorities, AI governance is especially important because decisions influence critical areas including food availability, public health protection,

regulatory compliance, and national resilience. AI-enabled systems can support authorities in monitoring food systems, improving risk assessment, strengthening inspection processes, and enhancing evidence-based policymaking. However, responsible implementation requires mechanisms that ensure transparency, accountability, explainability, and appropriate human oversight (Arrieta et al., 2020).

In the UAE context, AI adoption aligns with national digital transformation priorities. The Abu Dhabi AI Roadmap highlights the strategic importance of AI in improving government services, operational efficiency, and decision-making capabilities (Abu Dhabi Digital Authority, 2021). Consequently, public-sector agricultural authorities represent an important environment for examining how AI capabilities can contribute to improve food supply chain management.

2.2 Artificial Intelligence in Food Supply Chain Management

Food supply chain management involves the coordination of interconnected activities including agricultural production, sourcing, storage, logistics, distribution, quality assurance, and consumer delivery. Unlike conventional supply chains, food supply chains face additional challenges associated with perishability, safety risks, environmental uncertainty, demand fluctuations, traceability requirements, and regulatory compliance. These characteristics create a need for intelligent systems capable of supporting timely decisions and improving supply chain resilience (Manikas et al., 2022).

AI provides significant opportunities to enhance food supply chain management by improving efficiency, reducing waste, strengthening food safety, and supporting resource optimization. AI-based forecasting models can improve demand prediction and production planning, allowing organizations to better align supply and demand while reducing operational inefficiencies (Duan et al., 2019; Seyedan & Mafakheri, 2020). Similarly, AI-supported supply chain analytics can improve risk identification and resilience by detecting disruptions and supporting adaptive decision-making (Baryannis et al., 2019).

In agricultural environments, AI applications have demonstrated potential in improving productivity and sustainability through predictive analysis, environmental monitoring, and optimized resource allocation. Deep learning applications in agriculture have been widely examined for tasks such as crop monitoring, classification, prediction, and intelligent decision support (Kamilaris et al., 2017). Data-driven predictive approaches can also support smart farming by identifying patterns in agricultural data and improving operational decisions (Vashist et al., 2017).

Food safety represents another important area where AI can create value. AI-based monitoring systems can enhance traceability, contamination detection, and regulatory compliance. For example, AI systems have been developed to support food contamination control and improve safety management throughout supply chains (Li et al., 2019). More recent research highlights the potential of integrating AI, big data, and IoT technologies into food safety early-warning systems to improve risk identification and strengthen food system resilience (Mu et al., 2024).

Despite these benefits, AI-enabled food supply chains require overcoming significant implementation barriers. These include limitations in data quality, fragmented information systems, insufficient technological infrastructure, cybersecurity risks, shortage of AI-related skills, and organizational resistance to change. AI adoption therefore requires a comprehensive approach that integrates technological capabilities with organizational resources, governance structures, and institutional readiness (Dora et al., 2021).

2.3 AI Capabilities Relevant to Food Supply Chain Management

The contribution of artificial intelligence to food supply chain management depends on the functional characteristics of the technologies adopted and their alignment with specific operational requirements. AI should therefore not be treated as a single, homogeneous capability. Different approaches provide distinct forms of decision support, prediction, coordination, and optimization. This study distinguishes four capabilities that are particularly relevant to agricultural and food supply chain operations: Expert Systems, Machine Learning, Agent-Based Systems, and Artificial Neural Networks.

Table 1. AI capabilities and their applications in food supply chain management

AI capability	Application in food supply chain management	Supporting references
Expert Systems	Apply codified knowledge and predefined rules to support compliance assessment, inspection, operational recommendations, and quality management	Min (2010); Cavalcante de Oliveira et al. (2023)
Machine Learning	Learns from historical and real-time data to support forecasting, classification, risk prediction, and operational decision-making	Jordan and Mitchell (2015); Alzubi et al. (2018)
Agent-Based Systems	Enable autonomous entities to interact, coordinate, and adapt decisions across interconnected supply chain activities	Woschank et al. (2020)
Artificial Neural Networks	Identify complex and nonlinear patterns to support prediction, optimization, monitoring, and analysis of data-intensive supply chain problems	LeCun et al. (2015); Goodfellow et al. (2016)

These capabilities differ in both analytical logic and operational application. Expert Systems are most suitable for rule-based and knowledge-intensive activities, such as compliance evaluation and standardized quality-control decisions. Machine Learning is relevant to forecasting, classification, and risk prediction, although its effectiveness depends strongly on data quality and analytical maturity. Agent-Based Systems are particularly suited to coordination-intensive logistics environments involving multiple interacting actors and changing constraints. Artificial Neural Networks are appropriate for complex and nonlinear problems requiring advanced pattern recognition, prediction, and optimization.

Distinguishing among these capabilities provides a more precise basis for evaluating AI adoption. Rather than assuming that all AI technologies contribute equally, the proposed

framework examines whether each capability is associated with specific food supply chain outcomes. This capability-specific perspective supports more targeted investment decisions and stronger alignment between technological functionality and operational priorities.

2.4 Digital Transformation and AI Adoption in Public Agricultural Authorities

Public-sector agricultural authorities face growing pressure to strengthen food security, sustainability, regulatory effectiveness, and operational efficiency. These responsibilities require the coordination of complex activities involving production, sourcing, logistics, food safety, biosecurity, and quality assurance. Conventional management systems may be insufficient because they often rely on fragmented information, retrospective reporting, and limited predictive capability.

AI-enabled digital transformation can help agricultural authorities integrate data, improve forecasting, strengthen risk detection, and support evidence-based decision-making (Baryannis et al., 2019; Duan et al., 2019; Pournader et al., 2021). However, successful adoption depends on more than technology acquisition. It requires an enabling organizational environment supported by reliable data, interoperable infrastructure, skilled employees, institutional coordination, and effective change management. These conditions are especially important in the public sector, where AI systems must also meet requirements related to transparency, accountability, cybersecurity, and responsible use (Arrieta et al., 2020; Dora et al., 2021; Organisation for Economic Co-operation and Development [OECD], 2019).

Table 2. Organizational capabilities required for AI adoption in public agricultural authorities

Capability area	Strategic requirement
Data governance	Ensuring data quality, security, interoperability, accessibility, and responsible use
Technology infrastructure	Developing scalable and integrated digital platforms capable of supporting AI applications
Workforce capability	Building AI literacy, technical expertise, and the ability to interpret AI-supported decisions
Institutional coordination	Supporting collaboration among agricultural, food safety, logistics, regulatory, and technology stakeholders
Change management	Promoting organizational acceptance and integrating AI into existing workflows and responsibilities

From a resource-based perspective, AI generates value when technological resources are combined with complementary assets such as data, expertise, institutional knowledge, and effective organizational processes (Barney, 1991). Dynamic capability theory further suggests that public authorities must continually identify technological opportunities, mobilize resources, and adapt organizational routines in response to changing food-system risks and policy priorities (Teece et al., 1997).

Accordingly, AI adoption in public agricultural authorities should be treated as a strategic

transformation process rather than a stand-alone technology project. Its success depends on aligning AI capabilities with operational needs, institutional responsibilities, and public-sector objectives.

2.5 Research Gap and Framework Development Need

Although prior studies have highlighted the potential of artificial intelligence (AI) to improve supply chain performance, several important gaps remain in the literature. First, most existing studies focus on private-sector organizations, manufacturing settings, or isolated technological applications. As a result, there is still limited empirical evidence on how AI can be implemented within public-sector agricultural authorities, particularly those responsible for food security, food safety, and broader regulatory governance.

Second, much of the existing research approaches AI adoption primarily from a technological perspective, with insufficient attention to the broader organizational and institutional conditions that shape implementation outcomes. In public-sector contexts, AI adoption is not merely a technical issue; it must also align with governance requirements, organizational readiness, workforce capability, and policy objectives. This is especially important in agricultural and food safety authorities, where operational decisions are closely linked to public accountability and national strategic priorities.

Third, the literature often treats AI as a single or general capability, without adequately distinguishing among different AI technologies and their specific operational roles. However, AI capabilities such as Expert Systems, Machine Learning, Agent-Based Systems, and Artificial Neural Networks are conceptually and functionally distinct, and their contributions may vary depending on the supply chain function under consideration.

To address these gaps, this paper proposes and empirically validates an Artificial Intelligence Framework for Food Supply Chain Management based on evidence from a UAE public-sector agricultural authority. As illustrated in Figure 1, the proposed framework examines the extent to which four AI capabilities; Expert Systems, Machine Learning, Agent-Based Systems, and Artificial Neural Networks that contribute to three key food supply chain management outcomes: Production and Sourcing, Logistics and Distribution Efficiency, and Safety and Quality Control. By doing so, the framework provides a more differentiated understanding of how specific AI capabilities influence specific operational dimensions of food supply chain management.

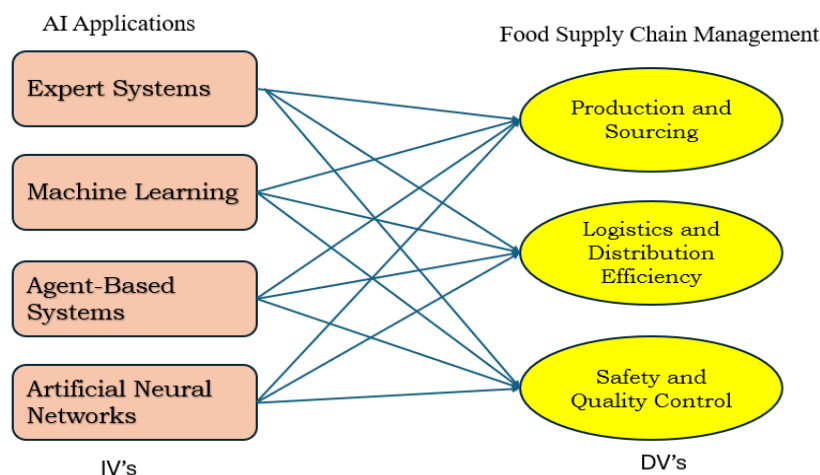


Figure 1. Proposed conceptual framework linking AI capabilities and food supply chain management outcomes

3. Research Methodology

3.1 Research Design

This study employed a quantitative, cross-sectional survey design to examine the relationships between artificial intelligence capabilities and food supply chain management outcomes within a UAE public-sector agricultural authority. The design was appropriate for measuring latent constructs, testing hypothesized relationships, and validating the proposed framework through statistical modelling (Fischer et al., 2023; Takona, 2024). Data were collected using a structured questionnaire administered to employees involved in agricultural operations, food safety, sourcing, logistics, distribution, and related supply chain activities. The survey approach enabled the collection of standardized organizational data from respondents with relevant operational knowledge (Leavy, 2022). As the study examined perceptions of existing AI capabilities and current supply chain practices, data were collected at a single point in time.

3.2 Research Context

The study was conducted at the Abu Dhabi Agriculture and Food Safety Authority (ADAFSA), a public-sector organization responsible for agricultural development, food safety regulation, biosecurity, and food security support in Abu Dhabi. ADAFSA was selected because its responsibilities cover key stages of the food supply chain, including production, sourcing, logistics coordination, inspection, safety monitoring, and quality assurance. The setting is particularly relevant because the UAE faces limited agricultural resources, water scarcity, climatic constraints, and reliance on international food supply networks. Consequently, resilient agri-food supply chains, digitalization, and forecasting capabilities are strategically important to national food security and sustainability objectives (Aldhaheri et al., 2023; Manikas et al., 2022). The public-sector context also enables consideration of institutional requirements related to accountability, regulatory responsibility, data governance,

and organizational readiness.

3.3 Population and Sample

The target population comprised 1,506 operational employees of the Abu Dhabi Agriculture and Food Safety Authority whose responsibilities were related to agricultural production, food safety, sourcing, logistics, distribution, or supply chain coordination. Purposive sampling was employed because the study required respondents with direct knowledge of the organization's operational and technological practices.

A total of 500 questionnaires were distributed, of which 455 were returned, representing a response rate of 91.0%. During data screening, 20 incomplete questionnaires and 33 outlier cases were excluded, resulting in 402 usable responses and an effective usable response rate of 80.4%. The final sample was considered sufficient for estimating the proposed PLS-SEM model, which contained four exogenous constructs, three endogenous constructs, and twelve structural paths.

Because the sample was drawn from a single public-sector authority using purposive sampling, the findings should be generalized only to comparable institutional and operational contexts. They should not be interpreted as representative of all agricultural authorities or food supply chain organizations in the UAE.

3.4 Measurement Constructs

The model comprised four exogenous AI capability constructs and three endogenous food supply chain management constructs. The AI capabilities were Expert System, Machine Learning, Agent-Based System, and Artificial Neural Network. The food supply chain outcomes were Production and Sourcing, Logistics and Distribution Efficiency, and Safety and Quality Control. All constructs were measured using multiple questionnaire items on a Likert-type scale. The items captured the perceived application of each AI capability and its association with planning, sourcing, logistics, distribution, food safety, quality assurance, traceability, and regulatory activities. The measurement design was informed by prior studies on AI applications, intelligent decision support, logistics, and food safety management (Jordan & Mitchell, 2015; Li et al., 2019; Min, 2010; Pournader et al., 2021; Woschank et al., 2020).

3.5 Data Analysis

The data were analyzed using SPSS and SmartPLS. SPSS was used for data screening, descriptive statistics, and respondent profiling. SmartPLS was used to estimate the measurement and structural models through Partial Least Squares Structural Equation Modelling. PLS-SEM was selected because the study emphasized prediction, framework validation, and the simultaneous assessment of multiple latent constructs and structural relationships (Hair et al., 2022). The analysis proceeded in two stages. First, the measurement model was assessed using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted, and discriminant validity. Second, the structural model was evaluated using variance inflation factors, path coefficients, coefficients of determination, effect sizes,

predictive relevance, and bootstrapping. Hypotheses were assessed using path coefficients, t-values, p-values, and confidence intervals generated from 5,000 bootstrap resamples.

4. Results and Framework Validation

4.1 Respondent Profile

The final dataset consisted of **402 valid responses** obtained from operational employees of the Abu Dhabi Agriculture and Food Safety Authority (ADAFSA). The respondents represented diverse demographic and professional characteristics, including age, educational background, work experience, and organizational position. This diversity provided a suitable basis for evaluating perceptions regarding artificial intelligence (AI) applications and food supply chain management practices.

The largest age group comprised respondents aged **31–35 years (24.1%)**, followed by those aged **36–40 years (23.1%)** and **26–30 years (20.1%)**. Respondents aged 41–45 years represented 17.2%, while those aged 46 years and above accounted for 15.4%. The distribution indicates that the sample largely consisted of employees within the active working-age categories, providing relevant operational insights.

Regarding educational attainment, the majority of respondents held a bachelor's degree (**43.3%**), followed by master's degree holders (**23.6%**). Diploma holders represented 15.7%, doctoral degree holders accounted for 10.9%, and respondents with high-school qualifications represented 6.5%. This educational profile indicates that most respondents possessed sufficient academic background to evaluate AI-related practices and supply chain activities.

In terms of work experience, respondents with **1–5 years of experience represented the largest group (31.1%)**, followed by those with 6–10 years (26.6%). Employees with more than 15 years of experience accounted for 17.2%, while those with 11–15 years represented 16.9%. Only 8.2% had less than one year of experience. Therefore, most participants had adequate organizational exposure to provide informed assessments.

Regarding organizational position, junior-level employees represented 46.5% of the sample, followed by senior-level employees (38.8%) and executive-level employees (14.7%). The respondent profile reflects appropriate representation of employees directly involved in operational processes related to food supply chain management.

4.2 Measurement Model Assessment

4.2.1 Indicator Reliability and Internal Consistency Reliability

All measurement indicators achieved factor loadings above the recommended minimum threshold of 0.50, demonstrating adequate indicator reliability. Consequently, no indicators were removed because all measurement items contributed meaningfully to their respective constructs.

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability. As shown in Table 3, Cronbach's alpha values ranged from 0.674 to 0.854, while composite reliability values ranged from 0.782 to 0.889.

Although the Cronbach's alpha values for Production and Sourcing and Safety and Quality Control were slightly below the conventional threshold of 0.70, their composite reliability values exceeded the recommended level. Given that composite reliability is considered a more appropriate reliability measure in PLS-SEM because it accounts for different indicator loadings, all constructs were retained for subsequent structural analysis (Hair et al., 2022).

Table 3. Measurement model assessment

Construct	Loading Range	Cronbach's Alpha	Composite Reliability	AVE
Expert System	0.702–0.734	0.847	0.885	0.523
Machine Learning	0.701–0.748	0.854	0.889	0.532
Agent-Based System	0.605–0.711	0.803	0.856	0.459
Artificial Neural Network	0.682–0.760	0.846	0.884	0.520
Production and Sourcing	0.550–0.613	0.693	0.792	0.352
Logistics and Distribution Efficiency	0.519–0.656	0.717	0.805	0.373
Safety and Quality Control	0.552–0.624	0.674	0.782	0.339

4.2.2 Convergent Validity

Convergent validity was assessed using average variance extracted. Expert System (AVE = 0.523), Machine Learning (AVE = 0.532), and Artificial Neural Network (AVE = 0.520) exceeded the recommended threshold of 0.50. In contrast, Agent-Based System (AVE = 0.459), Production and Sourcing (AVE = 0.352), Logistics and Distribution Efficiency (AVE = 0.373), and Safety and Quality Control (AVE = 0.339) fell below this threshold.

Although the composite reliability values for these constructs exceeded 0.70, satisfactory composite reliability does not fully compensate for weak convergent validity. The low AVE values indicate that a substantial proportion of indicator variance was not captured by the intended constructs. Accordingly, the measurement model should be regarded as demonstrating acceptable internal consistency and discriminant validity, but only partial convergent validity.

The structural estimates involving Agent-Based System, Production and Sourcing, Logistics and Distribution Efficiency, and Safety and Quality Control should therefore be interpreted cautiously. Future validation should reassess the content and wording of the associated indicators, remove weak items only when theoretically justified, and evaluate the revised scales in an independent sample.

4.2.3 Discriminant Validity

Discriminant validity was evaluated using the Fornell–Larcker criterion and Heterotrait–Monotrait ratio (HTMT). The Fornell–Larcker assessment confirmed that the

square root of AVE values exceeded correlations with other constructs, indicating that each construct represented a distinct theoretical concept.

Table 4. HTMT discriminant validity assessment

Construct	ES	ML	ABS	ANN	PS	LDE	SQC
Expert System	—						
Machine Learning	0.766	—					
Agent-Based System	0.729	0.714	—				
Artificial Neural Network	0.802	0.760	0.727	—			
Production and Sourcing	0.700	0.586	0.571	0.659	—		
Logistics and Distribution Efficiency	0.475	0.466	0.528	0.491	0.485	—	
Safety and Quality Control	0.579	0.519	0.513	0.604	0.701	0.413	—

All HTMT values were below the recommended threshold of 0.90. The highest HTMT value was observed between Expert System and Artificial Neural Network (0.802), confirming adequate discriminant validity among the seven constructs. Overall, the measurement model demonstrated acceptable reliability, satisfactory discriminant validity, and partial-to-acceptable convergent validity. Therefore, the constructs were considered appropriate for evaluating the structural relationships within the proposed AI framework.

4.3 Structural Model Results

4.3.1 Collinearity Assessment

Variance inflation factor (VIF) values ranged from 1.859 to 2.291, indicating that multicollinearity was not a concern. All values remained below accepted thresholds, confirming that the predictor constructs were sufficiently independent for structural model interpretation (Hair et al., 2022).

Table 5. Collinearity assessment

Predictor Construct	VIF
Expert System	2.291
Machine Learning	2.120
Agent-Based System	1.859
Artificial Neural Network	2.264

4.3.2 Explanatory Power of the Model

The structural model demonstrated different levels of explanatory power across the three food supply chain outcomes. The AI constructs explained 33.4% of the variance in Production and

Sourcing, 20.4% of the variance in Logistics and Distribution Efficiency, and 24.8% of the variance in Safety and Quality Control.

Production and Sourcing achieved the highest explanatory power, suggesting that AI capabilities contribute most strongly to planning, sourcing, and production-related activities. This finding is consistent with previous research highlighting the role of AI analytics in improving forecasting, planning, and operational decision-making in supply chain environments (Baryannis et al., 2019; Pournader et al., 2021).

Table 6. Structural model explanatory power

Endogenous Construct	R ²	Adjusted R ²
Production and Sourcing	0.334	0.327
Logistics and Distribution Efficiency	0.204	0.196
Safety and Quality Control	0.248	0.241

4.3.3 Predictive Relevance

The predictive relevance assessment demonstrated that all endogenous constructs achieved Q² values greater than zero, confirming that the model possessed predictive capability. Production and Sourcing recorded the strongest predictive relevance (Q² = 0.314), followed by Safety and Quality Control (Q² = 0.223) and Logistics and Distribution Efficiency (Q² = 0.177). These findings indicate that AI capabilities provide meaningful predictive value for food supply chain management outcomes.

Table 7. Predictive relevance

Construct	Q ²	RMSE
Production and Sourcing	0.314	0.254
Logistics and Distribution Efficiency	0.177	0.285
Safety and Quality Control	0.223	0.252

4.3.4 Hypothesis Testing

Artificial Neural Network emerged as the most influential AI capability, demonstrating significant relationships with all three food supply chain dimensions. This finding supports previous research emphasizing the ability of neural-network-based approaches to identify complex patterns, perform prediction, and optimize decision-making in agricultural and operational environments (LeCun et al., 2015; Kamilaris et al., 2017).

Expert System demonstrated significant relationships with Production and Sourcing and Safety and Quality Control, highlighting the continuing importance of knowledge-based

systems in environments characterized by regulatory requirements and standardized decision processes. Agent-Based System showed a significant relationship with Logistics and Distribution Efficiency, reflecting its suitability for coordination-intensive and adaptive supply chain activities.

Machine Learning did not demonstrate statistically significant direct relationships in the tested model. This result should not be interpreted as indicating limited practical value. Rather, machine learning effectiveness may depend on data maturity, organizational readiness, complementary technologies, and indirect mechanisms not captured within the current framework.

Table 8. Structural path results

Relationship	β	t-value	p-value	Decision
Expert System → Production and Sourcing	0.304	4.539	<0.001	Supported
Expert System → Logistics and Distribution Efficiency	0.093	1.350	0.177	Not supported
Expert System → Safety and Quality Control	0.178	2.622	0.009	Supported
Machine Learning → Production and Sourcing	0.076	1.269	0.204	Not supported
Machine Learning → Logistics and Distribution Efficiency	0.095	1.458	0.145	Not supported
Machine Learning → Safety and Quality Control	0.074	1.155	0.248	Not supported
Agent-Based System → Production and Sourcing	0.076	1.309	0.191	Not supported
Agent-Based System → Logistics and Distribution Efficiency	0.208	3.410	0.001	Supported
Agent-Based System → Safety and Quality Control	0.083	1.378	0.168	Not supported
Artificial Neural Network → Production and Sourcing	0.204	3.288	0.001	Supported
Artificial Neural Network → Logistics and Distribution Efficiency	0.133	2.029	0.042	Supported
Artificial Neural Network → Safety and Quality Control	0.239	3.741	<0.001	Supported

4.4 Empirically Supported Artificial Intelligence Framework

The proposed model specified twelve relationships between four AI capabilities and three food supply chain management outcomes. Six relationships were statistically supported. The resulting framework should be interpreted as an empirically supported structural model rather than as a fully measurement framework, because four constructs demonstrated AVE values below 0.50.

The findings nevertheless reveal a differentiated pattern of associations. Artificial Neural Network was positively associated with all three food supply chain outcomes. Expert System was associated with Production and Sourcing and Safety and Quality Control, while Agent-Based System was associated with Logistics and Distribution Efficiency. Machine Learning did not demonstrate significant direct associations.

Artificial Intelligence Framework for Food Supply Chain Management

Evidence from a UAE Public-Sector Agricultural Authority

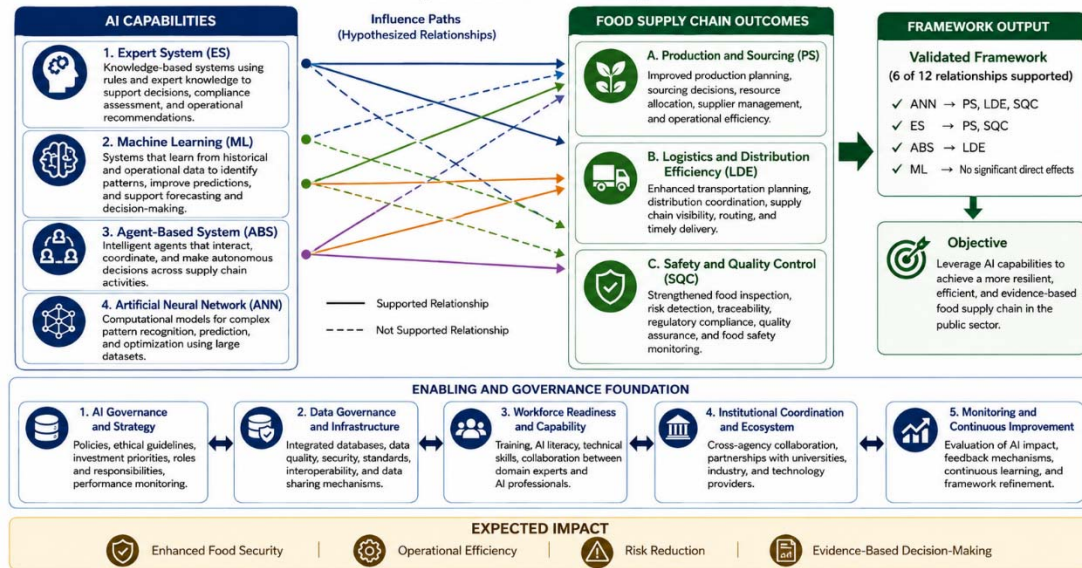


Figure 2. Integrated AI and policy framework for food supply chain management

Figure 2 integrates the empirically supported relationships with the broader organizational and policy conditions required for implementation. The framework positions AI governance, data infrastructure, workforce readiness, institutional coordination, and continuous monitoring as enabling foundations that support the translation of AI capabilities into operational value. These elements were not tested as structural relationships in the present model. Instead, they were derived from the empirical findings and the wider literature as policy conditions necessary for effective implementation.

Accordingly, the framework should be interpreted as an integrated empirical and policy model. Its empirical component identifies the AI capabilities associated with specific food supply chain outcomes, while its policy component specifies the organizational conditions required to support adoption, scaling, and responsible use. The framework therefore offers public-sector agricultural authorities a more targeted basis for aligning AI investment with operational priorities, institutional capacity, and food security objectives.

5. Policy Implications Related to the Findings

5.1 Establish a Strategic AI Governance Framework

The findings indicate that AI adoption should be governed through a structured strategic framework rather than implemented as isolated technology projects. Since different AI capabilities demonstrated different operational contributions, public-sector agricultural authorities should develop AI strategies that explicitly connect technological investments with specific food supply chain objectives.

A governance-oriented approach is particularly important in government environments

because AI implementation involves issues beyond operational efficiency, including transparency, accountability, responsible data use, and public trust. International AI governance frameworks emphasize that effective AI adoption requires institutional mechanisms that promote reliability, human oversight, transparency, and ethical implementation (Organisation for Economic Co-operation and Development [OECD], 2019; European Commission, 2020).

For UAE agricultural authorities, AI governance frameworks should therefore define strategic priorities, technology evaluation criteria, implementation responsibilities, performance measurement mechanisms, and responsible AI principles. Such governance structures would ensure that AI investments contribute directly to national food security objectives while maintaining regulatory accountability.

The findings suggest that governance decisions should consider technological suitability. Artificial Neural Networks should be prioritized for prediction, optimization, and complex analytical applications; Expert Systems should support regulatory and knowledge-intensive activities; and Agent-Based Systems should be considered for dynamic coordination and logistics environments. This capability-based governance model provides a more effective alternative to adopting AI as a general-purpose technology.

5.2 Develop AI-Enabled Food Supply Chain Intelligence Systems

The strong empirical contribution of Artificial Neural Networks across all three supply chain dimensions highlights the importance of developing integrated AI-enabled intelligence platforms within public agricultural authorities. Rather than deploying disconnected applications, authorities should develop interconnected systems capable of integrating production, logistics, food safety, and operational data. AI-enabled food supply chain intelligence systems can support predictive planning, operational optimization, and early risk identification. Previous research demonstrates that AI applications in supply chain environments improve forecasting capability, enhance visibility, and support proactive responses to uncertainty (Baryannis et al., 2019; Pournader et al., 2021). The policy applications of AI-enabled systems are summarized as in Table 9.

Table 9. Policy applications framework

Supply Chain Function	Policy Direction
Production and Sourcing	Develop predictive systems supporting production planning, resource allocation, supplier evaluation, and sourcing decisions
Logistics and Distribution Efficiency	Implement intelligent coordination systems supporting routing, distribution planning, and adaptive logistics management
Safety and Quality Control	Strengthen AI-enabled inspection, traceability, risk prediction, and food safety monitoring systems

For UAE agricultural authorities, this represents a transition from traditional information management systems toward integrated decision-support ecosystems capable of improving visibility and resilience across the food supply chain.

5.3 Strengthen Data Governance and Digital Infrastructure

Although AI provides significant opportunities for improving food supply chain performance, its effectiveness depends fundamentally on the availability of high-quality, accessible, and integrated data. The findings, particularly the limited direct effect of Machine Learning, highlight that technological capability alone is insufficient without appropriate data foundations and organizational readiness.

Previous research identifies data quality, interoperability, and information availability as critical success factors for AI implementation in supply chain environments (Dora et al., 2021; Hazen et al., 2014). Therefore, UAE agricultural authorities should prioritize the development of comprehensive data governance frameworks that support reliable AI deployment.

Key policy priorities include establishing integrated agricultural and food supply chain databases, implementing standardized data collection processes, improving data quality management, enabling secure information exchange, and ensuring interoperability between government digital platforms. Strengthening data governance should therefore be viewed as a strategic foundation for AI transformation rather than a technical support activity. Without reliable data ecosystems, even advanced AI technologies may fail to generate meaningful operational value.

5.4 Develop AI Capability and Workforce Readiness

The findings demonstrate that successful AI transformation requires human capabilities alongside technological investment. AI systems influence decision-making processes, operational responsibilities, and organizational workflows; therefore, employees must possess the knowledge and skills required to effectively adopt and manage these technologies. The development of AI capability should extend beyond technical specialists and include managers, policymakers, operational employees, and domain experts. This requirement reflects the broader understanding that AI adoption depends on complementary organizational capabilities rather than technology alone (Barney, 1991; Teece et al., 1997).

UAE agricultural authorities should therefore establish workforce development strategies that include AI awareness programs for leadership teams, technical training for employees managing AI systems, interdisciplinary collaboration between agricultural experts and AI specialists, and continuous professional development initiatives. Building workforce capability is particularly important in public-sector environments because AI implementation represents organizational transformation involving new decision-making processes, changing responsibilities, and evolving institutional practices.

5.5 Prioritize AI Implementation According to Operational Needs

The empirically supported framework demonstrates that AI technologies should not be adopted using a one-size-fits-all approach. Instead, implementation priorities should be

determined by operational requirements and empirical evidence regarding technological suitability. The findings support the following capability-based implementation strategy as in Table 10.

Table 10. Operational priority framework

Operational Priority	Recommended AI Capability	Policy Application
Production planning and sourcing	Artificial Neural Network + Expert System	Predictive planning, resource optimization, knowledge-based decision support
Logistics and distribution management	Artificial Neural Network + Agent-Based System	Supply chain coordination, routing optimization, adaptive logistics decisions
Food safety and quality assurance	Artificial Neural Network + Expert System	Risk detection, compliance monitoring, traceability improvement

This targeted implementation approach enables agricultural authorities to maximize AI investment value by ensuring that technology selection is aligned with specific operational challenges.

5.6 Enhance Institutional Coordination and AI Ecosystem Development

Food supply chain transformation requires collaboration among multiple stakeholders, including agricultural authorities, food safety organizations, producers, logistics providers, research institutions, and technology developers. AI implementation should therefore be supported through broader ecosystem development rather than isolated organizational initiatives. The UAE's public-sector AI transformation agenda emphasizes collaboration, innovation partnerships, and the development of institutional capabilities necessary for responsible AI adoption (Abu Dhabi Digital Authority, 2021). Similarly, dynamic capability theory highlights the importance of organizational networks and knowledge integration in responding to technological change (Teece et al., 1997). Accordingly, agricultural authorities should encourage partnerships with universities and research institutions, collaboration with AI technology providers, intergovernmental knowledge-sharing mechanisms, and joint innovation initiatives focused on agricultural applications.

5.7 Policy Contribution

This study contributes to policy development by providing empirical evidence regarding how different AI capabilities support specific food supply chain management functions within a UAE public-sector agricultural authority. Unlike technology-focused approaches that treat AI as a single capability, this research demonstrates that AI value depends on the alignment between technological characteristics and operational requirements. The findings indicate that AI transformation requires integration between AI capabilities, organizational readiness, data governance, workforce development, and institutional coordination. Therefore, policymakers should approach AI adoption as a strategic transformation initiative that strengthens national food security, operational resilience, and supply chain sustainability. By providing an

empirically supported framework and a policy implementation pathway, this study offers practical guidance for UAE agricultural authorities seeking to develop responsible, effective, and AI-enabled food supply chain systems.

6. Conclusion

The findings demonstrate that AI capabilities generate differentiated operational value rather than producing uniform effects across food supply chain activities. Artificial Neural Network emerged as the most broadly applicable capability, showing significant relationships with all three supply chain outcomes. This finding highlights the importance of advanced analytical capabilities for prediction, optimization, and intelligent monitoring in complex agricultural environments. Similarly, Expert System demonstrated significant contributions to Production and Sourcing and Safety and Quality Control, emphasizing its relevance for knowledge-based decision-making, regulatory compliance, and quality assurance. In addition, Agent-Based System showed particular value in Logistics and Distribution Efficiency, reflecting its suitability for coordination and adaptive decision-making. Although Machine Learning did not demonstrate significant direct effects in the tested model, the findings suggest that its value may depend on enabling conditions such as data maturity, organizational readiness, and integration with complementary capabilities.

Beyond these empirical findings, the study contributes to the AI and supply chain literature in three important ways. First, it advances understanding of AI adoption by demonstrating that different AI capabilities influence different operational dimensions of food supply chain management. Second, it extends existing research beyond private-sector and manufacturing contexts by providing empirical evidence from a public-sector agricultural authority responsible for food security and food safety governance. Third, it demonstrates that AI value creation depends not only on technological capability but also on organizational and institutional conditions, including data governance, workforce readiness, and strategic alignment.

From a policy perspective, the findings indicate that public-sector agricultural authorities should adopt a capability-based approach to AI transformation. Rather than implementing AI as a general technology initiative, authorities should align specific AI capabilities with operational priorities and organizational requirements. Furthermore, effective AI transformation requires strategic governance mechanisms, reliable data infrastructure, skilled personnel, institutional coordination, and responsible implementation practices. In the UAE context, the empirically supported framework provides an evidence-based foundation for prioritizing AI investments and strengthening food supply chain resilience.

Nevertheless, this study has several limitations that provide opportunities for future research. First, the research adopted a cross-sectional design based on employee perceptions within a single public-sector agricultural authority, which may limit the generalizability of the findings. Therefore, future studies could employ longitudinal designs, and comparative multi-organization approaches to examine how AI capabilities develop over time and across different institutional contexts. Second, the study examined direct relationships between AI capabilities and food supply chain outcomes. Consequently, future research could investigate

mediating and moderating factors, including organizational readiness, leadership support, data governance maturity, and digital transformation capability. Third, while the study examined operational dimensions associated with food supply chain management, future research should incorporate explicit sustainability indicators covering environmental, economic, and social performance outcomes.

Overall, this research demonstrates that AI can serve as a strategic enabler for food supply chain transformation in public-sector agricultural authorities. However, achieving meaningful impact requires moving beyond technology adoption toward an integrated approach that combines AI capabilities with governance, organizational capability development, and institutional strategy. Ultimately, the empirically supported framework provides practical guidance for UAE agricultural authorities and similar government organizations seeking to develop more resilient and intelligent food systems.

References

- Abu Dhabi Digital Authority. (2021). *Abu Dhabi AI roadmap*. Retrieved from <https://www.adda.gov.ae/en/strategies/ai-roadmap>
- Aldhaheer, M., Sharma, R., Sundarakani, B., & Manikas, I. (2023). *An investigation of the effect of supply chain digitalization and sustainability on food security through improved forecasting capabilities* (pp. 1–6). In 2023 IEEE International Conference on Technology Management, Operations and Decisions (ICTMOD). IEEE. <https://doi.org/10.1109/ICTMOD59086.2023.10438117>
- Alzubi, J., Nayyar, A., & Kumar, A. (2018). Machine learning from theory to algorithms: An overview. *Journal of Physics: Conference Series*, 1142(1), 012012. <https://doi.org/10.1088/1742-6596/1142/1/012012>
- Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Benetot, A., Tabik, S., Barbado, A., ... Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, 82–115. <https://doi.org/10.1016/j.inffus.2019.12.012>
- Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120. <https://doi.org/10.1177/014920639101700108>
- Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: State of the art and future research directions. *International Journal of Production Research*, 57(7), 2179–2202. <https://doi.org/10.1080/00207543.2018.1530476>
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
- Dora, M., Kumar, A., Mangla, S. K., Pant, A., & Kamal, M. M. (2021). Critical success factors influencing artificial intelligence adoption in food supply chains. *International Journal of Production Research*. <https://doi.org/10.1080/00207543.2021.1959665>
- Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making

in the era of Big Data—evolution, challenges and research agenda. *International Journal of Information Management*, 48, 63–71. <https://doi.org/10.1016/j.ijinfomgt.2019.01.021>

European Commission. (2020). *White paper on artificial intelligence: A European approach to excellence and trust*. European Commission.

Gesing, B., Peterson, S. J., & Michelsen, D. (2018). *Artificial intelligence in logistics*. DHL Customer Solutions & Innovation.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

Hellingrath, B., & Lechtenberg, S. (2019). Applications of artificial intelligence in supply chain management and logistics: Focusing onto recognition for supply chain execution. In *The art of structuring* (pp. 283–296). Springer. https://doi.org/10.1007/978-3-030-06234-7_27

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255–260. <https://doi.org/10.1126/science.aaa8415>

Kamilaris, A., Prenafeta-Boldú, F. X., & Ribeiro, A. (2017). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90. <https://doi.org/10.1016/j.compag.2018.02.016>

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>

Li, W., Wu, X., Jin, H., Wang, M., & Zhu, Q. (2019). An artificial intelligence system for regulating Salmonella contamination in food supply chain. *IEEE Access*, 7, 179264–179273.

Manikas, I., Sundarakani, B., Anastasiadis, F., & Ali, B. (2022). A framework for food security via resilient agri-food supply chains: The case of UAE. *Sustainability*, 14(10), 6375. <https://doi.org/10.3390/su14106375>

Min, H. (2010). Artificial intelligence in supply chain management: Theory and applications. *International Journal of Logistics Research and Applications*, 13(1), 13–39. <https://doi.org/10.1080/13675560902736537>

Mu, W., Kleter, G. A., Bouzembrak, Y., Dupouy, E., Frewer, L. J., Radwan Al Natour, F. N., & Marvin, H. J. P. (2024). Making food systems more resilient to food safety risks by including artificial intelligence, big data, and internet of things into food safety early warning and emerging risk identification tools. *Comprehensive Reviews in Food Science and Food Safety*, 23(1), e13296. <https://doi.org/10.1111/1541-4337.13296>

Organisation for Economic Co-operation and Development. (2019). *OECD principles on artificial intelligence*. OECD Publishing.

Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. *International Journal of Production Economics*, 241, 108250. <https://doi.org/10.1016/j.ijpe.2021.108250>

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7<509::AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z)

Vashist, P., Zeng, Y., Chen, S., & Wang, J. (2017). A data analytics approach to building predictive models for smart farming. *Computers and Electronics in Agriculture*, 141, 110–119.

World Health Organization. (2020). *The second global meeting of the FAO/WHO International Food Safety Authorities Network (INFOSAN), Abu Dhabi, United Arab Emirates, 9–11 December 2019: Meeting report*. World Health Organization.

Woschank, M., Rauch, E., & Zsifkovits, H. (2020). A review of further directions for artificial intelligence, machine learning, and deep learning in smart logistics. *Sustainability*, 12(9), 3760. <https://doi.org/10.3390/su12093760>

Zhang, T., Zhang, Z., Yang, Z., Zheng, X., Zhang, S., Wu, H., & Yu, H. (2020). An intelligent scheduling model for energy-efficient irrigation in agriculture using deep reinforcement learning. *Computers and Electronics in Agriculture*, 178, 105739. <https://doi.org/10.1016/j.compag.2020.105739>

Copyrights

Copyright for this article is retained by the author(s), with first publication rights granted to the journal.

This is an open-access article distributed under the terms and conditions of the Creative Commons Attribution license (<http://creativecommons.org/licenses/by/4.0/>).