

AI-Enabled Forecasting and Resilience Measurement in Perishable Goods Logistics: A Critical Integrative Review

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Publication Date: 2026/09/30

Abstract: Perishable-goods logistics faces intertwined uncertainty in demand, supply, product condition, temperature, and disruption, while limited shelf life narrows the time available for response. This critical integrative review examines how AI-enabled forecasting relates to supply-chain resilience and how predictive capability can be represented within resilience measurement. Thirty English-language scholarly studies published between 2020 and 2026 contributed to the final synthesis across predictive applications, operational use, disruption response, resilience mechanisms, measurement approaches, and reported outcomes. The evidence shows that AI and machine-learning methods can predict demand, product quality and marketability, temperature, and disruption-related conditions, but machine-learning performance varies by forecasting task, data, horizon, and operating context and does not consistently exceed conventional methods. Evidence for predictive performance and operational use is stronger than evidence linking prediction to observed resilience outcomes. The review develops an evidence-grounded, conditional prediction-to-resilience pathway in which predictive capability produces actionable information that may be converted through available response capacity into operational intervention, changes in system behavior during disruption, and an observed resilience outcome. The analysis also distinguishes predictive measures from response-capacity indicators and realized resilience measures, showing why forecast accuracy should not be treated as resilience itself. The review concludes that predictive capability is an enabling information capability within a broader resilience system. Stronger evidence of a prediction-to-resilience relationship would require studies that observe implemented interventions during defined disruptions and measure resulting changes in continuity, loss, performance decline, or recovery.

Keywords: Artificial Intelligence; Perishable Goods Logistics; Supply Chain Resilience; Predictive Analytics; Resilience Measurement.

How to Cite: Julius Albert Tommy Hai; Ebenezer Tetteh; Matthew Oman-Amoako (2026) AI-Enabled Forecasting and Resilience Measurement in Perishable Goods Logistics: A Critical Integrative Review. *International Journal of Innovative Science and Research Technology*, 11(9), 2030-2042. <https://doi.org/10.38124/ijisrt/26sep495>

I. INTRODUCTION

Perishable-goods logistics operates under conditions in which time, temperature, demand, and supply uncertainty can directly affect product quality, availability, and economic value. Unlike durable products, perishables can deteriorate while being stored, transported, or awaiting sale, making disruptions consequential for both operational continuity and food loss. Recent studies show that predictive and model-based methods can make changes in product condition and marketability more visible during distribution, including before deterioration is fully apparent to supply-chain stakeholders. Elashmawy et al. (2025), for example, developed machine-learning models for forecasting strawberry marketability and quality using product characteristics and temperature conditions during

distribution. Shrivastava et al. (2022) similarly used a digital-twin framework to estimate citrus quality and marketability from environmental conditions during refrigerated shipments. These applications show how prediction can make time-sensitive product changes more visible while intervention remains possible.

Predictive applications also extend to demand, supply, capacity, and disruption conditions. In a real California meat supply chain affected by COVID-19, Aljuneidi et al. (2024) combined demand and supply forecasting with rolling-horizon optimization and reported that the approach supported demand satisfaction and profitability during turbulent conditions. The study is useful because it connects predictive information to an operational decision process, although its forecasting component should not be treated as

direct evidence of AI-enabled forecasting. At the same time, the available evidence does not establish a general performance advantage for machine-learning methods. Jackson et al. (2025), for example, found that conventional seasonal forecasting methods outperformed machine-learning approaches in most of the cold-chain cases they evaluated. Model sophistication therefore cannot be treated as a proxy for practical predictive value.

Supply-chain resilience presents a related but distinct problem. Research on food systems has examined resilience through network structure, disruption exposure, redundancy, adaptation, continuity, and recovery, while other studies have developed metrics based on changes in performance during and after disruption. Karakoc et al. (2023) identified structural chokepoints in U.S. agri-food networks, illustrating how network configuration can shape exposure. Azzam et al. (2023) operationalized alternative measures of disruption and recovery in U.S. and European meat processing and showed that resilience judgments can depend on the metric applied. These findings indicate that resilience cannot be reduced to predictive accuracy or any single operational outcome.

The analytical problem addressed by this review lies in the relationship among these evidence streams. The literature provides evidence on predictive applications in perishable-goods logistics and on resilience and its measurement, but fewer studies directly connect predictive capability with an implemented operational response and an observed resilience outcome during disruption. Evidence that a prediction can inform a decision does not establish that the prediction caused a resilience outcome, and evidence of predictive accuracy does not establish that the resulting measure belongs in a resilience index. Four linked questions frame the analysis: what AI-enabled forecasting is being used to predict in perishable-goods logistics; through what mechanisms predictive information can become relevant to resilience; how resilience is represented and measured; and what evidence is available for connecting predictive capability to resilience measurement.

II. REVIEW DESIGN AND ANALYTICAL APPROACH

➤ *Review Design*

This study used a critical integrative review approach to examine the relationship between AI-enabled forecasting, perishable-goods logistics, supply-chain resilience, and resilience measurement. An integrative review was appropriate because the literature spans forecasting, operational models, disruption research, and resilience measurement (Whittemore & Knafl, 2005). The critical orientation supported examination of convergence, limitations, and contradictions across these forms of evidence (Torraco, 2005).

➤ *Literature Identification, Scope, and Selection*

Literature identification focused on AI and machine-learning prediction, forecasting, perishable-goods and food logistics, supply-chain disruption and resilience, and resilience measurement. Studies were considered when their

objectives, methods, context, or findings addressed at least one component of the review problem. The validated corpus comprised 40 English-language scholarly studies published between 2020 and 2026. Priority was given to U.S. food and perishable-goods supply chains, with relevant international studies retained where reasonable transferability existed. Thirty substantive studies provided direct evidence for the final synthesis, while two additional methodological sources supported the review design. The remaining 10 validated studies were excluded from the synthesis because their contribution was insufficiently direct, redundant with stronger evidence, or outside the relationships examined.

➤ *Evidence Organization and Critical Integrative Synthesis*

Evidence was organized according to predictive capability, forecasting target, operational application, disruption context, resilience mechanism, measurement approach, and reported outcomes. The synthesis distinguished predictive performance from operational use, modeled or simulated response, implemented intervention, and observed resilience outcomes. Findings were compared across studies and analytical domains, with differences in study design, context, and evidentiary strength retained. Claims were limited to the strongest relationships supported by the evidence, while indirect, conditional, contradictory, or unresolved findings were interpreted accordingly.

III. CONCEPTUALIZATION OF KEY CONSTRUCTS

AI-enabled forecasting, predictive capability, supply-chain resilience, and resilience measurement concern different aspects of perishable-goods logistics. Forecasting estimates future conditions or outcomes. Predictive capability concerns whether the resulting information is sufficiently useful for anticipation or decision-making. Resilience concerns how a supply system behaves under disruption. Resilience measurement concerns how that behavior, or the capacity associated with it, is represented through observable indicators. The constructs can be connected analytically, but they should not be treated as interchangeable.

➤ *AI-Enabled Forecasting and Predictive Capability*

AI-enabled forecasting refers to the use of artificial intelligence and machine-learning techniques to estimate future states or outcomes from available data. In perishable-goods logistics, the forecasting target extends beyond conventional demand. Models have been applied to product quality and marketability, temperature conditions, demand, supply, capacity, and disruption-related conditions. The meaning of a prediction therefore depends on both the variable being estimated and the operational decision for which the information is relevant. The review distinguishes direct evidence on AI-enabled forecasting from adjacent predictive, optimization, digital-twin, and decision-learning studies that are used only where they clarify how predictive information can become operationally relevant to resilience.

Product-condition prediction illustrates this distinction. Elashmawy et al. (2025) developed machine-learning models for forecasting strawberry marketability and quality from

product characteristics and temperature conditions during distribution. Shrivastava et al. (2022) similarly used a digital-twin approach to estimate citrus quality and marketability from environmental conditions during refrigerated shipments. These studies concern changing product states rather than demand alone. Loisel et al. (2022) addressed another physical condition by examining machine-learning approaches for predicting temperature along the food cold chain. Together, such applications show that predictive models can estimate conditions that are difficult to observe continuously during distribution.

Predictive capability is broader than forecast accuracy alone. Predictive capability refers to whether predictive information is relevant, timely, and sufficiently reliable to support anticipation or an operational decision. An accurate forecast may have limited practical value if it arrives after the decision window or concerns a condition that cannot be acted upon. For this review, predictive usefulness is treated as depending not only on conventional accuracy but also on whether information is sufficiently timely and relevant to support a feasible response. Predictive capability is therefore treated as an operational property of information, not as a synonym for model complexity.

➤ *Supply-Chain Resilience*

For this review, supply-chain resilience concerns how a supply system withstands, adapts to, and recovers from disruptive conditions. It is consequently concerned with system behavior under stress rather than normal operating performance alone. A supply chain can operate efficiently under stable conditions while remaining highly exposed when transportation is interrupted, suppliers become unavailable, demand changes sharply, or environmental conditions affect production and distribution.

Resilience can be shaped by structural characteristics and organizational responses. Karakoc et al. (2023) identified structural chokepoints in U.S. agri-food networks, while Stevens and Teal (2024) examined diversification among U.S. agrifood firms; Adewumi et al. (2024) likewise identify supplier diversification, inventory, forecasting and demand planning, contingency planning, and information sharing as components of U.S. supply-chain resilience. Karan et al. (2023) further showed that the resilience value of centralized and distributed food systems varied according to the disruption considered. These studies place resilience at the level of the wider supply system and its response options rather than at the level of a predictive model.

Resilience also has a temporal dimension. Disruption can produce an initial decline in performance, a period of adaptation while the disturbance persists, and subsequent recovery. These phases need not move together. A system that limits its initial losses may recover slowly, while another may experience a larger initial decline and restore performance rapidly. Resilience is therefore not fully represented by a single observation of operating performance.

➤ *Resilience Measurement*

Resilience measurement translates a system-level property into observable indicators. For analytical purposes, the literature can be distinguished between indicators of conditions or capacities associated with resilience and indicators of observed performance during or after disruption. Diversification, redundancy, alternative sourcing, network connectivity, and available capacity can represent response options. Measures of performance decline, recovery time, degree of recovery, or continuity instead describe what happened under disturbance. The literature does not use a single universal taxonomy; the distinction is used here to interpret the different forms of evidence in the corpus.

Azzam et al. (2023) provide a direct illustration of measurement sensitivity. Their analysis of U.S. and European meat-processing resilience used alternative metrics based on production declines and rebounds during the COVID-19 disruption. The resulting assessment of chicken-processing resilience depended on the metric applied. Rao et al. (2022) approached resilience from a network perspective by developing node-level and network-level measures for U.S. agricultural multi-commodity flow networks. Tack et al. (2026) proposed climate-related resilience metrics combining weather shocks and trade flows for agricultural supply chains. The choice of metric consequently depends on the phenomenon being assessed, the system boundary, the disruption, and the variables selected.

Forecast error, prediction accuracy, and disruption-prediction performance describe properties of a predictive system. Recovery time, production loss, continuity, or network functionality describe properties of the supply system under disruption. The measures may be related, but they answer different questions. A predictive model can perform well while the supply chain remains unable to respond because of limited capacity, supplier concentration, transportation constraints, or other structural conditions. Measurement therefore requires the construct to be specified before indicators are combined.

➤ *Conceptual Boundaries*

The constructs are related but non-equivalent. Predictive information describes a future condition; operational decisions determine whether that information is acted upon; supply-chain behavior under disruption provides the observable basis for resilience assessment. The sequence establishes conceptual relationships without making each element a measure of the next.

Forecast lead time may represent an opportunity for intervention, predictive accuracy may represent model performance, and information availability may represent an organizational capability. None directly measures whether the supply system maintained or recovered performance during disruption. Combining such variables with resilience outcomes would require an explicit rationale for construct definition, scaling, weighting, and aggregation. That measurement question should remain distinct from the definition of the constructs themselves.

IV. AI-ENABLED FORECASTING IN PERISHABLE GOODS LOGISTICS

AI-enabled forecasting in perishable-goods logistics has been applied to demand and sales, product quality and marketability, temperature conditions, supply and capacity, and disruption-related conditions. This breadth reflects the different sources of uncertainty that affect products as they move through production, storage, transportation, and distribution. The forecasting problem is therefore not limited to estimating how much product will be needed. It also concerns whether products will remain saleable and whether operational conditions will permit their movement within the available time.

Demand forecasting is a prominent application. Eiglsperger et al. (2024) found that multivariate machine-learning models, particularly XGBoost, performed strongly in horticultural sales forecasting when statistical, calendar, and weather-related variables were incorporated. Their results also indicated that models developed for individual datasets performed better than a generalized model. Lopes Gerum et al. (2026) addressed high-frequency grocery demand forecasting with a deep-learning approach designed to distinguish structural demand patterns from shorter-term fluctuations. The studies point to the importance of matching model design and information inputs to the forecasting problem rather than assuming that one architecture will perform uniformly across products and settings.

Forecasting becomes more operationally relevant when it is connected to planning or decision support. Birkmaier et al. (2024) and Umoren et al. (2025) examined how data-driven forecasting could inform planning for perishable food and identified implications for inventory and waste-prevention decisions. Aljuneidi et al. (2024) combined demand and supply forecasting with rolling-horizon optimization in a California meat supply chain during COVID-19. The latter study is useful as evidence that forecasts can be incorporated into planning, but it should not be classified as direct AI evidence unless the forecasting method itself is established as AI or machine learning. The operational value of a forecast depends on whether the variables being predicted correspond to decisions that can actually be changed.

Product-condition prediction represents a different forecasting target. Elashmawy et al. (2025) developed machine-learning models for strawberry marketability and quality using initial product characteristics and time-temperature information during distribution. Shrivastava et al. (2022) used a digital-twin framework to estimate citrus quality and marketability from environmental conditions during refrigerated shipments. Unlike demand forecasts, these models estimate changing biological or physical states that affect whether a product remains saleable. Their significance for logistics lies in making deterioration more visible while the product is still within the distribution system.

Temperature prediction addresses a related cold-chain problem. Loisel et al. (2022) examined neural-network approaches for predicting food-pallet temperature and found that models trained on experimental data performed better than those trained exclusively on synthetic data. Gaye et al. (2025) similarly emphasize data integrity, validation, and model reliability as conditions affecting the practical use of AI-driven prediction in food-related supply-chain settings. The result highlights a practical limitation of data-intensive forecasting: a large training set does not guarantee useful predictions if the data do not adequately represent actual operating conditions. Prediction quality is consequently affected by data provenance as well as model architecture.

Machine-learning methods do not consistently outperform conventional forecasting. Jackson et al. (2025) found that seasonal forecasting methods outperformed machine-learning approaches in most of the cold-chain cases they evaluated. Eiglsperger et al. (2024), by contrast, reported strong performance from multivariate machine-learning models in horticultural sales forecasting. These findings are not necessarily contradictory because the studies address different datasets, variables, forecasting conditions, and benchmarks. They indicate that model performance is conditional on the forecasting problem and that AI methods should be evaluated against credible alternatives rather than against an assumption that greater complexity produces better forecasts.

The timing of prediction is also consequential. An accurate estimate that arrives after an inventory, routing, production, or handling decision has been made may have limited practical value. The same estimate may be useful when it provides enough warning for an alternative action to remain feasible. This issue is particularly acute in perishable logistics because the decision window can narrow as remaining shelf life declines. Forecasts of demand, temperature, product condition, or supply constraints therefore have different operational value depending on when the information becomes available and what actions remain possible.

Disruption-oriented prediction extends the forecasting problem beyond routine operating variation. Hosseini Shekarabi et al. (2025) combined neural-network prediction of disruption conditions with robust optimization for a perishable-product supply-chain network. The model used predicted disruption risk as an input to decisions under uncertainty. This represents a stronger connection between prediction and operational response than a forecasting model evaluated only through predictive accuracy. It remains, however, a model-based demonstration and does not establish that the predictive component produced an observed resilience improvement in an operating supply chain.

Decision-learning applications extend the operational picture beyond conventional forecasting. Yang et al. (2022) examined AI-supported dynamic pricing and information disclosure in fresh-produce settings, while Wang et al. (2021) applied deep reinforcement learning to pricing and inventory decisions for perishable products. These studies show that AI-

based learning can operate within decision systems involving price, inventory, and allocation. Their relevance to this review lies in demonstrating how AI can shape operational decisions surrounding perishable products, while remaining conceptually distinct from forecasting.

The strongest support concerns the ability of AI and machine-learning approaches to estimate particular variables under defined conditions. Demand, quality, temperature, and disruption-related prediction are all represented in the corpus, but their performance varies with product, data, horizon, and operating context. Evidence concerning operational benefit is more conditional because it depends on the use of the information within a decision process. Forecasting performance should therefore be evaluated as a task-specific capability, not as an automatic indicator of broader logistics performance or resilience.

V. AI-ENABLED FORECASTING AND SUPPLY CHAIN RESILIENCE

Predictive capability becomes relevant to supply-chain resilience when predictive information can inform or alter decisions that affect the supply system before or during disruption. Forecasts can provide information about demand, supply, product condition, capacity, or disruption risk, but information alone does not change system performance. Its practical contribution depends on timing, decision relevance, available response options, and the severity of the disturbance. Prediction can therefore be linked to resilience-related activity without being treated as resilience itself.

➤ *Predictive Capability for Anticipation and Preparedness*

Anticipation can create time for inventory, sourcing, capacity, transportation, or handling decisions to be adjusted. This is particularly relevant to perishables because the period available for intervention can shrink as product quality or remaining shelf life declines. Jauhar et al. (2025) developed a customer-segmented demand-forecasting framework for a perishable-product supply chain using clustering, machine learning, LSTM, and explainable AI. Umoren et al. (2025) likewise link AI-enabled forecasting and predictive analytics with inventory management, resource utilization, waste reduction, and proactive supply-chain response. The approach reduced forecasting error relative to the unsegmented process. The authors linked the improvement to stronger resilience, but the study did not observe a disruption in which the forecasting improvement could be isolated as a measured resilience outcome. Its evidence is therefore direct for predictive performance and prospective for resilience.

Aljuneidi et al. (2024) provide complementary evidence for the prediction-to-decision mechanism. In a real California beef supply chain during COVID-19, demand and processing-capacity forecasts were incorporated into rolling-horizon planning. The study reported demand satisfaction and maintained profitability under the modeled planning conditions during pandemic turbulence. Because the study does not establish its forecasting component as an AI intervention, it is better interpreted as evidence that predictive information can become operationally relevant when

embedded in planning, rather than as direct evidence that AI forecasting improved resilience.

Preparedness is also constrained by the structure of the system receiving the information. Karakoc et al. (2023) identified structural chokepoints in U.S. agri-food networks, while Stevens and Teal (2024) examined diversification among U.S. agrifood firms. These studies show that information cannot create response options that the network or organization does not possess. A warning about an impending supply constraint is more useful when alternative suppliers, routes, capacity, or inventory positions can actually be activated. Burgos and Ivanov (2021) similarly showed through food-retail disruption scenarios that visibility, inventory, demand, and capacity management interact during disruption. Their digital-twin analysis should not be read as evidence that AI forecasting itself produced resilience.

➤ *Predictive Capability in Disruption Response and Adaptation*

Once disruption is underway, predictive information may need to be updated as demand, supply, capacity, transportation, or product availability changes. Aljuneidi et al. (2024) illustrate this through rolling-horizon planning, in which updated forecasts informed revised decisions during pandemic turbulence. The evidence is useful because it connects changing information with adaptation, although the contribution cannot be attributed independently to forecasting because planning flexibility and other system characteristics also matter.

Hosseini Shekarabi et al. (2025) provide a more direct AI example by incorporating neural-network disruption prediction into a robust optimization framework for a perishable-product network. Predicted disruption risk is used with optimization to support decisions under uncertainty. This is stronger evidence of prediction being embedded in a response mechanism than evidence based only on forecast accuracy. It remains a model-based demonstration rather than an observed intervention in an operating supply chain, so the resilience implication should remain conditional.

Adaptation also depends on alternative configurations. Yim and Dall'Erba (2025) examined extreme weather in the U.S. domestic food-manufacturing supply chain and found that the ability to shift the origin and volume of flows and substitute agricultural inputs supported resilience. Prediction may improve the timing of such adjustments, but it cannot generate alternative sources or inputs where none exist. Moynihan et al. (2022) similarly modeled changes in food flows, production, prices, and regional vulnerabilities under a hypothetical multistate contamination shock. Their scenarios are planning evidence rather than observations of a realized disruption, but they reinforce the role of reallocating flows and resources in adaptation.

➤ *Predictive Capability and Resilience-Related Outcomes*

A stronger evidentiary test asks whether predictive information is associated with measurable changes in supply-chain performance during disruption. Relevant outcomes include maintained supply, reduced losses, smaller

performance declines, continuity, or recovery. Such relationships are difficult to isolate because operational outcomes are simultaneously affected by network structure, inventory, capacity, sourcing, transportation, managerial decisions, and disruption severity.

Burgos and Ivanov (2021) illustrate this complexity. Their food-retail digital-twin analysis of COVID-19 scenarios showed that pandemic intensity, restrictions, inventory-ordering dynamics, customer behavior, demand surges, and supplier shutdowns affected system performance. The study supports the importance of visibility and scenario analysis but does not isolate a predictive technology as the cause of resilience. Aljuneidi et al. (2024) comes closer to an operational pathway because forecasting was directly connected to planning and the authors reported demand satisfaction and profitability during turbulence. Even there, the forecasting contribution cannot be separated from the planning model and the flexibility of the supply chain.

Jauhar et al. (2025) present a different evidentiary situation. Their AI forecasting framework produced improved predictive performance and was designed to support perishable-product inventory decisions, but its resilience claim is prospective. The study therefore supports the plausibility of a pathway from better prediction to resilience-related decisions without demonstrating a disruption outcome attributable to the forecasting improvement. Azzam et al. (2023) further show why outcome measurement must remain distinct from predictive performance: their assessment of meat-processing resilience changed according to the metric used to represent disruption and recovery.

Taken together, the studies support an asymmetric evidentiary pattern. Evidence is comparatively stronger for prediction and for the incorporation of predictive information into planning or response mechanisms than for a demonstrated effect on realized resilience. The difference is consequential because operational use introduces response capacity and managerial action as intervening conditions. The literature therefore supports treating predictive capability as a potential contributor to resilience-related action while withholding the stronger inference that improved prediction produces improved resilience. This distinction provides the basis for examining how predictive capability should be represented within resilience measurement.

VI. RESILIENCE MEASUREMENT IN PERISHABLE GOODS LOGISTICS

Resilience measurement in perishable-goods logistics requires attention to both system performance and the changing condition of the product moving through the system. A disruption can reduce throughput, delay deliveries, interrupt supply, increase product losses, or alter product quality, while recovery may occur at a different rate and to a different level. The meaning of a resilience measure therefore depends on the disruption, system boundary, time horizon, and aspect of performance being represented.

For analytical purposes, the corpus can be distinguished between measures representing conditions or capacities associated with resilience and measures representing observed performance during or after disruption. Diversification, redundancy, alternative sourcing, decentralization, network connectivity, and available capacity describe response options. Production decline, disruption duration, recovery time, continuity, and degree of recovery describe what happened under disturbance. This is an analytical distinction for interpreting heterogeneous evidence, not a claim that the literature has adopted a single universal taxonomy.

Across the resilience literature, structural conditions and observed disruption outcomes represent related but different forms of measurement evidence. Karan et al. (2023) show that the resilience value of centralized and distributed food systems varies with the disruption considered, while Miller (2021) identifies transportation, diversity, and distribution structure as conditions shaping regional food-flow resilience. These findings indicate that structural characteristics describe the response options and vulnerabilities within a system, but they do not by themselves establish how the system performed during a disruption. Outcome-based measures address that second question. Azzam et al. (2023), for example, show that assessments of meat-processing resilience can change depending on whether resilience is represented through the magnitude of performance decline, recovery speed, or the extent of performance restoration. Taken together, these studies indicate that resilience measurement requires a distinction between the conditions that shape response capacity and the performance trajectory observed when disruption occurs. Time is particularly consequential in perishable systems because delay can alter the product itself. A disruption may reduce throughput while also reducing remaining shelf life, marketability, or usable product volume. Dong et al. (2022) quantified food loss and waste across the U.S. food supply chain and found that high-demand perishable products accounted for a substantial share of food waste. Their framework was not a resilience index, so food loss should not be treated as resilience by itself. It is nevertheless a relevant observed outcome when disruption causes deterioration or product loss. A resilience measure that considers only the final operating state may miss losses accumulated during a prolonged disruption.

The measurement boundary also matters. Rao et al. (2022) developed node-level and network-level resilience measures for the U.S. agricultural multi-commodity flow network, showing how dependence, supplier relationships, and network structure can be represented quantitatively. Their approach also illustrates the sensitivity of network metrics to specification choices. Karakoc et al. (2023) identified structural chokepoints in U.S. agri-food networks, reinforcing the point that facility-level measures may miss vulnerabilities created by wider network structure. Tack et al. (2026) provides broader agricultural evidence by combining weather shocks and trade flows to construct climate-related resilience metrics. The study is not specific to perishable logistics, but it demonstrates how exposure and alternative

supply relationships can be incorporated into a system-level measurement framework.

The corpus consequently supports several recurring measurement dimensions: disruption magnitude, duration of impaired performance, recovery time, degree of recovery, continuity of supply, network functionality, and response capacity. These dimensions should not be assumed to be interchangeable. Recovery time may be appropriate when

restoration is the principal concern, whereas performance decline may better represent disruption severity. Network measures are relevant when resilience depends on interconnected flows, while product loss and quality preservation become more salient when deterioration is a material consequence of delay. The principal measurement dimensions identified across the corpus are summarized in Table 1.

Table 1 Measurement Dimensions Relevant to Resilience in Perishable-Goods Logistics.

Dimension	What it represents	Illustrative indicator	Interpretive caution
Disruption magnitude	Extent of initial performance deterioration	Production or throughput decline	Does not indicate recovery
Disruption duration	Persistence of impaired performance	Time below baseline	Duration alone does not capture severity
Recovery	Speed or extent of restoration	Recovery time or rebound	Depends on baseline and recovery definition
Continuity	Ability to maintain supply or service	Demand satisfaction or flow continuity	May conceal product deterioration
Product preservation	Loss of usable or saleable product	Food loss, quality or marketability loss	Relevant outcome, not resilience by itself
Network resilience	Exposure and response options created by interconnected flows	Supplier concentration, connectivity, alternative flows	Sensitive to system boundary and specification
Response capacity	Options available before or during disruption	Diversification, redundancy, alternative sourcing	Capacity does not demonstrate realized performance

Composite measurement introduces an additional problem. Forecast accuracy, temperature deviation, food loss, delivery continuity, disruption magnitude, recovery time, and network concentration may all be relevant to logistics performance, but they represent different properties and different positions in the sequence from exposure to response and outcome. Combining them into one score requires decisions about construct definition, scaling, weighting, aggregation, and temporal alignment. The existence of several measurable variables does not establish that they form one coherent construct. Resilience measurement should therefore begin with specification of the construct, disruption, system boundary, temporal window, and observable outcome before indicators are selected or combined.

VII. PREDICTIVE CAPABILITY AND RESILIENCE MEASUREMENT

The relationship between predictive capability and resilience measurement is not a matter of adding forecasting performance to an existing resilience construct. A predictive system produces information about a future condition, whereas resilience becomes observable through how a supply system performs when exposed to disturbance. The analytical connection lies in what happens between these two points. Predictive information may create an opportunity to anticipate a problem, revise an operational decision, or prepare an alternative response. Whether that opportunity contributes to resilience depends on the response options available and on what subsequently happens to system performance during disruption.

Evidence from perishable-goods research illustrates this distinction. Lejarza et al. (2021), for example, incorporated

product-quality degradation and environmental conditions into a real-time decision framework for fresh produce and used online optimization to address demand uncertainty, operating costs, and inventory spoilage. The study demonstrates how information about product condition can be incorporated into operational control, but it is not evidence of AI-enabled forecasting producing a resilience outcome. A similar distinction applies to Wang et al. (2021), whose deep reinforcement learning model determines pricing and inventory policies for perishable products. The study concerns decision learning rather than conventional forecasting. Its relevance here is that AI can influence operational choices under changing inventory and demand conditions, not that reinforcement learning itself constitutes a resilience measure.

Forecasting and decision learning should be separated because predictive capability has a narrower meaning than AI-supported decision-making generally. A forecast estimates a future state or outcome. A decision system determines what action should be taken given the information and constraints available. Some studies combine these functions, while others address only one. Hosseini Shekarabi et al. (2025) provide a particularly relevant example of the former. Their framework uses a neural network to predict disruption rates from risk indicators and feeds those predictions into a robust supply-chain network optimization model for perishable products. The study consequently provides direct evidence that AI-based disruption prediction can be embedded in a resilience-oriented decision process. Its evidence remains model-based, however. The analysis does not observe an operating supply chain experiencing a disruption and then measure whether the predictive component produced a superior resilience outcome.

This narrower definition places predictive capability at a specific point within the resilience framework. Forecast accuracy, warning lead time, calibration, and disruption-prediction performance describe properties of the information system. Inventory availability, supplier diversification, alternative flows, spare capacity, and decision flexibility describe the conditions under which a response can be made. Continuity, performance decline, recovery time, degree of recovery, and product loss describe what happens when the system is exposed to disturbance. These categories can be related, but they do not describe the same property. An accurate warning cannot compensate for the absence of an alternative supplier or available transportation capacity. Conversely, a diversified and flexible supply system may absorb a disruption even when no advanced predictive technology is present.

Evidence from the broader agricultural supply-chain literature reinforces this point. Yin et al. (2025) examined AI applications, information sharing, supply-chain resilience, and supply-chain performance among agricultural enterprises, while Okonkwo et al. (2025) examined AI-enabled supply-chain applications in U.S. medical supply distribution with explicit attention to resilience and operational efficiency. Their findings place AI within a wider organizational and informational environment rather than treating it as an isolated determinant of resilience. Because the study concerns agricultural supply chains more broadly, rather than perishable-goods logistics specifically, its relevance is conceptual rather than direct. It nevertheless supports the interpretation that the value of AI depends partly on how information is shared and incorporated into broader supply-chain capabilities.

These relationships have direct implications for measurement. A resilience framework that includes predictive variables should distinguish between leading information, response capacity, and realized performance under disturbance. Predictive measures may indicate whether a system can identify an emerging condition with sufficient accuracy and lead time. Response-capacity measures indicate whether the system has viable options for acting on that information. Resilience outcomes indicate what the system actually experienced during the disruption and how it performed afterward. Treating these layers as separate does not deny their relationship. It prevents an expected benefit from being mistaken for an observed outcome.

The temporal dimension is particularly important in perishable-goods logistics. Product condition can deteriorate while a decision is being made, so the value of information depends partly on whether it arrives while intervention remains feasible. Elashmawy et al. (2025) and Shrivastava et al. (2022) demonstrate the practical relevance of predicting product quality and marketability while products remain within distribution systems. Dong et al. (2022) provide broader U.S. food-system evidence on the scale and distribution of food loss and waste, including the substantial contribution of high-demand perishable products. Such losses can be relevant to resilience assessment when they occur as part of a defined disruption, but food loss alone does not

establish that a system was less resilient. Its interpretation depends on the disruption, expected performance, and trajectory of the system.

A comparable issue arises when a predictive model is used to establish an expected operating trajectory. A forecast can provide a reference point for assessing disruption-related performance, and a forecast explicitly representing expected performance in the absence of the disturbance can serve as a counterfactual benchmark. The forecast itself, however, is not the resilience outcome. Azzam et al. (2023) demonstrate why this distinction matters. Their alternative resilience metrics capture different features of production decline and recovery during the COVID-19 disruption, and the resulting assessment of resilience can vary according to the metric used. Predictive information may help establish what performance might otherwise have been, but the resilience assessment still depends on how the observed disturbance and subsequent recovery are represented.

A forecast evaluated through predictive accuracy tells us about the forecasting system itself. When that forecast is incorporated into an operational model, the evidence extends to whether predictive information can inform a response. Stronger inference becomes possible when an intervention is documented during an actual disruption and accompanied by an appropriate measure of continuity, loss, performance decline, or recovery. Even then, attribution can remain difficult when inventory, sourcing, capacity, transportation, or managerial practices change at the same time. These distinctions indicate the need for an explicit analytical pathway connecting prediction, action, and observed system performance.

The available evidence does not support treating predictive capability as a necessary condition for resilience. Structural redundancy, supplier diversification, alternative sourcing, network configuration, and organizational flexibility can provide response capacity independently of advanced forecasting. Yim and Dall'Erba (2025), for example, show how alternative flows and network relationships shape the propagation of extreme-weather disturbances through U.S. food-manufacturing supply chains, although their study does not examine a predictive intervention. Predictive capability is therefore better understood as one possible enabling capability within a broader resilience system. In practical terms, response capacity should be evaluated not only by whether an alternative exists, but also by whether it can be activated within the remaining decision and product-life window.

The same reasoning places limits on composite resilience measures. Forecast accuracy, disruption-prediction performance, temperature deviation, food loss, delivery continuity, network concentration, and recovery time may all be relevant to different aspects of a perishable-goods supply system. They occupy different positions in the sequence from information and exposure through response to outcome. Combining them into a single score would require a defensible construct definition and an explicit rationale for how the variables relate. Rao et al. (2022) illustrate the

importance of system boundary and network specification in resilience measurement, while Tack et al. (2026) demonstrate how exposure to climate shocks and supply relationships can be incorporated into broader resilience metrics.

Multidimensional measurement is therefore possible, but multidimensionality alone does not establish that the resulting variables constitute one construct.

Table 2 Conditions Under which Predictive Capability can Contribute to Resilience Assessment.

Predictive function	Potential operational response	Possible resilience implication	Evidentiary requirement
Demand forecasting	Inventory, replenishment, or allocation adjustment	Potential improvement in continuity or reduction in avoidable surplus	Forecast use must be linked to an implemented decision and an observed outcome
Disruption prediction	Pre-positioning, sourcing, routing, or capacity adjustment	Potential improvement in preparedness or reduction in performance decline	The warning and subsequent response must be observable during a defined disturbance
Temperature or product-condition prediction	Handling, routing, storage, or dispatch intervention	Potential reduction in deterioration or product loss	Product outcomes must be assessed in relation to the disruption and intervention
Quality or marketability prediction	Allocation, pricing, or dispatch adjustment	Potential reduction in avoidable loss	Decision use and resulting product or service outcome must be observable
Predictive accuracy alone	No demonstrated operational intervention	No direct inference about resilience	Insufficient basis for treating prediction performance as a resilience measure
Prediction + implemented intervention + disruption outcome	Documented adaptive response	Measurable change in continuity, loss, decline, or recovery	Strongest basis among the evidence types considered, although attribution still requires appropriate comparison and analytical control.

The evidence therefore supports a layered interpretation of predictive capability in resilience measurement. For practical assessment, the layers can be treated as a diagnostic sequence: a predictive application should first be evaluated for the relevance and timing of its information, then for the response options available to the receiving operation, then for whether prediction-informed action can be observed, and finally for whether system performance during a defined disturbance can be measured against an appropriate reference condition. The absence of evidence at a later layer does not invalidate the earlier capability, but it limits the strength of any claim about resilience.

Predictive capability should consequently not be treated as resilience itself, nor should improved predictive accuracy be assumed to produce greater resilience. Its contribution is contingent on the decisions that information enables, the response options available to the supply system, and the performance that follows when disruption occurs. This distinction preserves the analytical value of AI-enabled forecasting without allowing a property of the information system to be mistaken for a property of the supply chain under stress.

➤ A Conceptual Prediction-to-Resilience Pathway

The evidence supports a conditional pathway through which predictive capability can become relevant to resilience, although the complete pathway has not been empirically established as a single causal sequence. Predictive capability first produces information about an anticipated demand, supply, product-condition, or disruption-related state. Its value depends on whether the information is sufficiently timely and relevant to create an actionable opportunity. Where response capacity exists, that opportunity may be translated into an operational intervention involving inventory, sourcing, routing, allocation, capacity, or product handling. The resulting change in system behavior can then be evaluated during disruption through measures of continuity, performance decline, product loss, recovery, or other outcomes appropriate to the resilience construct. Figure 1 presents this conceptual and conditional prediction-to-resilience pathway and the contextual conditions that can influence movement between its stages.

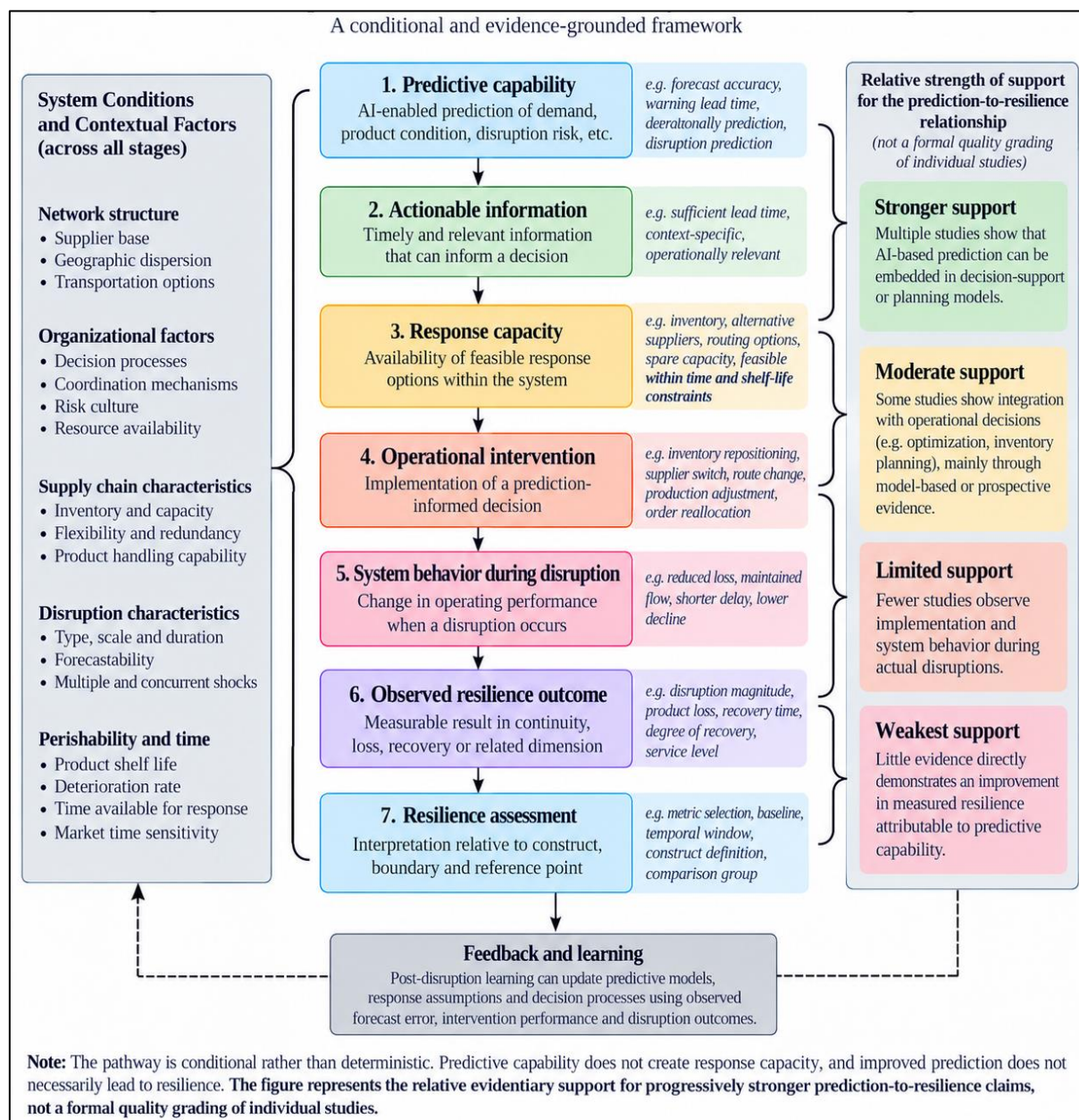


Fig 1 A Conceptual Prediction-to-Resilience Pathway in Perishable-Goods Logistics

The transitions within this pathway are conditional. Predictive information does not create response capacity, and response capacity does not guarantee that an intervention will be implemented. Similarly, an intervention does not establish resilience unless its relationship to system performance under a defined disturbance can be observed. This interpretation is consistent with evidence showing that predictive systems can be incorporated into operational decisions while the empirical link to realized resilience remains less direct. Hosseini Shekarabi et al. (2025), for example, integrate neural-network disruption prediction with robust optimization for a perishable-product network, providing evidence of prediction embedded within a response mechanism. Jauhar et al. (2025) connect improved AI-based demand forecasting with inventory decision support, but the resilience implication remains prospective rather than an observed disruption outcome.

The pathway is also conditioned by characteristics of the supply system that exist independently of predictive technology. Supplier diversification, alternative flows, inventory, network configuration, available capacity, and organizational flexibility can determine whether a prediction can be converted into action. A predictive warning may have limited practical effect when no feasible response option exists. The available evidence therefore supports treating predictive capability as one possible enabling capability within a wider resilience system, while structural and organizational sources of response capacity may operate independently of advanced forecasting.

The evidentiary boundary follows from these differences in what each type of evidence can demonstrate. Evidence of predictive performance supports a claim about the capability of the information system. Evidence that predictions inform decisions supports a stronger claim about

operational use. Evidence of an implemented intervention during a defined disruption, followed by measurement of a relevant performance outcome, provides a stronger basis for associating predictive capability with resilience. The inference becomes more demanding as the claim moves from prediction to realized resilience because each intervening relationship must be supported rather than assumed.

The pathway also clarifies the role of measurement. Predictive accuracy, warning lead time, and disruption-prediction performance describe the predictive system; inventory flexibility, alternative sourcing, and network redundancy describe response capacity; and continuity, disruption magnitude, product loss, and recovery describe system behavior under disturbance. These measures may be related within a resilience process, but they should not be treated as interchangeable. A resilience assessment must retain the distinction between what the system predicted, what the organization could do, what it actually did, and what happened to system performance when disruption occurred.

The framework is therefore conceptual and evidence-grounded rather than empirically validated. Its contribution lies in specifying the intervening conditions that must be considered before predictive capability can be interpreted as contributing to resilience. It also provides a basis for evaluating the strength of future evidence: studies that measure prediction alone establish predictive capability; studies that connect prediction with operational decisions establish an information-to-action relationship; and studies that observe those interventions during disruption and measure the resulting system trajectory provide the strongest basis for assessing a prediction-to-resilience relationship.

The framework can also be used as a diagnostic structure for evaluating predictive applications in practice. An organization considering an AI-enabled forecasting application can ask, first, whether the prediction concerns a condition that matters to a defined operational decision; second, whether the information arrives with sufficient lead time and reliability to support action; third, whether feasible response capacity exists; fourth, whether a prediction-informed intervention can be identified and observed; and finally, whether the effect of that intervention can be evaluated against a defined disruption, baseline, or reference condition. Failure at any of these points does not mean that the predictive model lacks technical value, but it limits the basis for interpreting the application as a resilience capability. This diagnostic use preserves the distinction between evaluating a forecasting system and evaluating its contribution to supply-chain resilience.

VIII. LIMITATIONS OF THE EVIDENCE AND REVIEW

Several limitations constrain interpretation of the synthesis. First, the evidence base combines empirical forecasting studies, optimization and simulation models, digital-twin applications, network analyses, and resilience measurement studies. These designs answer different questions and do not provide equivalent evidence for a

prediction-to-resilience relationship. Second, the corpus includes studies from broader agricultural and food-supply contexts when their findings were considered transferable to perishable-goods logistics. Such transferability is analytical rather than empirical and may be limited by differences in products, network structures, operating environments, and disruption characteristics. Third, many studies evaluate predictive or decision-system performance without observing an implemented intervention during a defined disruption. The proposed prediction-to-resilience pathway should therefore be interpreted as an evidence-grounded conceptual synthesis rather than a validated causal model. Finally, resilience measures vary in construct definition, system boundary, temporal window, and outcome specification. These differences limit direct comparison across studies and constrain the extent to which predictive performance can be related to a common resilience metric.

IX. CONCLUSION

The evidence indicates that AI-enabled forecasting has operational relevance in perishable-goods logistics, but its relationship with supply-chain resilience is more conditional than the literature sometimes implies. Predictive models can estimate demand, product condition, temperature, supply conditions, and disruption risk, providing information that may create time for inventory, sourcing, routing, allocation, or handling decisions. The practical contribution of that information depends on whether it is available within the decision window and whether the supply system possesses feasible options for responding to it. Predictive capability and resilience are distinct constructs. Forecast accuracy, warning lead time, and disruption-prediction performance describe the predictive system, whereas continuity, performance decline, product loss, recovery, and network functionality describe system behavior under disturbance. Treating these measures as interchangeable would obscure the difference between an anticipated condition, an available response, an implemented intervention, and an observed resilience outcome.

The principal integrative contribution is an evidence-grounded prediction-to-resilience pathway that places actionable information, response capacity, and operational intervention between predictive capability and realized resilience. The framework also establishes an evidentiary gradient: evidence of predictive performance establishes predictive capability, evidence that prediction informs an operational decision provides an information-to-action relationship, and observed intervention during disruption accompanied by measured system outcomes provides stronger evidence for a prediction-to-resilience relationship.

For research and practice, the implication is not that resilience should be reduced to predictive performance. Future studies should examine when predictive information is converted into operational action and whether that action changes system behavior under defined disturbances. For current practice, the framework can be used to assess whether a predictive application has progressed beyond technical forecasting toward operational resilience: the relevant questions concern the decision supported, the lead time

available, the response capacity that can be activated, the intervention actually implemented, and the system outcome observed during disruption. Such assessment requires explicit resilience constructs, appropriate reference conditions, temporal alignment, and outcome measures suited to the perishability and disruption characteristics of the system. Until stronger evidence is available, AI-enabled forecasting is best understood as an enabling capability within a broader resilience system, not as resilience itself.

REFERENCES

- [1]. Adewumi, G., Dada, S. A., Azai, J. S., & Oware, E. (2024). A systematic review of strategies for enhancing pharmaceutical supply chain resilience in the U.S. *International Medical Science Research Journal*, 4(11), 961–972. <https://doi.org/10.51594/imsrj.v4i11.1711>
- [2]. Aljuneidi, T., Punia, S., Jebali, A., & Nikolopoulos, K. (2024). Forecasting and planning for a critical infrastructure sector during a pandemic: Empirical evidence from a food supply chain. *European Journal of Operational Research*, 317(3), 936–952. <https://doi.org/10.1016/j.ejor.2024.04.009>
- [3]. Azzam, A., Gren, I.-M., & Andersson, H. (2023). Comparative resilience of US and EU meat processing to the COVID-19 pandemic. *Food Policy*, 119, 102517. <https://doi.org/10.1016/j.foodpol.2023.102517>
- [4]. Birkmaier, A., Imeri, A., & Reiner, G. (2024). Improving supply chain planning for perishable food: Data-driven implications for waste prevention. *Journal of Business Economics*, 94, 891–926. <https://doi.org/10.1007/s11573-024-01191-x>
- [5]. Burgos, D., & Ivanov, D. (2021). Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. *Transportation Research Part E: Logistics and Transportation Review*, 152, 102412. <https://doi.org/10.1016/j.tre.2021.102412>
- [6]. Dong, W., Armstrong, K., Jin, M., Nimbalkar, S., Guo, W., Zhuang, J., & Cresko, J. (2022). A framework to quantify mass flow and assess food loss and waste in the US food supply chain. *Communications Earth & Environment*, 3(1), 83. <https://doi.org/10.1038/s43247-022-00414-9>
- [7]. Eiglsperger, J., Haselbeck, F., Stiele, V., Serrano, C. G., Lim-Trinh, K., Menrad, K., Hannus, T., & Grimm, D. G. (2024). Forecasting seasonally fluctuating sales of perishable products in the horticultural industry. *Expert Systems with Applications*, 249, 123438. <https://doi.org/10.1016/j.eswa.2024.123438>
- [8]. Elashmawy, R., Doron, M., Kanjilal, R., Brecht, J. K., & Uysal, I. (2025). The digital cold chain: Sensor-driven product quality with AI. *Postharvest Biology and Technology*, 230, 113714. <https://doi.org/10.1016/j.postharvbio.2025.113714>
- [9]. Gaye, A., Paflo, B. N., & Oware, D. A. (2025). Assessing the reliability of AI-driven predictive models in food safety risk management. *Computer Science & IT Research Journal*, 6(2), 49–58. <https://doi.org/10.51594/csitrj.v6i2.1832>
- [10]. Hosseini Shekarabi, S. A., Mavi, R. K., & Macau, F. R. (2025). An extended robust optimisation approach for sustainable and resilient supply chain network design: A case of perishable products. *Engineering Applications of Artificial Intelligence*, 152, 110846. <https://doi.org/10.1016/j.engappai.2025.110846>
- [11]. Jackson, I., Namdar, J., Sáenz, M. J., Elmquist, R. A., III, & Dávila Novoa, L. R. (2025). Revolutionize cold chain: An AI/ML driven approach to overcome capacity shortages. *International Journal of Production Research*, 63(6), 2190–2212. <https://doi.org/10.1080/00207543.2024.2398583>
- [12]. Jauhar, S. K., Harinath, S., Krishnaswamy, V., & Paul, S. K. (2025). Explainable artificial intelligence to improve the resilience of perishable product supply chains by leveraging customer characteristics. *Annals of Operations Research*, 354, 103–142. <https://doi.org/10.1007/s10479-024-06348-z>
- [13]. Karan, E. P., Asgari, S., & Asadi, S. (2023). Resilience assessment of centralized and distributed food systems. *Food Security*, 15(1), 59–75. <https://doi.org/10.1007/s12571-022-01321-9>
- [14]. Karakoc, D. B., Konar, M., Puma, M. J., & Varshney, L. R. (2023). Structural chokepoints determine the resilience of agri-food supply chains in the United States. *Nature Food*, 4(7), 607–615. <https://doi.org/10.1038/s43016-023-00793-y>
- [15]. Lejarza, F., Pistikopoulos, I., & Baldea, M. (2021). A scalable real-time solution strategy for supply chain management of fresh produce: A Mexico-to-United States cross border study. *International Journal of Production Economics*, 240, 108212. <https://doi.org/10.1016/j.ijpe.2021.108212>
- [16]. Loisel, J., Cornuéjols, A., Laguerre, O., Tardet, M., Cagnon, D., Duchesne de Lamotte, O., & Duret, S. (2022). Machine learning for temperature prediction in food pallet along a cold chain: Comparison between synthetic and experimental training dataset. *Journal of Food Engineering*, 335, 111156. <https://doi.org/10.1016/j.jfoodeng.2022.111156>
- [17]. Lopes Gerum, P. C., Herrero, J. R., Chung, M., & Giaretti, M. (2026). Improving high-frequency demand forecasts for omnichannel grocery retail. *International Journal of Forecasting*. Advance online publication. <https://doi.org/10.1016/j.ijforecast.2025.10.003>
- [18]. Miller, M. (2021). Identifying critical thresholds for resilient regional food flows: A case study from the U.S. Upper Midwest. *Frontiers in Sustainable Food Systems*, 5, 684159. <https://doi.org/10.3389/fsufs.2021.684159>
- [19]. Moynihan, E., Avraam, C., Siddiqui, S., & Neff, R. (2022). Optimization based modeling for the food supply chain's resilience to outbreaks. *Frontiers in Sustainable Food Systems*, 6, 887819. <https://doi.org/10.3389/fsufs.2022.887819>
- [20]. Okonkwo, F. C., Akonor, B. G., & Adukpo, T. K. (2025). Artificial intelligence in healthcare supply chain management: Enhancing resilience and

- efficiency in U.S. medical supply distribution. *EPRA International Journal of Economics, Business and Management Studies*, 12(1), 285–291. <https://doi.org/10.36713/epra19901>
- [21]. Rao, J., Gao, S., Miller, M., & Morales, A. (2022). Measuring network resilience via geospatial knowledge graph: A case study of the US multi-commodity flow network. In *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Geospatial Knowledge Graphs (GeoKG '22)* (pp. 1–9). Association for Computing Machinery. <https://doi.org/10.1145/3557990.3567569>
- [22]. Shrivastava, C., Berry, T., Cronje, P., Schudel, S., & Defraeye, T. (2022). Digital twins enable the quantification of the trade-offs in maintaining citrus quality and marketability in the refrigerated supply chain. *Nature Food*, 3(6), 413–427. <https://doi.org/10.1038/s43016-022-00497-9>
- [23]. Stevens, A. W., & Teal, J. (2024). Diversification and resilience of firms in the agrifood supply chain. *American Journal of Agricultural Economics*, 106(2), 739–778. <https://doi.org/10.1111/ajae.12398>
- [24]. Tack, J. B., Ala-Kokko, K., Gardner, G. E., Breneman, V., Arita, S., & Cooper, J. (2026). Climate-based measures of supply chain resilience. *Agricultural Finance Review*, 86(1), 3–24. <https://doi.org/10.1108/AFR-03-2024-0054>
- [25]. Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. *Human Resource Development Review*, 4(3), 356–367. <https://doi.org/10.1177/1534484305278283>
- [26]. Umoren, J., Agbadamasi, T. O., Adukpo, T. K., & Mensah, N. (2025). Leveraging artificial intelligence in healthcare supply chains: Strengthening resilience and minimizing waste. *EPRA International Journal of Economics, Business and Management Studies*, 12(2), 190–196. <https://doi.org/10.36713/epra20385>
- [27]. Umoren, J., Utomi, E., & Adukpo, T. K. (2025). AI-powered predictive models for U.S. healthcare supply chains: Creating AI models to forecast and optimize supply chain. *EPRA International Journal of Multidisciplinary Research*, 11(6), 784–795. <https://doi.org/10.36713/epra22481>
- [28]. Wang, R., Gan, X., Li, Q., & Yan, X. (2021). Solving a joint pricing and inventory control problem for perishables via deep reinforcement learning. *Complexity*, 2021, Article 6643131. <https://doi.org/10.1155/2021/6643131>
- [29]. Whitemore, R., & Knafl, K. (2005). The integrative review: Updated methodology. *Journal of Advanced Nursing*, 52(5), 546–553. <https://doi.org/10.1111/j.1365-2648.2005.03621.x>
- [30]. Yang, C., Feng, Y., & Whinston, A. (2022). Dynamic pricing and information disclosure for fresh produce: An artificial intelligence approach. *Production and Operations Management*, 31(1), 155–171. <https://doi.org/10.1111/poms.13525>
- [31]. Yim, H., & Dall'Erba, S. (2025). Impact of extreme weather events on the US domestic supply chain of food manufacturing. *Proceedings of the National Academy of Sciences of the United States of America*, 122(41), e2424715122. <https://doi.org/10.1073/pnas.2424715122>
- [32]. Yin, F., Lo, M. C., Mohamad, A. A., & Sin, K. Y. (2025). The impact of AI applications, information sharing, and supply chain resilience on agricultural supply chain performance. *Journal of Data, Information and Management*, 7, 287–300. <https://doi.org/10.1007/s42488-025-00155-2>