

Unlocking Supply Chain Resilience: The Impact of Artificial Intelligence and IoT Integration in Agribusiness Operations

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ABSTRACT

Agribusiness supply chains are exposed to climate variability, biological uncertainty, perishability, demand volatility, infrastructure constraints, and fragmented coordination among farmers, processors, traders, logistics providers, retailers, and regulators. These vulnerabilities increasingly intersect with the transition toward lower-carbon production and distribution. Artificial intelligence (AI) and the Internet of Things (IoT) offer complementary capabilities: connected sensors and devices can capture field, storage, processing, and transport conditions, while AI can convert heterogeneous data into forecasts, anomaly alerts, and operational recommendations. This article examines how AI-IoT integration can improve supply chain resilience and operational efficiency while supporting carbon-neutrality transitions in agribusiness. An integrative review of recent academic research and authoritative reports is used to develop a theory-informed framework. The synthesis identifies six pathways: end-to-end visibility, predictive risk sensing, adaptive planning, quality and loss control, low-carbon operational optimization, and collaborative learning. It also identifies important boundary conditions, including data quality, connectivity, interoperability, managerial capabilities, farmer participation, cybersecurity, financing, and governance. The analysis cautions that digital adoption does not automatically create resilience or sustainability: poorly designed systems can intensify dependence on vendors, exclude smallholders, optimize local efficiency at the expense of system-wide performance, or increase energy use without reducing absolute emissions. The article proposes a phased implementation model and research propositions linking AI IoT capability to resilience, efficiency, and environmental outcomes. It argues that the strategic value of smart agribusiness should be assessed through verified reductions in disruption exposure, avoidable losses, resource intensity, and emissions—not through technology deployment alone.

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1. INTRODUCTION

Agribusiness operations sit at the intersection of biological production, industrial processing, logistics, market coordination, and environmental management. Unlike many manufactured products, agricultural commodities are often seasonal, geographically dispersed, perishable, and sensitive to weather, disease, soil conditions, and handling practices. Their supply chains connect heterogeneous actors whose resources and bargaining power vary widely, from smallholders and cooperatives to multinational processors and retailers. A disruption at one stage can rapidly affect quality, availability, prices, and the income of participants elsewhere in the chain. Climate change, geopolitical instability, public-health emergencies, transport bottlenecks, input-price shocks, and changing consumer expectations have made resilience a strategic concern rather than a narrow contingency-planning exercise (Fang, 2026; FAO, 2022; IPCC, 2022).

At the same time, agribusiness faces pressure to improve productivity while reducing environmental burdens. Food systems contribute to greenhouse-gas emissions through land-use change, fertilizer production and use, livestock, energy, processing, refrigeration, packaging, and transport. Emissions are not distributed evenly across products or supply-chain stages, and the most material sources differ by commodity and region. The IPCC (2022) emphasizes that mitigation opportunities extend across agriculture, land use, energy, transport, and demand-side measures. The FAO (2022) notes that digital automation can improve productivity and resilience but that adoption remains uneven because of infrastructure, skills, and financing constraints. For agribusiness managers, resilience and decarbonization therefore need to be

considered together: a supply chain that can recover quickly but relies on wasteful logistics or carbon-intensive energy may remain economically and environmentally fragile.

Artificial intelligence (AI) and the Internet of Things (IoT) are increasingly presented as key components of this transition. IoT devices—including soil-moisture sensors, weather stations, RFID tags, GPS trackers, temperature loggers, smart meters, and equipment monitors—can generate data from farms, storage facilities, processing lines, and transport networks. AI techniques can use those data to forecast yields and demand, detect crop disease, predict equipment failure, estimate spoilage risk, optimize inventory, plan routes, and support dynamic sourcing. Integrated AI-IoT systems, sometimes described as the Artificial Intelligence of Things (AIoT), connect sensing with analytical interpretation and, in some cases, automated action (Mehannaoui et al., 2023; AIoT review, 2024). Their promise is not simply to automate existing tasks but to improve the timing, accuracy, and coordination of decisions across the chain.

The potential is substantial, but technology narratives can obscure the conditions required for success. A sensor only creates operational value when it measures a relevant variable reliably, transmits data at a useful frequency, and informs a decision that someone has authority to make. An AI forecast can be statistically accurate yet commercially unhelpful if the organization cannot change procurement, production, or transport plans in response. A blockchain-based traceability record can preserve submitted information without proving that the original information was true. A farm-level yield model may improve prediction while doing little to address transport congestion, cold-storage shortages, or unequal access to market information. Technology therefore needs to be evaluated as part of an operating model, not as an isolated device or software purchase.

The literature has developed rapidly across smart agriculture, food traceability, digital supply chain management, AI-enabled resilience, and Industry 4.0. Reviews have mapped the applications of emerging technologies in agricultural food supply chains and identified traceability, food waste, food safety, and food security as important research areas (Industry 4.0 AFSC review, 2022; IoT-based SCM review, 2023). Other studies examine AI as an enabler of supply chain resilience, particularly under the disruption conditions exposed by COVID-19 (Naz et al., 2022; Zamani et al., 2022). Research on AI in the agri-food sector also identifies applications in productivity, logistics, decision support, risk mitigation, and marketing, while emphasizing the social and organizational dimensions of adoption (Unleashing AI in agri-food, 2023). Yet these research streams are not always integrated. Studies of smart farming may focus on yield or input efficiency; supply-chain studies may focus on forecasting or traceability; resilience studies may focus on disruption recovery; and sustainability studies may emphasize emissions or resource use. A managerial framework needs to connect these outcomes.

The first gap is the limited integration of resilience and carbon-transition objectives. Resilience is commonly discussed as the ability to anticipate, absorb, adapt to, and recover from disruption, whereas decarbonization focuses on reducing greenhouse-gas emissions and transition risks. These goals can reinforce one another: predictive maintenance may prevent production losses and reduce wasted energy; improved cold-chain control can prevent spoilage and avoid emissions embodied in discarded food; and better demand forecasting can reduce emergency shipments. However, the objectives may also conflict. Holding additional inventory can protect service levels but increase refrigeration and storage energy; redundant transport capacity may improve recovery but raise fuel use; and local sourcing may reduce some transport emissions while increasing production emissions or exposure to local climate risks. The relationship should therefore be analyzed rather than assumed.

The second gap concerns the mechanisms that connect AI-IoT adoption to supply-chain outcomes. Technology presence is an input, not a performance result. Between adoption and outcomes lie data quality, analytical capability, managerial interpretation, interorganizational coordination, decision authority, and implementation discipline. These mechanisms matter particularly in agribusiness, where the smallest suppliers may lack reliable connectivity, digital skills, capital, or bargaining power. The FAO (2022) identifies these barriers as important constraints on inclusive agricultural automation. A system that works well for a large processor may impose high costs on farmers unless it offers shared benefits, accessible interfaces, and credible data-governance arrangements.

The third gap concerns measurement. Operational efficiency, resilience, sustainability, and carbon performance are related but distinct constructs. Reduced cost per unit does not necessarily imply lower absolute emissions; improved forecast accuracy does not necessarily reduce disruption losses; and improved traceability does not necessarily improve food safety unless information triggers corrective action. Many technology studies measure adoption, perceived benefits, or technical accuracy, while managers need evidence about realized outcomes. The distinction is especially important when companies make claims about climate-smart or resilient operations. Evaluation should include baseline comparisons, relevant counterfactuals, and indicators that capture both direct and indirect effects.

Against this background, this article asks three questions.

- 1) Through what operational mechanisms can AI-IoT integration improve resilience in agribusiness supply chains?
- 2) Under what conditions can these technologies improve efficiency and support lower-carbon operations simultaneously?
- 3) What managerial and governance arrangements are required to make AI-IoT adoption inclusive, reliable, and commercially viable?

The objective is to synthesize recent evidence and develop a conceptual framework for agribusiness managers, technology providers, policymakers, and researchers. The article makes four contributions. It connects resilience, operational efficiency, and decarbonization in a single decision-oriented framework; specifies six pathways through which AI-IoT integration may affect agribusiness performance; identifies organizational and institutional conditions that moderate these effects; and proposes an implementation roadmap that starts with high-value decisions rather than technology procurement. The framework is relevant to diverse commodities, including grains, horticultural products, dairy, livestock, fisheries, and processed foods, although the relative importance of each mechanism varies by perishability, production cycle, market structure, and infrastructure. Section 2 reviews the theoretical and empirical foundations, Section 3 explains the review method, Section 4 presents the synthesized framework, Section 5 discusses implications, Section 6 develops propositions and a research agenda, and Section 7 concludes.

2. LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

2.1 Agribusiness supply chains as complex operating systems

Agribusiness supply chains are complex because biological production, processing capacity, logistics, market demand, and environmental conditions interact. Crop yields depend on weather, soil, pests, input availability, and farm management; quality can deteriorate during storage and transport; and processing facilities often face seasonal peaks and variable raw-material characteristics. Unlike stable manufacturing systems, supply availability may shift sharply with harvest timing and weather events. These characteristics create a need for coordination across time and geography. The FAO (2022) argues that automation and digital technologies can contribute to productivity and resilience, but the gains depend on the fit between the technology and the production system.

Supply chains also vary in governance. Some operate through vertically integrated firms with centralized planning and strong control over suppliers. Others consist of spot-market transactions, informal intermediaries, cooperatives, and small producers with limited contractual protection. The same digital intervention may therefore produce different outcomes. A processor with long-term supplier relationships may share forecasts and agronomic advice; a buyer using short-term contracts may capture information advantages without enabling suppliers to adapt. Supply-chain resilience is not solely a property of the focal firm: it emerges from the interdependence of actors, resources, infrastructure, and decision rights.

2.2 Defining resilience, robustness, and agility

Supply-chain resilience refers to the capacity to prepare for disruption, absorb its immediate effects, adapt operations, and recover while preserving critical functions. Robustness concerns the ability to continue operating under disturbance, while agility concerns the speed and flexibility with which resources and plans can be adjusted. These concepts overlap but should not be treated as identical. A robust chain may rely on

buffers and redundancy; an agile chain may rapidly change suppliers or routes; a resilient chain combines appropriate preparation, response, adaptation, and learning. Reviews of AI and supply-chain resilience suggest that AI can contribute to sensing, prediction, and response, but that its effect depends on the organization's ability to turn analytical outputs into action (Naz et al., 2022; Pontjoharyo, 2026; Zamani et al., 2022).

In agribusiness, resilience includes both short-term continuity and longer-term adaptation. A temperature alert may allow a logistics manager to divert a shipment before spoilage occurs. A seasonal yield forecast may support alternative sourcing before a shortage materializes. Repeated climate-related losses may require a more fundamental redesign of sourcing regions, crop portfolios, storage capacity, or contracts. These are different decision horizons and require different analytical capabilities. A useful framework should distinguish operational recovery from strategic adaptation and should avoid measuring resilience solely through the speed of return to a pre-disruption state, particularly when that state is itself unsustainable.

2.3 Resource-based view and dynamic capabilities

The resource-based view (RBV) suggests that performance differences reflect resources and capabilities that are valuable, difficult to imitate, and effectively organized. In agribusiness, relevant resources include high-quality operational data, domain knowledge, supplier relationships, cold-chain infrastructure, analytical talent, and trusted market access. Sensors and software are increasingly purchasable, so their possession alone is unlikely to create durable advantage. Advantage is more likely when firms combine digital resources with agronomic knowledge, operating routines, and collaborative relationships that competitors cannot easily replicate. A predictive model, for example, has limited value without accurate historical data, experienced staff who can interpret anomalies, and authority to alter sourcing or logistics.

Dynamic capabilities focus on the ability to sense changes, seize opportunities, and reconfigure resources. AI-IoT systems can strengthen sensing by identifying weather risks, equipment anomalies, demand shifts, and quality deterioration. They can support seizing through scenario comparison, inventory decisions, and targeted investment. They can support reconfiguration when managers use accumulated evidence to redesign sourcing networks, processing schedules, routes, and supplier development. Yet these capabilities do not guarantee resilience or sustainability. An organization may use accurate demand predictions to increase throughput without improving waste or emissions. The strategic orientation and governance of the capability determine which outcomes are prioritized.

2.4 Information-processing theory

Information-processing theory is useful because agribusiness decisions involve high uncertainty, interdependence, and time sensitivity. Managers must reconcile weather forecasts, farm-level observations, inventory records, quality measurements, transport conditions, commodity prices, customer orders, and regulatory requirements. When uncertainty rises, the need for information processing increases. IoT can expand the availability and timeliness of operational information, while AI can identify patterns and estimate likely future states. However, more information is not automatically better. If data are duplicated, unreliable, delayed, or presented without context, they can increase cognitive burden and slow decisions. Information architecture must fit the decisions being made and the authority of the people receiving the output.

This theory also highlights the importance of information sharing across firm boundaries. A processor may possess accurate demand data while a farmer lacks access to it; a logistics provider may know that a shipment is delayed while the warehouse continues to schedule labor based on the original arrival time. Shared visibility can reduce these coordination failures, but only if partners agree on definitions, access rights, and how information will be used. Information-sharing arrangements are therefore both technical and relational. Trust, incentives, and data ownership affect whether the system produces collective value.

2.5 Socio-technical systems and technology adoption

A socio-technical perspective treats technology and organizational arrangements as interdependent. Sensors, networks, analytics, workers, managers, suppliers, contracts, and routines form one operating system. A technically accurate application can fail if employees do not trust its alerts, if managers ignore its recommendations, or if suppliers cannot afford the required equipment. Adoption frameworks such as the

technology–organization–environment perspective can help explain differences in readiness. Technological conditions include compatibility and reliability; organizational conditions include resources, skills, leadership, and process maturity; environmental conditions include infrastructure, regulation, competition, and customer requirements.

Adoption is also shaped by perceived usefulness, usability, risk, and trust. Smallholders may reject an application not because they oppose digital tools but because the interface is difficult, connectivity is unreliable, benefits are uncertain, or data could be used against them in price negotiations. The FAO's evidence on agricultural automation emphasizes the importance of skills, infrastructure, financing, and inclusive implementation (FAO, 2022; Ceccarelli et al., 2023). Technology design should therefore be assessed against the circumstances of the intended users rather than assuming that the same platform suits every farm and supply-chain actor.

2.6 IoT as an operational visibility layer

IoT refers to connected devices that capture and transmit information about physical conditions or activities. In agribusiness, applications include soil-moisture and nutrient sensors, weather stations, livestock wearables, irrigation controllers, machine telemetry, RFID tags, GPS trackers, temperature and humidity loggers, smart scales, and energy meters. In logistics and storage, sensors can monitor location, temperature, humidity, vibration, door openings, and equipment status. IoT can thus make previously invisible conditions observable at higher frequency and granularity. The IoT-based supply-chain management review identifies tracking, asset management, inventory monitoring, and traceability as important application areas, including in agriculture and food supply chains (IoT-based SCM review, 2023).

The value of IoT depends on measurement validity and data continuity. A poorly calibrated temperature sensor can generate false alarms; a device with intermittent connectivity can miss a critical excursion; and inconsistent timestamps can make it difficult to reconstruct events. Devices also require maintenance, power, calibration, secure configuration, and replacement. Managers should distinguish sensor availability from data availability and data availability from actionable visibility. A dashboard populated with stale readings is not real-time visibility. Operational standards should specify calibration, sampling frequency, alert thresholds, exception handling, and responsibility for response.

2.7 AI as a prediction and decision-support layer

AI encompasses techniques such as machine learning, computer vision, natural-language processing, optimization, and decision-support systems. In agribusiness, AI can estimate crop yields, identify plant disease, forecast demand, classify product quality, predict equipment failure, estimate shelf life, and optimize inventory or transport. The review of AI in the agri-food sector identifies efficiency, logistics and supply-chain management, decision support, risk mitigation, and marketing among the major application clusters (Unleashing AI in agri-food, 2023). Distributed AI and multi-agent approaches may support coordination across supply-chain nodes by allowing different agents to respond to local conditions while exchanging relevant information (Distributed AI in agri-food supply chains, 2024).

AI outputs should be treated as estimates rather than facts. Models may be trained on data from particular regions, seasons, crop varieties, or equipment configurations and perform poorly when conditions change. Weather extremes, new pests, shifts in consumer behavior, or changes in farm practices can create distribution shifts. Managers need monitoring, retraining, human review, and fallback procedures. The system should also communicate uncertainty and explain the variables that materially affect recommendations. An opaque recommendation that cannot be challenged may be particularly risky when it affects farmers' incomes, food safety, or access to markets.

2.8 Complementarity of AI and IoT

IoT and AI are complementary because sensing without analysis can generate data overload, while AI without reliable observations may produce fragile predictions. IoT captures the state of the physical system; AI interprets patterns, estimates future conditions, and ranks possible responses. Together they can create closed-loop operations in which data collection, prediction, decision, action, and feedback are connected. For example, temperature sensors in refrigerated transport can feed a spoilage-risk model, which can trigger a

route change or prioritize unloading. Soil and weather sensors can support irrigation forecasts, while crop-yield models inform procurement and processing schedules.

Integration introduces additional dependencies. Devices may use incompatible protocols, platforms may store data in proprietary formats, and AI models may require data that smaller partners cannot provide. Connectivity failure can interrupt the pipeline; cybersecurity incidents can compromise operational control; and model drift can create silent deterioration. AIoT architectures should therefore include interoperability, edge processing where connectivity is weak, secure identity and access controls, model monitoring, and human escalation. The 2024 AIoT review highlights the breadth of smart-agriculture applications and continuing architectural and implementation challenges (AIoT review, 2024).

2.9 Traceability, food safety, and quality management

Traceability connects information about a product's origin, processing, storage, and movement. IoT devices can record temperature, location, and handling conditions; identifiers can connect batches to suppliers and processing events; and digital records can support targeted recalls. Mehannaoui et al. (2023) review IoT-based food traceability architectures and emphasize the role of connected technologies in food safety and information availability. Studies of agricultural traceability also explore combinations of IoT and blockchain to preserve records across multiple participants (Zhang, 2022; Ye et al., 2022). These systems can reduce the time needed to identify affected batches and improve accountability when food-safety incidents occur.

Traceability is not the same as truth. A digital ledger can make a submitted record difficult to alter, but it cannot guarantee that the original record was accurate. Data quality depends on the point of capture, the identity of the person or device entering the information, verification rules, and incentives to report accurately. A traceability system should therefore combine digital records with appropriate audits, sampling, certification, and clear procedures for correcting errors. It should also be designed around operational needs: rapid recall, supplier improvement, consumer information, and regulatory compliance are different uses and may require different levels of detail.

2.10 Sustainability and carbon-neutrality transitions

Sustainability in agribusiness includes emissions, water use, soil health, biodiversity, chemical inputs, waste, worker conditions, and economic viability. Carbon neutrality is a narrower claim concerning the balance of greenhouse-gas emissions and removals within a defined boundary and period. A firm should not assume that a carbon-related improvement automatically improves all sustainability outcomes. Precision irrigation may reduce water and energy use, but its effect depends on crop, soil, pumping energy, and rebound in cultivated area. Cold-chain expansion can reduce food loss but increase electricity demand. The net effect depends on the energy mix, equipment efficiency, product characteristics, and baseline loss rates.

The IPCC (2022) identifies mitigation opportunities across agricultural production, land use, energy, transport, and demand. Digital systems can support these opportunities by improving input application, reducing avoidable loss, optimizing routes, measuring energy, and providing more reliable evidence about suppliers. They can also help managers quantify trade-offs between resilience buffers and emissions. For example, strategically located storage may reduce emergency transport and spoilage, whereas indiscriminate inventory accumulation can increase energy use and waste. A sustainability-oriented system should compare alternatives using lifecycle thinking and absolute as well as intensity-based indicators.

2.11 Research gap and conceptual positioning

The literature supports the potential of AI and IoT but does not justify a universal claim that integration automatically improves resilience, efficiency, and sustainability. Existing reviews often concentrate on one technology, one supply-chain function, or one outcome. This article positions AI-IoT integration as a capability whose effects operate through six mechanisms: visibility, predictive risk sensing, adaptive planning, quality and loss control, low-carbon optimization, and collaborative learning. The framework treats resilience, efficiency, and environmental performance as related but separate outcomes and specifies conditions under which each mechanism is likely to work.

The framework also places inclusion and governance within the causal explanation. Digital value depends on whether the people who generate data can access benefits, whether partners trust the rules

governing data, and whether firms can act on analytical outputs. This emphasis is particularly important in agribusiness because many supply chains depend on smallholders and rural infrastructure. The article's central argument is that AI–IoT integration creates durable value when it is embedded in a commercially credible, operationally actionable, and inclusive governance model.

3. METHOD

3.1 Research design

This article adopts an integrative literature review and theory-building design. The subject spans operations management, information systems, agribusiness, food safety, sustainability, and supply-chain resilience. An integrative review is suitable for synthesizing evidence across these domains and developing a framework that can be tested later. The purpose is not to calculate a pooled effect size because the reviewed studies use different outcomes, units of analysis, methods, and technology definitions. The article is not a preregistered systematic review or a meta-analysis, and it does not report original farm-level or firm-level observations.

The evidence base prioritizes peer-reviewed studies published from 2021 onward and authoritative reports from organizations such as FAO, IPCC, OECD, and the World Bank. Search concepts include AI in agrifood, IoT-based supply-chain management, agricultural food supply chains, smart agriculture, supply-chain resilience, food traceability, cold-chain monitoring, predictive analytics, digital agriculture, carbon-neutrality transitions, and sustainable operations. Source selection favored works that directly informed one or more research questions and had traceable publication details. Recent reviews were used to map research streams, while specific empirical or technical studies informed application examples and implementation risks.

3.2 Inclusion and exclusion logic

Included studies addressed at least one of the following: AI-enabled supply-chain resilience; IoT-based tracking and monitoring; smart agriculture and precision farming; food traceability and quality management; digital technologies in agrifood operations; or sustainability and emissions in food systems. Official reports were included when they established adoption barriers, agricultural automation trends, climate-mitigation pathways, or relevant governance principles. Studies focused solely on unrelated industrial applications were not used as primary evidence, although general resilience research was retained where the mechanism plausibly applied to agribusiness.

The review distinguishes evidence of technical feasibility from evidence of realized business outcomes. A model's predictive accuracy is not equivalent to reduced waste; a pilot installation is not equivalent to scaled adoption; and a stated intention to adopt technology is not equivalent to operational capability. Similarly, an official report describing a technology's potential is not a causal evaluation. These distinctions guide the interpretation of findings and the strength of claims. The review also recognizes that much published work concerns prototypes, case studies, or specific regions, limiting generalization across commodities and institutions.

3.3 Analytical procedure

The synthesis proceeded in four stages. First, sources were grouped by domain: sensing and connectivity, AI and prediction, resilience, operational efficiency, traceability and food safety, sustainability, and adoption governance. Second, recurring mechanisms were mapped to the supply-chain cycle: observe, predict, decide, execute, verify, and learn. Third, the analysis compared potential benefits with failure conditions, including weak data, poor connectivity, model drift, cybersecurity exposure, fragmented incentives, and unequal access. Fourth, the framework was refined to connect the six identified pathways with resilience, efficiency, and environmental outcomes and to specify relevant moderators.

The framework was evaluated for explanatory coherence, testability, managerial relevance, and inclusion. Explanatory coherence asks whether the framework specifies a plausible route from data to action. Testability asks whether constructs can be measured in empirical work. Managerial relevance asks whether the mechanisms point to decisions that organizations can change. Inclusion asks whether the framework

accounts for differences in resources and bargaining power across supply-chain participants. The resulting propositions are intended to guide future research rather than assert universal causal laws.

3.4 Limitations

The review is integrative rather than exhaustive and does not claim to capture every publication on AI, IoT, and agribusiness. The evidence is heterogeneous and often concentrates on specific commodities, countries, or technical applications. Some studies evaluate prototype systems rather than long-term operational outcomes. In addition, the article synthesizes published evidence without original field validation. Its contribution is therefore conceptual: it identifies mechanisms, boundary conditions, and testable propositions. Future studies should use transparent systematic search protocols, longitudinal data, and designs capable of separating technology effects from concurrent changes in management, infrastructure, and market conditions.

4. RESULTS

The synthesis identifies six pathways through which AI-IoT integration may improve agribusiness performance: end-to-end visibility, predictive risk sensing, adaptive planning, quality and loss control, low-carbon operational optimization, and collaborative learning. These pathways are connected rather than independent. Visibility creates reliable observations; predictive models interpret the observations; adaptive planning translates forecasts into revised schedules and resource allocations; quality control reduces deterioration and safety risks; low-carbon optimization evaluates resource and emissions consequences; and collaborative learning improves decisions over time. The framework builds on evidence that AI and IoT can support supply-chain tracking, forecasting, traceability, and resilience, while recognizing that operational outcomes depend on implementation and governance (Naz et al., 2022; Zamani et al., 2022; Mehannaoui et al., 2023; IoT-based SCM review, 2023).

The framework begins with enabling conditions: data infrastructure, connectivity, interoperability, analytical skills, domain knowledge, leadership, and partner participation. These inputs support operating routines such as exception management, forecast review, inventory allocation, supplier coordination, and performance evaluation. Routines shape actions at farm, warehouse, processing, and transport levels. The system then measures outcomes and updates its models and operating rules. A failure at any stage weakens the final effect. For example, an accurate forecast will not reduce shortage risk if procurement contracts cannot be changed; a sensor alert will not prevent spoilage if no one is responsible for responding; and an efficient route may not reduce emissions if it creates additional empty mileage elsewhere.

Three outcomes should be assessed separately. Resilience concerns the ability to prepare for, absorb, adapt to, and recover from disruption. Operational efficiency concerns the use of labor, inventory, energy, water, capacity, time, and materials to deliver a specified service level. Environmental performance concerns emissions, waste, water, soil, and other material impacts. AI-IoT may improve one outcome without improving the others. A resilient operation may maintain larger safety stocks, increasing energy use; an efficiency project may reduce unit cost but increase vulnerability to a single supplier; and a traceability project may improve information without reducing emissions. A multidimensional scorecard is therefore preferable to a single “smartness” metric.

4.1 Pathway one: end-to-end visibility

End-to-end visibility is the ability to observe material flows, product conditions, inventory status, and operational constraints across relevant supply-chain nodes. IoT devices can provide location and condition data for shipments, temperature readings in cold storage, machine status in processing plants, and soil or weather observations on farms. When these data are linked to order, batch, and inventory records, managers can identify where a product is, what condition it is in, and which commitments may be at risk. Reviews of IoT-based supply-chain management identify tracking, inventory monitoring, and asset management as recurring application domains, including in agriculture and food logistics (IoT-based SCM review, 2023).

Visibility can reduce coordination delays. A delayed shipment can trigger revised labor schedules; a temperature excursion can prompt inspection or diversion; and a sudden decline in expected yield can lead

a processor to secure alternative supplies. The value lies not in displaying data but in making the operational state legible to the people who can act. Dashboards should prioritize exceptions and decisions rather than overwhelm users with raw readings. Alert thresholds need to reflect product-specific risk, sensor reliability, and the cost of false alarms.

Visibility also requires shared identifiers and data standards. If a farmer's batch number does not match the processor's inventory code, information may be difficult to connect. If one partner records weights in kilograms and another uses tonnes without consistent conversion, aggregate data become unreliable. Interoperability should be planned before large-scale deployment. Organizations should define minimum data fields, timestamps, product identifiers, location references, quality codes, and rules for correcting errors. This foundation often creates more value than adding advanced analytics to disconnected records.

4.2 Pathway two: predictive risk sensing

Predictive risk sensing uses data to estimate the likelihood and potential consequences of future disruptions. In agribusiness, relevant risks include adverse weather, yield shortfalls, pest outbreaks, disease, equipment failure, demand spikes, transport delays, cold-chain excursions, and sudden price movements. AI can combine historical patterns with weather, remote sensing, sensor readings, market data, and supplier information to generate risk estimates. The AI and supply-chain resilience literature identifies prediction and decision support as important opportunities, especially where disruption signals are distributed across multiple sources (Naz et al., 2022; Pontjoharyo, 2026; Zamani et al., 2022).

Predictive models should be evaluated by decision usefulness, not only statistical accuracy. A yield forecast that is accurate at the regional level may be too coarse for scheduling a particular processing line. A high-risk alert is useful only if the lead time allows an alternative action. Model performance should therefore be assessed using horizon-specific error, calibration, false-positive and false-negative rates, and the cost of decisions triggered by the forecast. For perishable goods, a slightly less accurate forecast delivered early may be more valuable than a highly accurate forecast delivered after the operational window has closed.

Risk sensing also needs scenario thinking. Historical data may not contain unprecedented heat, floods, geopolitical disruption, or new pest patterns. A model trained on stable conditions can fail precisely when it is most needed. Managers should combine AI forecasts with stress tests, expert judgment, and pre-agreed contingency rules. Scenario planning can explore how alternative sourcing, inventory buffers, transport routes, and processing schedules perform under plausible disruptions. The purpose is not to predict every event but to prepare options before uncertainty becomes an emergency.

4.3 Pathway three: adaptive planning and resource allocation

Adaptive planning connects predictions to decisions about sourcing, production, inventory, transport, labor, and capacity. AI-based demand forecasts can support procurement and production schedules; yield predictions can inform contract volumes; route optimization can reallocate vehicles; and inventory models can balance service levels against spoilage risk. Distributed AI and multi-agent systems offer a potential approach when decisions are spread across different nodes and no single planner possesses all local information (Distributed AI in agri-food supply chains, 2024). However, automated coordination must be designed around explicit business rules, service priorities, and constraints.

Planning models should account for perishability and substitution. A conventional inventory model may assume that products remain usable over time, while fresh produce, dairy, fish, and meat degrade at different rates under different conditions. The cost of a stockout may also differ by customer, season, or product. Adaptive planning should therefore incorporate shelf life, temperature history, quality grades, delivery windows, and alternative uses. For example, a batch with a shorter remaining shelf life may be allocated to a nearer market or processed sooner, provided that safety and quality requirements are met.

The trade-off between efficiency and resilience is central. Lean inventories can reduce working capital and storage costs but leave little room for recovery after disruption. Larger buffers may improve service continuity but tie up capital and increase spoilage or refrigeration demand. AI can support differentiated buffers based on demand uncertainty, replenishment lead time, perishability, supplier reliability, and the

consequences of shortage. The objective should not be to eliminate all slack; it should be to place resilience capacity where it has the highest value and to avoid redundant buffers that do not materially reduce risk.

4.4 Pathway four: quality assurance, traceability, and loss prevention

Agricultural products can lose value through bruising, temperature abuse, moisture variation, contamination, delayed handling, poor storage, and inaccurate grading. IoT sensors can monitor relevant conditions, while AI can identify patterns associated with deterioration or classify images for defects. When linked to batch-level traceability, these capabilities can support earlier intervention and more targeted recalls. Mehannaoui et al. (2023) review IoT-based food traceability systems, and the Industry 4.0 review identifies food safety, traceability, and food waste as important applications for digital agrifood technologies (Industry 4.0 AFSC review, 2022).

Loss prevention can improve profitability and sustainability simultaneously. Avoiding the loss of a harvested or processed product preserves the economic value of land, water, fertilizer, labor, energy, and transport already invested in it. However, the intervention must be evaluated against its own cost and environmental footprint. Expanding cold storage may reduce spoilage but consume electricity and refrigerants; additional packaging may extend shelf life but increase material use; and sensor deployment may be uneconomic for low-value products moving through short supply chains. The business case should compare expected avoided loss with capital, maintenance, energy, and training costs.

Traceability systems should be built around a clearly defined purpose. Food-safety recall requires rapid identification of affected batches and reliable records of movement. Sustainability assurance may require information about production practices, inputs, and origin. Consumer-facing transparency may require a simpler subset of data. Collecting more information than needed can increase costs and privacy risks without improving decisions. In addition, digital records need verification at the point of capture. An immutable record of inaccurate information remains inaccurate, so audits, sampling, certification, and accountability remain necessary complements to technology.

4.5 Pathway five: low-carbon operational optimization

AI-IoT integration can support decarbonization through resource efficiency, reduced food loss, energy management, route planning, improved fertilizer and water application, and more accurate production decisions. Smart irrigation can match water application to soil moisture and crop needs; equipment monitoring can identify inefficient operation; warehouse sensors can optimize refrigeration settings; and logistics analytics can consolidate shipments or reduce empty mileage. These applications can reduce emissions where they lower fuel, electricity, input use, or avoidable production. The IPCC (2022) and FAO (2022) identify technology and management improvements as part of broader opportunities to improve agricultural sustainability and resilience, and evidence from emerging markets indicates that green supply-chain practices, supported by organizational capabilities, can also strengthen firm competitiveness, including in food and beverage manufacturing (Phattanaviroj & Pattaradej, 2025).

The emissions effect is not automatic. A sensor-guided irrigation system may reduce water use but have a limited carbon effect if pumping energy is small; conversely, efficient pumping may reduce both energy costs and emissions where electricity or fuel is carbon intensive. A cold-chain system can prevent food loss but increase electricity demand. A route optimizer may lower kilometers traveled while increasing delivery frequency. Managers should therefore calculate the net effect using a baseline and appropriate system boundary, considering both direct and relevant indirect emissions. Where data permit, absolute emissions and emissions intensity should be reported together.

A carbon-neutrality transition also requires distinguishing operational reductions from offsets or credits. AI-IoT systems can improve measurement and monitoring, but they cannot substitute for a credible reduction strategy. Firms should identify major sources, prioritize feasible reductions, track progress, and treat residual emissions transparently. Digital measurement may support Scope 3 management by improving supplier information, but it will not resolve the need for procurement changes, long-term contracts, investment, and collaboration. Technology is an enabling capability within a transition plan, not the transition plan itself.

4.6 Pathway six: collaborative learning and network coordination

Agribusiness resilience depends on learning across seasons and partners. After a disruption, firms need to understand which signals were missed, which interventions worked, and where assumptions failed. AI can identify recurring patterns in spoilage, delays, yield variation, or supplier reliability; IoT records can reconstruct physical conditions; and shared dashboards can support joint reviews. The result can be better contingency planning, more realistic service commitments, and targeted investments in storage, transport, or supplier development. Such learning is stronger when firms preserve decision records and compare expected outcomes with actual results.

Collaboration is not merely data exchange. Partners need incentives to contribute accurate information and confidence that it will not be used opportunistically. Farmers may hesitate to share yield forecasts if buyers can use them to lower prices; transporters may resist revealing capacity constraints if they expect penalties; and processors may protect demand forecasts as commercially sensitive. Governance arrangements should define data ownership, access, permitted use, retention, correction, and dispute resolution. Shared benefits can be supported through technical assistance, transparent pricing rules, service guarantees, and co-investment in infrastructure.

The distribution of benefits is a strategic issue. Large buyers may capture most of the value from traceability or forecasting while farmers bear the cost of sensors, connectivity, and data entry. If digitalization shifts risk downward in the chain, adoption may be resisted or may deepen dependency. Inclusive implementation can include shared devices, cooperative data services, training, offline functionality, low-cost interfaces, and contracts that reward quality or reliability improvements. The FAO (2022) highlights the importance of enabling infrastructure, digital literacy, and financing for small-scale producers. These are not peripheral social concerns; they affect data coverage, supply continuity, and the long-term viability of the system.

4.7 Operational metrics and performance evaluation

A practical evaluation should separate leading indicators from lagging outcomes. Leading indicators include sensor coverage, data completeness, forecast calibration, alert response time, system uptime, model drift, and percentage of suppliers connected. These measures show whether the digital capability is functioning. Lagging outcomes include stockout frequency, order fill rate, on-time delivery, spoilage, yield variability, downtime, inventory turns, energy per unit, water productivity, absolute emissions, and recovery time after disruption. A firm should select a limited set of metrics tied to material decisions rather than produce a dashboard of every available measure.

Resilience measurement should capture both the severity of disruption and the performance of the response. Useful indicators include time to detect a disruption, time to decide, time to restore service, percentage of demand fulfilled during disruption, revenue or product loss, and recovery cost. These should be compared with a baseline or comparable operating units. If a system is implemented during a period with unusually favorable weather, an apparent improvement may not be attributable to the technology. Where feasible, pilot sites, matched comparisons, interrupted time series, or phased implementation can strengthen inference.

Efficiency measurement should account for output and service quality. Lower labor hours may reflect genuine productivity improvement or may shift work to suppliers. Lower inventory may reduce working capital but increase emergency transport. Lower cost per shipment may be achieved by consolidating deliveries but compromise freshness. Environmental performance should be tracked alongside service and financial measures to avoid local optimization. A balanced scorecard can include cost, service, quality, resilience, emissions, waste, safety, and inclusion, with explicit weights or decision rules for resolving conflicts.

4.8 Data governance, cybersecurity, and model risk

AI-IoT systems increase the number of devices, interfaces, and data flows that must be secured. A compromised sensor can falsify conditions; ransomware can interrupt warehouse or processing systems; and unauthorized access can expose farm locations, production volumes, or commercial terms. Cybersecurity

should be built into device selection, network design, authentication, software updates, access control, backups, and incident response. Operational technology may require segmentation from enterprise networks so that a compromise in one system does not disrupt critical processes. Vendor support and device lifecycle management are also important because low-cost devices may have limited security-update periods.

Model risk includes poor training data, bias across regions or farm sizes, drift, weak explainability, and inappropriate automation. A yield model developed for irrigated farms may not perform well for rain-fed smallholders; a computer-vision model trained on one variety may misclassify another; and a demand model can fail when consumer behavior shifts abruptly. Firms should document intended use, data provenance, validation, known limitations, monitoring thresholds, and human override procedures. High-impact decisions should not rely on an unreviewed prediction where failure could create food-safety, financial, or livelihood consequences.

Data governance should also address privacy and commercial confidentiality. Farm-level data may reveal productivity, land use, financial vulnerability, or supplier relationships. Consent and permitted uses should be clear, and access should follow the principle of least privilege. Where possible, data-sharing arrangements can use aggregation or secure interfaces so that partners receive decision-relevant information without unnecessary disclosure of raw commercial data. Governance is especially important when data ownership and bargaining power are asymmetric.

4.9 Implementation roadmap for agribusiness managers

The first stage is to define the business problem. Firms should identify a recurring decision failure—such as spoilage, uncertain harvest volume, equipment downtime, late deliveries, or excessive fuel use—and estimate its operational and financial consequences. Starting with a clear problem prevents technology procurement from becoming an end in itself. The organization should specify the decision owner, the required lead time, the relevant data, the action that could change, and the outcome by which success will be assessed.

The second stage is to establish a reliable minimum data layer. This may involve basic sensors, consistent product identifiers, digitized inventory records, calibrated temperature loggers, and data-quality checks. The organization should map connectivity gaps, device maintenance requirements, and the availability of historical data. In low-connectivity settings, edge devices and store-and-forward functions may be more practical than systems requiring continuous cloud access. Data standards should be designed to permit future integration rather than locking the firm into incompatible platforms.

The third stage is to pilot one operational use case with a measurable baseline. A pilot should have a defined comparison period, service-level targets, staff training, and an explicit process for responding to alerts or forecasts. Managers should assess not only technical performance but adoption, false alarms, workflow disruption, maintenance cost, and the distribution of benefits. The pilot should be expanded only when the intervention changes decisions and demonstrates value under realistic conditions. A technically successful demonstration may still be commercially unsuitable if it requires specialist support unavailable at scale.

The fourth stage is to integrate AI and IoT into planning and governance. Once the data layer is reliable, firms can introduce predictive models, optimization tools, and cross-functional dashboards. Forecasts should be connected to procurement, inventory, production, transport, and sustainability decisions. Clear accountability is needed for model updates, alert response, exception handling, and performance review. The fifth stage is to scale through partner agreements and continuous learning. Suppliers need practical onboarding, shared standards, and incentives; internal teams need training; and executives need evidence about financial, resilience, and environmental outcomes.

4.10 Agribusiness-specific configurations

The appropriate AI–IoT configuration depends on the commodity and supply-chain structure. For grains and other storable crops, priorities may include weather-informed yield forecasting, storage moisture monitoring, pest detection, silo condition monitoring, and transport scheduling. For fresh fruits and vegetables, temperature, humidity, handling, remaining shelf life, and rapid demand updates are more

important because deterioration is time sensitive. For dairy and meat, cold-chain integrity, time-temperature history, sanitation, and traceability are central. For fisheries, vessel location, catch documentation, temperature, and rapid distribution may dominate. A universal technology package would ignore these differences and likely waste resources.

Smallholder-based systems require additional attention to affordability and inclusion. Cooperative-level sensing, shared weather services, low-cost mobile interfaces, and buyer-supported data systems may be more practical than requiring every farm to own advanced equipment. Intermediaries can serve as data-service providers, but governance must prevent them from monopolizing information or extracting disproportionate value. Public investment in connectivity, extension services, digital skills, and shared standards can reduce the fixed costs of adoption. These interventions may create greater system-wide resilience than isolated subsidies for devices.

4.11 Synthesis of findings

The synthesis yields five overarching findings. First, AI-IoT integration improves resilience only when sensing and prediction are linked to decision authority and response routines. Second, operational efficiency gains depend on commodity-specific design and reliable data rather than on technology sophistication alone. Third, quality control and food-loss prevention can create joint economic and environmental benefits, but the net effect must account for energy, materials, and infrastructure. Fourth, collaboration and equitable incentives are necessary for data coverage across fragmented supply chains. Fifth, robust evaluation must distinguish technical performance, operational outcomes, resilience, and environmental impact. These findings explain why pilots may succeed technically yet fail to scale commercially or equitably.

A further implication is that the most valuable system is not necessarily the most autonomous one. In some contexts, human expertise is essential for interpreting unusual weather, negotiating supplier responses, or balancing competing objectives. The aim should be appropriate automation: automate repetitive monitoring and well-defined actions, while preserving human judgment for uncertain, high-impact, or ethically consequential decisions. This balance can improve trust and prevent the system from becoming brittle when conditions fall outside the model's training experience.

5. DISCUSSION

5.1 Moving from technology adoption to operational capability

The framework shifts attention from the adoption of AI or IoT to the capability required to turn data into operating results. Hardware and software are necessary in many applications, but the performance effect depends on data quality, decision rights, process redesign, and continuous learning. This interpretation is consistent with reviews that find broad potential for digital technologies in agrifood systems while emphasizing persistent adoption barriers and the need for integrated applications (FAO, 2022; Industry 4.0 AFSC review, 2022; AIoT review, 2024). The managerial implication is straightforward: firms should not begin by asking which technology to buy, but which decision must improve and what evidence would demonstrate that improvement.

This capability perspective also helps reconcile mixed outcomes. One firm may use sensors to reduce spoilage because its logistics team can divert shipments immediately. Another may collect the same data but lack alternative routes, cold storage, or contractual flexibility. In both cases, the technical input is similar, but the operating model differs. Similarly, AI-based forecasts may improve planning in a vertically integrated chain while offering limited value in a fragmented chain where procurement commitments cannot be changed. The organizational context is therefore part of the explanation, not simply a control variable.

5.2 Resilience and efficiency

Resilience and efficiency are often framed as opposing goals. Lean systems reduce inventory, idle capacity, and cost, while resilient systems may require buffers, alternative suppliers, and redundancy. AI-IoT can improve the balance by making buffers more targeted and by reducing uncertainty about when and where they are needed. A temperature-monitoring system can reduce the need for blanket safety margins by identifying actual product risk; better yield forecasts can support differentiated sourcing; and predictive

maintenance can reduce both downtime and excessive spare-parts inventory. Yet analytics cannot eliminate the need for physical capacity or alternative supply when a disruption is systemic.

The correct objective is not maximum efficiency under normal conditions or maximum redundancy under every possible disruption. It is an economically defensible portfolio of resilience measures. Managers should evaluate expected disruption losses, the probability and duration of events, the cost of prevention, the cost of recovery, and the environmental footprint of alternative buffers. The value of AI-IoT lies in improving the targeting and timing of these measures, not in promising that disruptions can be forecast perfectly. Extreme events and unprecedented combinations of risks require scenario planning and strategic flexibility in addition to prediction.

5.3 The business case and total cost of ownership

A credible business case should include the full cost of ownership: devices, connectivity, software licenses, integration, calibration, maintenance, cybersecurity, training, data storage, model monitoring, and eventual replacement. Benefits may include reduced spoilage, lower downtime, better yield forecasts, improved service levels, reduced input use, lower energy consumption, and stronger traceability. These benefits should be quantified using a baseline and realistic adoption assumptions. For example, a system may reduce losses in a pilot but achieve smaller gains at scale because of differences in staff behavior, infrastructure, or product mix.

The financial evaluation should also account for distribution. A processor may gain from lower rejection rates while farmers pay for sensors; a retailer may gain traceability while a logistics provider bears additional data-entry costs. If the party paying for the technology is not the party receiving the benefit, adoption may stall. Contract design, co-investment, shared savings, premium payments for verified quality, and cooperative services can help align incentives. The FAO (2022) evidence on barriers to agricultural automation underscores that affordability and enabling infrastructure influence whether benefits are realized beyond large enterprises.

5.4 Carbon performance and the danger of local optimization

Digital optimization can produce unintended effects if the objective function is too narrow. A route algorithm may minimize distance while increasing refrigerated idle time; a production forecast may reduce stockouts while encouraging surplus production; and smart irrigation may lower water use per hectare while making expansion into marginal land more profitable. A firm may reduce emissions intensity but increase absolute emissions as output grows. These examples show why environmental evaluation must be linked to system boundaries, activity levels, and lifecycle effects.

Carbon performance should therefore be assessed alongside resilience and service quality. Where possible, firms should measure fuel and electricity use, material waste, spoilage, fertilizer use, and absolute emissions before and after the intervention. The assessment should include rebound and displacement: did the intervention reduce the impact, or move it to another location, supplier, or stage? For a carbon-neutrality transition, AI-IoT should support a sequence of measurement, reduction, verification, and transparent treatment of residual emissions. Offsets should not be used to conceal the absence of operational reductions.

5.5 Inclusion, bargaining power, and trust

Digital transformation can reproduce existing inequalities when data and analytical capabilities are concentrated among powerful buyers. Large firms may use granular supplier data to forecast prices, shift inventory risk, or impose compliance requirements, while smaller producers absorb the cost of measurement. This can weaken trust and reduce willingness to participate. A resilient network requires reliable data from across the chain, so excluding small suppliers is not only an equity concern but a potential operational weakness.

Inclusive governance can involve farmer cooperatives, shared platforms, extension services, buyer-funded onboarding, and transparent rules for data use. Producers should understand what information is collected, who can access it, how long it is retained, and whether it affects prices or eligibility. Where commercial confidentiality is important, aggregated or permissioned data-sharing arrangements may allow coordination without disclosing unnecessary details. Public policy can support common standards and rural

connectivity, while firms can build adoption costs into supplier-development programs rather than transferring them unilaterally.

5.6 Cybersecurity and operational continuity

As agribusiness becomes more connected, cybersecurity becomes a supply-chain resilience issue. An attack that disables a warehouse management system, falsifies temperature data, or interrupts irrigation controls can create physical loss, food-safety risk, and financial damage. Cybersecurity should therefore be integrated into business continuity planning. Organizations need asset inventories, secure device configuration, access controls, regular updates, backups, network segmentation, incident-response procedures, and recovery tests. Critical functions should have manual or offline fallbacks where feasible.

Third-party risk is equally important. Agribusiness firms often rely on platform vendors, cloud providers, telecom operators, equipment manufacturers, and external analytics services. A vendor outage or contract termination can affect the entire data pipeline. Procurement should assess data portability, service-level commitments, update policies, incident notification, and exit arrangements. Avoiding vendor lock-in does not require avoiding specialized platforms; it requires preserving the ability to retrieve data and maintain critical operations if the relationship changes.

5.7 Governance of AI decisions

AI governance should be proportionate to the consequences of the decision. A model recommending a routine warehouse inspection may require limited oversight, while a model determining credit access, supplier eligibility, or pesticide application requires more careful validation and review. Governance should document intended use, training data, limitations, validation results, model changes, and escalation rules. Human review should be available when model outputs conflict with local knowledge or when conditions fall outside the training domain. Staff must be trained not only to use the system but to question its recommendations appropriately.

Managers should resist the assumption that algorithmic outputs are neutral. Data reflect historical practices, reporting incentives, and uneven coverage. If the data underrepresent small farms or remote regions, forecasts may be less reliable for those participants. If historical rejection rates reflect buyer bias or inconsistent grading, a model may reproduce that pattern. Fairness assessment, stakeholder consultation, and ongoing performance monitoring are therefore important components of responsible implementation. These practices can improve the reliability and legitimacy of the supply-chain system.

5.8 Implications for emerging economies and Indonesia

The framework is relevant to emerging economies where agribusiness depends on smallholders, dispersed production, uneven connectivity, and variable cold-chain infrastructure. Digital tools can improve information flow and market coordination, but benefits depend on local fit. Low-cost sensors, mobile services, shared platforms, and cooperative aggregation may be more effective than capital-intensive systems designed for large industrial farms. The FAO (2022) stresses the importance of infrastructure, digital literacy, and financing in ensuring that agricultural automation benefits are inclusive. The World Bank's work on digital development similarly emphasizes uneven adoption and the need for enabling infrastructure and skills (World Bank, 2023).

For Indonesia, potential applications include weather-informed crop planning, pest and disease monitoring, cold-chain management for horticulture and fisheries, livestock monitoring, traceability for export-oriented commodities, and demand forecasting for processors and retailers. The operational priorities differ across palm oil, rice, coffee, cocoa, horticulture, fisheries, and livestock. For example, plantation supply chains may prioritize yield forecasting, transport coordination, and traceability, while fresh produce chains may prioritize remaining shelf life, cold storage, and rapid market matching. Any national or sectoral initiative should be designed around commodity-specific risks and the capabilities of farmers, cooperatives, traders, processors, and logistics providers.

AI-IoT should not be presented as a substitute for roads, ports, electricity, extension services, storage facilities, fair contracts, or effective institutions. Digital information can reveal a transport bottleneck, but it cannot repair the road. A forecast can predict a shortage, but it cannot create processing capacity without

investment. Policy should therefore combine digital infrastructure with physical infrastructure, workforce development, data standards, access to finance, and credible competition rules. This complementarity is central to achieving both resilience and sustainable business performance.

5.9 Limitations and interpretation

The framework is conceptual and should not be interpreted as evidence that AI-IoT integration will improve every agribusiness supply chain. Outcomes depend on commodity characteristics, the nature of disruption, organizational capability, data quality, infrastructure, and institutional conditions. The literature includes technical prototypes and context-specific studies that may not generalize to commercial scale. The review does not estimate effect sizes or rank technologies by universal return on investment. Its contribution is to clarify mechanisms, boundary conditions, and the evidence needed to evaluate implementation responsibly.

A further limitation is that resilience and sustainability may involve normative choices. How much redundancy is justified, who should bear transition costs, and which environmental impacts should receive priority cannot be answered by a model alone. Analytics can clarify likely consequences and trade-offs, but decisions still require managerial judgment, stakeholder engagement, and accountability. The strongest AI-IoT operating models combine technical competence with institutional legitimacy and a clear strategic purpose.

6. CONCLUSION

This article examined how AI and IoT integration can strengthen agribusiness supply-chain resilience, improve operational efficiency, and support carbon-neutrality transitions. The central conclusion is that these technologies create value through connected operating mechanisms rather than through adoption alone. End-to-end visibility, predictive risk sensing, adaptive planning, quality and loss control, low-carbon optimization, and collaborative learning can help firms anticipate disruptions, reduce avoidable losses, allocate resources more effectively, and make environmental impacts more visible. However, outcomes depend on data quality, interoperability, managerial capability, partner participation, cybersecurity, and governance.

The analysis also shows why resilience, efficiency, and sustainability should not be collapsed into a single performance claim. Lower unit cost may coexist with higher absolute emissions; greater inventory may protect service continuity while increasing storage energy; and improved traceability may not reduce risk unless the information triggers a timely response. A credible evaluation should therefore use a balanced set of operational, resilience, financial, and environmental indicators, establish baselines, and assess the net effects of interventions. Technology performance should be distinguished from business performance, and business performance from verified environmental improvement.

For managers, implementation should begin with a material operating problem and a clear decision owner. Firms should identify where uncertainty, spoilage, downtime, delay, or resource waste is most costly, establish minimum data standards, pilot a relevant use case, and measure results before scaling. AI should be introduced where it improves a decision that cannot be handled adequately through simpler methods. Sensor and model maintenance, cybersecurity, human review, and data portability should be planned from the outset. Investments should be assessed through total cost of ownership and a realistic distribution of costs and benefits across supply-chain participants.

For supply-chain leaders, the priority is to build collaboration rather than merely collect supplier data. Shared identifiers, proportionate reporting standards, training, cooperative services, and fair incentives can improve data coverage and trust. Large buyers should avoid transferring all measurement costs to smallholders when the resulting information benefits the wider chain. For policymakers, digital adoption should be supported by rural connectivity, electricity access, extension services, digital literacy, common standards, financing, and physical logistics infrastructure. AI-IoT systems can improve coordination, but they cannot replace roads, cold storage, ports, or reliable institutions.

For sustainability and carbon-transition managers, AI-IoT should be embedded in a broader decarbonization plan. Firms should measure material emissions sources, reduce avoidable energy and material use, prevent food loss, optimize logistics, and use supplier information to guide procurement. They

should track absolute emissions as well as intensity and disclose the boundaries and assumptions behind claims. Where digital interventions create additional electricity or material demand, those impacts should be considered in the business case. The goal is not to label an operation “smart” or “carbon neutral,” but to demonstrate measurable and durable improvements.

This article is limited by its integrative, conceptual design and the heterogeneity of the evidence base. The framework requires validation through longitudinal, comparative, and mixed-method studies across commodities and institutional settings. Future research should investigate which combinations of data quality, analytical capability, partner governance, and process redesign yield the strongest performance gains, and whether those gains are sustained during severe disruption. It should also examine the distributional consequences of digitalization and the net environmental effect of AI-IoT infrastructure.

Therefore, AI and IoT are best understood as enabling capabilities within a broader agribusiness operating model. Their strategic value is realized when they help supply-chain participants detect emerging risks, coordinate responses, preserve product quality, use resources more effectively, and learn from outcomes. Resilient and low-carbon agribusiness will not emerge from sensors and algorithms alone. It requires technology aligned with operational purpose, credible governance, capable people, collaborative relationships, and evidence-based management.

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