AMERICAN JOURNAL OF LOGISTICS AND SUPPLY CHAIN (AJLSC)

VOLUME 1 ISSUE 1 (2026)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of
Logistics and Supply Chain (AJLSC)

Volume 1 Issue 1, Year 2026
https://journals.e-palli.com/home/index.php/ajlsc

The Role of Smart Logistics Technologies in Enhancing Operational Efficiency in Food and Beverage Supply Chains: Implications for U.S. Firms

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Article Information

Received: May 25, 2026

Accepted: August 13, 2026

Published: September 22, 2026

Keywords

Blockchain, Food And Beverage Supply Chains, Iot, Operational Efficiency, Smart Logistics, Warehouse Automation

ABSTRACT

This qualitative systematic review synthesizes evidence on how smart logistics technologies (IoT sensing, blockchain, artificial intelligence (AI) and big-data analytics, and warehouse automation) relate to operational efficiency in food and beverage supply chains, with attention to conditions relevant to U.S. firms. Following PRISMA-informed procedures, the review synthesizes 39 peer-reviewed articles published between 2007 and 2024. Rather than presenting new quantitative measurements, the review organizes and interprets findings that the underlying articles themselves report, identifying where the literature converges, diverges, and which contextual factors shape outcomes. IoT-enabled monitoring is most consistently associated with improved cold-chain visibility; blockchain applications concentrate on traceability and provenance verification, with adoption constrained by partner-participation and integration costs; AI and analytics capabilities link to forecasting improvements, contingent on data quality and organizational maturity; and warehouse automation shows productivity gains alongside substantial capital and change-management barriers. The review's contribution is to organize this fragmented, technology-specific literature around operational efficiency dimensions relevant to food and beverage logistics, surface implementation success factors and barriers recurring across technology categories, and translate this synthesis into prioritization guidance for practitioners. Limitations, including reliance on secondary literature not specific to the U.S. food and beverage sector, are discussed alongside directions for future research.

INTRODUCTION

The U.S. food and beverage sector is large, logistics-intensive, and structurally exposed to product perishability, strict regulatory oversight, and volatile demand, all of which make logistics performance a first-order determinant of cost and product quality (Gurrala & Hariga, 2022). Traditional, largely manual logistics processes are increasingly viewed as inadequate for managing these pressures, motivating growing interest in "smart" logistics technologies that use sensing, connectivity, and computation to make supply chain operations more visible, predictive, and responsive (Abideen *et al.*, 2021; Winkelhaus & Grosse, 2020).

"Smart logistics" in this review refers collectively to Internet of Things (IoT) sensing and connectivity, blockchain and distributed-ledger traceability systems, artificial intelligence (AI), machine learning, and big-data analytics, and automated or robotic warehouse systems (Winkelhaus & Grosse, 2020; Lezoche *et al.*, 2020). Reviews of the broader Industry 4.0 and "Logistics 4.0" literature describe how these technologies are increasingly discussed as interacting components of a connected logistics ecosystem rather than as isolated tools (Winkelhaus & Grosse, 2020; Büyüközkan & Göçer, 2018; Yadav *et al.*, 2022).

Despite this growing body of work, the literature specifically addressing food and beverage logistics remains fragmented across technology-specific reviews: blockchain and traceability studies form one cluster (Kamilaris *et al.*, 2019; Feng, 2020; Kouhizadeh *et al.*, 2021), IoT and cold-chain monitoring studies form another (Badia-Melis *et al.*, 2018; Tsang *et al.*, 2018; Rejeb *et al.*, 2021), and AI, big-data, and warehouse-automation studies are largely reviewed within general operations and supply chain management rather than food and beverage contexts specifically (Toorajipour *et al.*, 2021; Bag *et al.*, 2020; Azadeh *et al.*, 2019). Few reviews synthesize across these technology clusters to identify cross-cutting operational efficiency patterns, and fewer still examine how findings generated largely from general manufacturing, retail, or agri-food contexts translate to the regulatory and operational conditions specific to U.S. food and beverage firms (Gurrala & Hariga, 2022; Mustafa *et al.*, 2024).

This review addresses that gap. It synthesizes 39 peer-reviewed articles spanning IoT, blockchain, AI/big-data analytics, and warehouse automation to examine how these technologies relate to operational efficiency in food and beverage-relevant supply chains, what implementation conditions the literature associates with success or failure, and what this fragmented evidence base implies for firms operating under U.S. regulatory and market conditions.

Contribution of the Study

This review contributes to the literature in four ways. First, it synthesizes fragmented, largely technology-specific

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evidence on smart logistics technologies into a single account organized around food and beverage-relevant operational efficiency dimensions, rather than presenting each technology in isolation. Second, it organizes existing evidence according to operational efficiency outcomes: visibility and monitoring, traceability, forecasting and decision support, and physical throughput and accuracy; rather than by individual technology alone, making cross-technology patterns visible. Third, it identifies implementation success factors and persistent barriers that recur across technology categories, rather than treating each technology's adoption challenges as unique. Fourth, it translates this synthesis into prioritization guidance intended for food and beverage logistics managers, technology vendors, and policymakers, discussed in Section 8.

Significance of the Study

For scholars, the review offers a consolidated evidence base spanning information systems, operations, and supply chain management research that can support further theory-building on technology-enabled logistics transformation in perishable-goods contexts. For practitioners, it organizes evidence on demonstrated benefits, implementation conditions, and common failure modes in a form intended to reduce uncertainty in technology investment decisions. For policymakers and industry associations, the review's discussion of traceability, food-safety, and workforce implications is intended to inform regulatory and workforce-development discussions. More broadly, because logistics efficiency in this sector bears on food waste, cost, and food safety outcomes, the review's synthesis is relevant to sustainability and food-security discussions (Abideen *et al.*, 2021; Mustafa *et al.*, 2024).

Problem Statement

U.S. food and beverage firms operate logistics networks that must reconcile perishability, cold-chain requirements, and food-safety regulation with cost and service pressures (Gurrala & Hariga, 2022). Smart logistics technologies are widely promoted as a response to these pressures, yet the empirical and review literature evaluating them is scattered across technology-specific silos, general (non-food) operations contexts, and non-U.S. settings (Toorajipour *et al.*, 2021; Winkelhaus & Grosse, 2020; Idrissi *et al.*, 2024). This fragmentation makes it difficult for researchers to identify where the evidence is strong and consistent versus contested or context-dependent, and difficult for practitioners to translate the literature into implementation priorities. This review addresses the problem by systematically identifying, synthesizing, and interpreting the available evidence across technology categories, asking: how do smart logistics technologies relate to operational efficiency in food and beverage-relevant supply chains, and what conditions the literature associates with successful implementation.

LITERATURE REVIEW

The literature on smart logistics technologies has developed largely along technology-specific lines, with distinct research clusters forming around blockchain traceability, IoT-enabled monitoring, AI and big-data analytics, and warehouse automation. This section summarizes each cluster before turning, in Section 4, to a cross-cutting synthesis.

Blockchain and Traceability

A substantial cluster examines blockchain and distributed-ledger applications for food supply chain traceability and provenance verification (Feng, 2020; Galvez *et al.*, 2018; Kamilaris *et al.*, 2019). This literature documents blockchain's technical capacity to create tamper-resistant, shared transaction records supporting faster source identification during quality or safety incidents (Casino *et al.*, 2019; Patel *et al.*, 2023), and catalogues bibliometric trends in the field's rapid growth (Pandey *et al.*, 2022) and distributed-ledger applications specifically within food supply chains (Nurgazina *et al.*, 2021). A parallel stream examines adoption rather than technical capability, identifying organizational, economic, and inter-firm barriers, including coordinated partner participation, integration costs, and unclear near-term ROI, that constrain diffusion even where technical benefits are demonstrated (Agi & Jha, 2022; Kouhizadeh *et al.*, 2021).

IoT and Cold-Chain Monitoring

A second cluster addresses IoT sensing and connectivity, with emphasis on cold-chain and food-quality monitoring. Reviews of IoT applications in supply chain management document sensing, connectivity, and data-integration capabilities relevant to logistics broadly (Taj *et al.*, 2023), while food-specific work examines IoT-based traceability architectures (Mehannaoui *et al.*, 2023) and monitoring systems for temperature-sensitive distribution (Badia-Melis *et al.*, 2018; Tsang *et al.*, 2018). Related work applies machine learning to cold-chain break detection (Loisel *et al.*, 2021), and IoT has also been reviewed in halal food supply chains, illustrating how monitoring and traceability concerns intersect (Rejeb *et al.*, 2021).

Artificial Intelligence, Machine Learning, and Big-Data Analytics

A third, larger cluster addresses AI, machine learning, and big-data analytics in supply chain management generally. Systematic reviews document AI applications across forecasting, planning, and decision-support functions (Toorajipour *et al.*, 2021), with more recent work reviewing empirical studies specifically (Culot *et al.*, 2024), building on foundational work establishing AI's theoretical and applied relevance to supply chain problems (Min, 2010) and machine-learning-based demand forecasting specifically (Carbonneau *et al.*, 2008). A related stream reframes the question toward organizational capability rather than technology: Bag *et al.* (2020), Arunachalam *et* *al.* (2018), Mikalef *et al.* (2020), and Wamba *et al.* (2020) collectively find that big-data analytics benefits depend heavily on analytics capability: data governance, cross-functional integration, and dynamic capability; rather than on data or algorithmic sophistication alone.

Warehouse Automation and Robotics

A fourth cluster reviews robotized and automated warehouse systems, covering autonomous mobile robots, automated storage and retrieval systems, and related technologies (Azadeh *et al.*, 2019), with e-commerce-driven demand identified as a key accelerant of this research area (Boysen *et al.*, 2019). Foundational and more recent order-picking research frames automation benefits as inseparable from picking-system design (storage assignment, routing, and batching) rather than a property of the automation technology alone (de Koster *et al.*, 2007; van Gils *et al.*, 2018).

Cross-Cutting Digitalization and Industry 4.0 Frameworks

Beyond these technology-specific clusters, an integrative body of work takes a broader view. Winkelhaus and Grosse (2020) synthesize 114 articles into a "Logistics 4.0" framework spanning technological triggers, enabling technologies, human factors, and logistics tasks. Büyüközkan and Göçer (2018) review digital supply chain literature and propose a framework for future research, and Lezoche *et al.* (2020) survey Agri-Food 4.0 technologies across agricultural and food supply chains specifically. Industry 4.0 technologies have also been reviewed in relation to agricultural food supply chains (Yadav *et al.*, 2022) and supply chain performance more generally (Rad *et al.*, 2022), while related reviews address the operational dimensions of supply chain digitalization (Deepu & Ravi, 2023) and its organizational implications (Perano *et al.*, 2023). Sector-adjacent reviews extend this integrative perspective to logistics technology adoption in agribusiness (Soledispa-Cañarte *et al.*, 2023), the joint treatment of blockchain, IoT, and AI in logistics and transportation (Idrissi *et al.*, 2024), food supply chain transformation broadly (Abideen *et al.*, 2021), persistent food supply chain challenges (Gurrala & Hariga, 2022), and cold-chain logistics developments specifically (Mustafa *et al.*, 2024).

Read together, this literature suggests a field matured technology by technology but not yet consolidated around the operational efficiency questions most relevant to food and beverage logistics managers, nor examined systematically for the U.S. context specifically. Sections 3 and 4 describe how this review addresses that gap.

MATERIALS AND METHODS

This review follows established qualitative systematic review procedures for management and information systems research (Tranfield *et al.*, 2003; Webster & Watson, 2002), informed by PRISMA 2020 reporting guidance (Page *et al.*, 2021) and PRISMA-S guidance for reporting literature search strategies (Rethlefsen *et al.*, 2021). Consistent with Snyder's (2019) guidance on review methodology and Xiao and Watson's (2019) guidance on conducting systematic literature reviews in management research, the review uses explicit, reportable search and screening procedures rather than an unstructured narrative approach.

Search Strategy

The search combined three concept clusters using Boolean operators:

1. technology terms ("smart logistics," "logistics 4.0," "IoT," "Internet of Things," "blockchain," "artificial intelligence," "machine learning," "big data analytics," "automation," "robotics");
2. logistics and supply chain terms ("supply chain," "logistics," "warehouse," "distribution," "transportation," "inventory management," "cold chain," "order picking"); and
3. sector terms ("food," "beverage," "agri-food," "perishable"), combined with the Boolean structure (Technology terms) AND (Logistics/Supply Chain terms) AND (Sector terms).

The search was conducted in Scopus and Web of Science Core Collection on 15 January 2025, restricted to peer-reviewed journal articles published in English between 2007 and 2024, and supplemented by citation chasing in Google Scholar to identify additional relevant articles not returned by the two primary databases. Table 1 summarizes the search protocol.

Table 1: Search protocol: databases, search date, publication window, and Boolean search string.

Element	Detail
Databases searched	Scopus; Web of Science Core Collection (primary databases); Google Scholar (supplementary citation chasing only)
Search date	15 January 2025
Publication year filter	2007–2024
Boolean search string	("smart logistics" OR "logistics 4.0" OR IoT OR "Internet of Things" OR blockchain OR "artificial intelligence" OR "machine learning" OR "big data analytics" OR automation OR robotics) AND ("supply chain" OR logistics OR warehouse OR distribution OR transportation OR "inventory management" OR "cold chain" OR "order picking") AND (food OR beverage OR agri-food OR perishable)
Supplementary citation chasing	Reference lists and citing articles of key identified papers were screened in Google Scholar to capture additional eligible articles not indexed by the primary Boolean search

Inclusion and Exclusion Criteria

Articles were included if they:

1. were peer-reviewed journal articles published in English between 2007 and 2024;
2. addressed one or more smart logistics technologies as defined in Section 1;
3. examined applications within supply chain, logistics, or warehouse operations, with priority given to food, beverage, or agri-food contexts where available; and
4. offered findings, frameworks, or synthesized evidence relevant to operational efficiency, adoption, or implementation outcomes.

Articles were excluded if they were conference abstracts, editorials, book chapters, or dissertations; if they were duplicate publications of an already-included study; if they addressed a technology only in a purely technical or engineering sense without logistics or operational relevance; or if they lacked sufficient methodological detail to support data extraction. The search was conducted in Scopus and Web of Science Core Collection, and supplemented through citation chasing in Google Scholar, as detailed in Section 3.1.

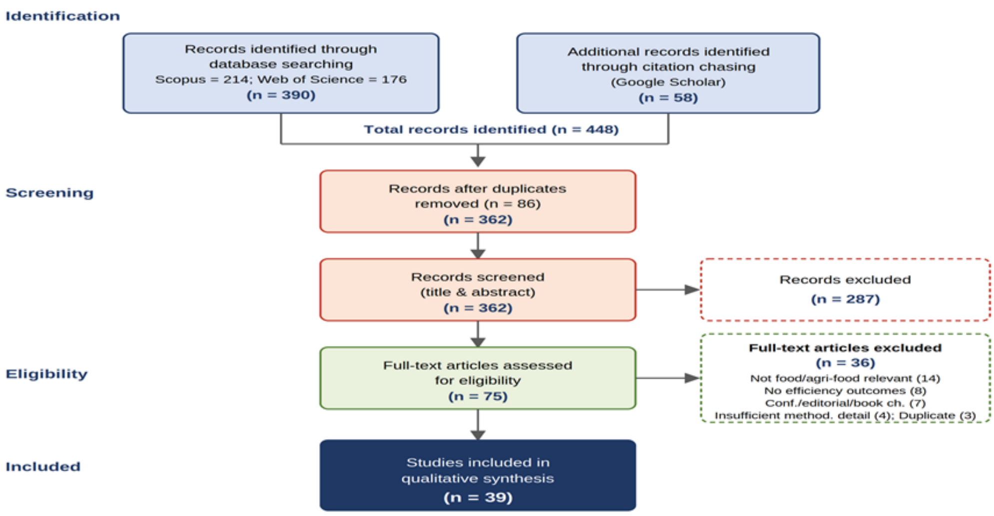

Figure 1: PRISMA 2020 flow diagram of the literature identification and screening process.

Data Extraction and Coding

For each included study, the following were extracted: author(s) and year, research design, technology category examined, sector or application context, and key reported findings relevant to operational efficiency. Extracted findings were coded into four technology categories (blockchain/traceability, IoT/monitoring, AI-ML/big-data analytics, warehouse automation/robotics) and, within each, by operational efficiency dimension (visibility and monitoring, traceability and food safety, forecasting and decision support, throughput and accuracy, and adoption/implementation factors). Coding was conducted by close reading of each article's stated contribution, findings, and (where the article was itself a review) its synthesized conclusions, rather than by re-analyzing any primary data, since this review synthesizes existing review and empirical literature rather than raw datasets.

Quality Considerations

Because included articles range from empirical investigations to systematic reviews of primary literature, quality was assessed qualitatively rather than through a single numeric scoring instrument: for empirical articles, attention was given to whether the research design, sample, and context were clearly reported; for review articles, attention was given to whether search and inclusion procedures were described with sufficient transparency to assess scope and rigor (e.g., Winkelhaus & Grosse, 2020; Toorajipour *et al.*, 2021). Each article was classified as High, Moderate, or Limited methodological transparency based on clarity of research purpose, method, data source, analytical procedure, and relevance to the review question; this classification is reported in the Quality column of Supplementary Table S1. Articles with Limited transparency were retained only where they contributed conceptual or framework-level insight not otherwise available in the sample, and this is noted explicitly where relevant in Section 4.

Data Extraction Table

Each included article was coded by author(s) and year, research design, technology category, application context, quality classification (High / Moderate / Limited methodological transparency, per Section 3.4), and its key contribution to the synthesis in Section 4. Of the 39 included articles, 9 concentrate on blockchain and traceability, 6 on IoT and cold-chain monitoring, 8 on AI, machine learning, and big-data analytics, 4 on warehouse automation and robotics, and 12 on cross-cutting digitalization and Industry 4.0 frameworks (Section 2). The full data extraction table is provided as

Supplementary Table S1 to keep the main manuscript within the journal's word limit.

Evidence Synthesis

This section synthesizes the reviewed literature by operational efficiency theme rather than summarizing each study individually, following the four technology clusters identified in Section 2. Because the underlying studies use varied methods, contexts, and metrics, the synthesis below emphasizes the direction and consistency of reported effects and the conditions under which the literature suggests those effects hold, rather than pooled quantitative estimates. Figure 2 previews the conceptual structure of this synthesis, linking each technology cluster to the operational efficiency dimension it is most consistently associated with in the reviewed literature.

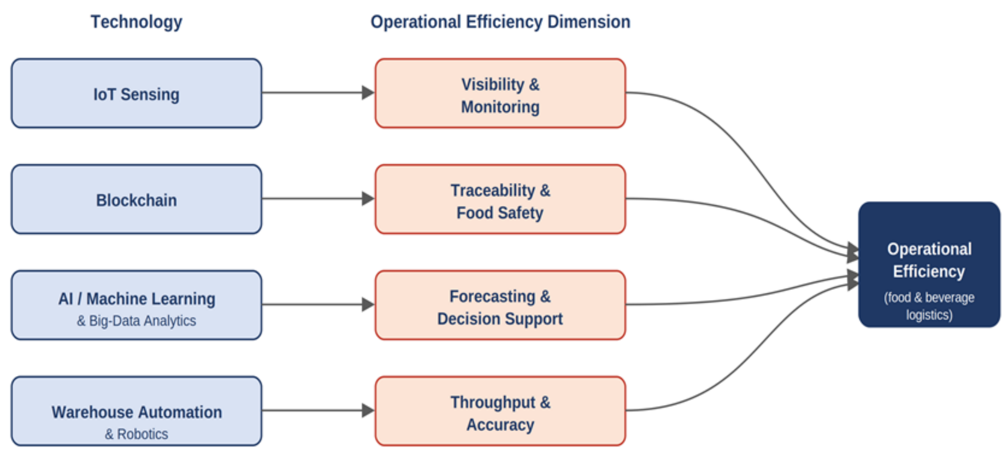

Figure 2: Conceptual framework linking smart logistics technologies to operational efficiency dimensions.

Visibility and Monitoring (IoT)

Across the IoT and cold-chain monitoring cluster, reviewed studies consistently associate sensor-based, real-time monitoring with improved visibility into product condition and location relative to periodic manual checks (Badia-Melis *et al.*, 2018; Tsang *et al.*, 2018). This pattern holds across general supply chain IoT reviews (Taj *et al.*, 2023) and food-specific traceability architectures (Mehannaoui *et al.*, 2023), and extends to machine-learning-based detection of cold-chain breaks, framed as a proactive alternative to threshold-based alerting (Loisel *et al.*, 2021). Reviewed work on IoT in halal supply chains illustrates that monitoring and provenance concerns are often intertwined rather than separate use cases (Rejeb *et al.*, 2021). The literature diverges on implementation depth: monitoring benefits materialize most clearly when sensor data is integrated into decision workflows rather than simply logged, and partial deployments deliver more limited operational benefit (Tsang *et al.*, 2018; Mehannaoui *et al.*, 2023).

Traceability and Food Safety (Blockchain)

The blockchain cluster is the largest in the reviewed sample and shows strong convergence on blockchain's technical capacity to support faster, more granular source identification during quality or safety events, compared with paper-based or siloed digital records (Kamilaris *et al.*, 2019; Casino *et al.*, 2019; Feng, 2020). Bibliometric and review evidence indicates this has become one of the most actively studied blockchain applications in food contexts (Pandey *et al.*, 2022; Nurgazina *et al.*, 2021), including food-safety and livestock-traceability contexts (Patel *et al.*, 2023). The literature diverges sharply between technical-capability studies, which emphasize what blockchain can do, and adoption-focused studies, which emphasize why it often is not done: Kouhizadeh *et al.* (2021) and Agi and Jha (2022) both identify coordinated participation across multiple, often reluctant, supply chain partners, together with integration cost and unclear near-term ROI, as persistent barriers even where traceability benefits are not in dispute. Galvez *et al.* (2018) similarly frame future adoption as contingent on resolving these implementation, rather than technical, challenges. This convergence-on-capability/divergence-on-adoption pattern is one of the clearest cross-cutting findings in the reviewed literature.

Forecasting and Decision Support (AI, Machine Learning, and Big-Data Analytics)

Reviewed studies on AI and machine learning in supply chain management report consistent application across demand forecasting, planning, and decision-support functions (Toorajipour *et al.*, 2021; Culot *et al.*, 2024), building on foundational work establishing AI's relevance to supply chain problems (Min, 2010) and machine-learning-based demand forecasting specifically (Carbonneau *et al.*, 2008). A closely related stream reframes the question from "which algorithm" to "which organizational capability": Bag *et al.* (2020), Arunachalam *et al.* (2018), Mikalef *et al.* (2020), and Wamba *et al.* (2020) collectively find that big-data analytics benefits depend heavily on organizational analytics capability rather than on data or algorithmic sophistication alone. This cluster suggests AI/analytics benefits in logistics are conditional:

the literature associates strong outcomes with firms that pair analytical tools with the organizational capacity to use them, and weaker outcomes where that capacity is absent.

Throughput and Accuracy (Warehouse Automation and Robotics)

The warehouse automation cluster documents substantial attention to autonomous mobile robots, automated storage and retrieval systems, and related technologies (Azadeh *et al.*, 2019), with e-commerce-driven demand identified as a key accelerant (Boysen *et al.*, 2019). Order-picking research frames automation benefits as inseparable from picking-system design choices (storage assignment, routing, and batching) rather than a property of the automation technology alone (de Koster *et al.*, 2007; van Gils *et al.*, 2018), suggesting reported productivity gains are contingent on integration with underlying warehouse process design.

Table 2 draws these four subsections together into a single comparison across technology clusters.

Table 2: Cross-technology comparison of operational bottlenecks, evidence patterns, and conditions for benefit realization.

Technology	Primary Operational Bottleneck Addressed	Consistent Finding Across Studies	Main Condition for Benefit Realization	Key Sources
IoT Sensing	Limited real-time visibility into product condition and location	Consistently associated with improved cold-chain visibility relative to periodic manual checks	Sensor data integrated into decision workflows, not merely logged	Badia-Melis *et al.* (2018); Tsang *et al.* (2018); Mehannaoui *et al.* (2023)
Blockchain	Slow, fragmented source identification during quality/safety events	Strong convergence on technical capacity for traceability; sharp divergence on adoption	Coordinated participation across supply chain partners	Kamilaris *et al.* (2019); Kouhizadeh *et al.* (2021); Agi & Jha (2022)
AI / Big-Data Analytics	Weak forecasting, planning, and decision quality	Benefits consistently reported as conditional on organizational capability, not algorithm choice	Data governance and dynamic capability to act on insights	Toorajipour *et al.* (2021); Mikalef *et al.* (2020); Wamba *et al.* (2020)
Warehouse Automation	Constrained physical throughput and picking accuracy	Gains reported as inseparable from underlying process design	Integration with storage assignment, routing, and batching design	Azadeh *et al.* (2019); de Koster *et al.* (2007); van Gils *et al.* (2018)

Cross-Cutting Implementation Themes

Several implementation themes recur across all four technology clusters rather than being specific to any one. First, adoption consistently depends on more than technical capability: this is explicit in the blockchain literature (Kouhizadeh *et al.*, 2021; Agi & Jha, 2022) and implicit in the analytics-capability literature (Arunachalam *et al.*, 2018; Mikalef *et al.*, 2020), and is echoed in integrative reviews of digitalization and Industry 4.0 adoption more broadly (Rad *et al.*, 2022; Deepu & Ravi, 2023; Perano *et al.*, 2023). Second, cross-technology, ecosystem-level framing is increasingly common in recent reviews (Winkelhaus & Grosse, 2020; Idrissi *et al.*, 2024), suggesting the field is moving away from single-technology evaluation toward integrated logistics-system thinking. Third, food- and agriculture-specific reviews (Lezoche *et al.*, 2020; Yadav *et al.*, 2022; Soledispa-Cañarte *et al.*, 2023; Abideen *et al.*, 2021; Gurrala & Hariga, 2022; Mustafa *et al.*, 2024) consistently note that perishability, regulatory compliance, and cold-chain requirements intensify both the potential benefits and the implementation complexity of smart logistics technologies relative to non-perishable goods contexts, a pattern directly relevant to the U.S. food and beverage context addressed in Section 5.

Relevance to the U.S. Food and Beverage Context

Although only a portion of the reviewed studies are set explicitly in the United States, several structural features of the U.S. food and beverage sector make the cross-cutting patterns identified in Section 4 particularly consequential there. U.S. food and beverage firms operate under FDA oversight and, since 2011, the Food Safety Modernization Act (FSMA), which places explicit emphasis on preventive controls and traceability records, conditions that align directly with the traceability and food-safety findings reported in the blockchain literature (Kamilaris *et al.*, 2019; Patel *et al.*, 2023). The scale and complexity of U.S. food distribution networks, spanning long-haul, multi-modal, and last-mile cold-chain segments, is consistent with the cold-chain monitoring and warehouse-automation literatures' emphasis on visibility and throughput across extended, multi-node networks (Badia-Melis *et al.*, 2018; Boysen *et al.*, 2019). Relatively high U.S. labor costs create automation incentives broadly consistent with the productivity and accuracy motivations documented in the warehouse-automation literature (Azadeh *et al.*, 2019; de Koster *et al.*, 2007), while comparatively advanced U.S. logistics infrastructure (transportation networks, connectivity, and third-party logistics capacity) plausibly lowers some of the integration barriers the analytics-capability literature associates with weaker outcomes (Arunachalam *et al.*, 2018; Mikalef *et al.*, 2020). Finally, rising U.S. consumer expectations around traceability and food safety mirror the adoption drivers identified in the blockchain and IoT literatures (Feng, 2020; Nurgazina *et al.*, 2021). Because few of the reviewed studies test these mechanisms in U.S. samples specifically, these are presented as plausible extensions of the general findings rather than as U.S.-specific empirical conclusions; a limitation discussed further in Section 9.

Discussion

The synthesis in Section 4 suggests that smart logistics technologies do not produce operational efficiency uniformly; rather, each technology cluster shows a consistent pattern of benefit contingent on a specific organizational or structural condition. Why might this be so? A plausible explanation is that each technology addresses a different bottleneck: visibility (IoT), trust and verification (blockchain), decision quality (AI/analytics), and physical throughput (automation); and that the constraint limiting benefit realization sits precisely where the reviewed literature says implementation most often fails: partner coordination for blockchain, analytics capability for AI, and process-design integration for automation (Kouhizadeh *et al.*, 2021; Mikalef *et al.*, 2020; van Gils *et al.*, 2018). This reframes "implementation success" not as a generic project-management competency but as a technology-specific capability that firms must build deliberately. Table 3 summarizes this bottleneck-condition-consequence logic across the four technology clusters.

Why does implementation success differ across organizations reviewing similar technologies? The analytics-capability literature offers the clearest answer available in this sample: Mikalef *et al.* (2020) and Wamba *et al.* (2020) both frame benefit realization as mediated by dynamic capabilities: the organization's ability to reconfigure processes and routines around new data and tools; rather than by the technology's inherent features. This is consistent with, and helps explain, the blockchain adoption-barrier literature's emphasis on inter-organizational coordination capability rather than technical readiness (Agi & Jha, 2022), and with recent Industry 4.0 and digitalization reviews that frame organizational readiness as central to whether digital investments translate into performance (Rad *et al.*, 2022; Deepu & Ravi, 2023).

Table 3: Technology-specific bottlenecks, conditions for benefit realization, and consequences of partial implementation.

Technology	Bottleneck It Addresses	Condition Required for Benefit	Consequence If Absent
IoT Sensing	Limited real-time visibility into product condition and location	Sensor data integrated into decision workflows (alerts, replenishment)	Data logged but unused; limited operational benefit
Blockchain	Slow, unreliable source identification during safety events	Coordinated participation across supply chain partners; governance	Partial adoption; benefits undermined by non-participating partners
AI / Big-Data Analytics	Weak forecasting and planning decision quality	Organizational analytics capability and dynamic capability to act on data	Tools deployed without capability; benefits unrealized
Warehouse Automation	Constrained physical throughput and picking accuracy	Process-design integration (storage assignment, routing, batching)	Automation added onto poor process design; gains fall short

These findings extend, more than they contradict, prior operations and supply chain theory. The dynamic-capabilities perspective evident in the analytics literature (Mikalef *et al.*, 2020; Wamba *et al.*, 2020) is consistent with earlier resource-based and capability-based views of technology-enabled performance, while the recurring finding that benefits depend on process-design integration (de Koster *et al.*, 2007; van Gils *et al.*, 2018) echoes long-standing operations management emphasis on fit between technology and process rather than technology adoption alone. Compared with prior integrative reviews such as Winkelhaus and Grosse (2020), which propose a unifying Logistics 4.0 framework spanning triggers, technologies, human factors, and tasks, this review's contribution is narrower in technology scope but more specific in operational efficiency framing, and it extends that integrative perspective specifically toward the perishability, regulatory, and cold-chain conditions characteristic of food and beverage logistics (Lezoche *et al.*, 2020; Mustafa *et al.*, 2024).

Limitations

- The review synthesizes existing published studies rather than analyzing new primary data; where those studies report quantitative findings, this review reports them qualitatively (directionally and comparatively) rather than restating specific figures out of their original methodological context.
- A substantial share of the included literature addresses supply chain management, agriculture, or logistics broadly rather than U.S. food and beverage firms

specifically; Section 5's discussion of U.S. relevance is therefore an interpretive extension rather than a direct empirical finding.

- Although a transparent search protocol was employed across Scopus and Web of Science with supplementary citation chasing through Google Scholar, relevant articles indexed only in other databases may have been missed. Restricting the review to English-language, peer-reviewed journal articles may also have excluded valuable evidence from grey literature and non-English publications.
- Because included studies range from single empirical investigations to broad systematic reviews, direct comparison of "findings" across studies necessarily involves some loss of methodological nuance; Section 3.4 describes how quality differences were handled qualitatively rather than through a single numeric instrument.
- The technology landscape continues to evolve quickly; several of the included studies are more than five years old relative to the review's writing, and newer applications (e.g., generative AI, advanced robotics) are underrepresented in the sample.

Practical Implications

The following implications are organized around the managerial decisions the reviewed literature is most directly relevant to, rather than as generic recommendations. Table 4 summarizes these decisions before each is discussed in turn.

Technology Investment Prioritization

Because the reviewed evidence associates each technology cluster with a distinct operational bottleneck (Section 6), firms should prioritize technologies based on which bottleneck is most binding for them, rather than pursuing a fixed adoption sequence: visibility gaps point toward IoT monitoring investment; recurring traceability or recall exposure points toward blockchain, contingent on securing partner participation; forecasting or planning weaknesses point toward AI/analytics investment, contingent on building analytics capability first; and picking or throughput constraints point toward automation, contingent on process-design readiness (Bag *et al.*, 2020; Kouhizadeh *et al.*, 2021; van Gils *et al.*, 2018).

Table 4: Decision-prioritization matrix for practitioners.

Managerial Decision	Trigger Condition	Recommended Action	Prerequisite
Technology Investment Prioritization	Visibility, traceability, forecasting, or throughput gap identified	Match technology choice to the specific bottleneck it addresses (Section 6)	Clear diagnosis of which bottleneck is most binding
Phased Implementation Strategies	New technology under consideration	Sequence organizational/inter-organizational readiness alongside deployment	Readiness assessment completed before rollout
Organizational Capability Development	Analytics or data-driven tools being adopted	Budget for data governance, cross-functional integration, and analytical skills	Executive buy-in for capability investment, not just tool purchase
Workforce Readiness	Automation or process redesign planned	Plan retraining and role redesign alongside technology deployment	Workforce transition plan developed pre-deployment
Technology Integration Planning	Any single smart logistics technology evaluated	Assess connections to adjacent systems (ERP, WMS, sensors, analytics)	Systems architecture review completed
Supply Chain Collaboration	Blockchain or traceability investment considered	Treat partner engagement and governance design as a prerequisite	Commitment from key supply chain partners secured

Phased Implementation Strategies

Across technology clusters, the reviewed literature associates unsuccessful implementations with deploying technology ahead of the organizational or inter-organizational capability needed to use it; for example, blockchain systems deployed before partner coordination is secured, or analytics tools deployed before data governance and cross-functional integration are in place (Agi & Jha, 2022; Arunachalam *et al.*, 2018). This suggests firms should sequence investment in organizational readiness alongside, or ahead of, technology deployment rather than treating readiness-building as a parallel or secondary workstream.

Organizational Capability Development

The analytics-capability literature indicates that data governance, cross-functional integration, and the dynamic capability to reconfigure processes around new information are more predictive of benefit realization than the sophistication of the underlying tool (Mikalef *et al.*, 2020; Wamba *et al.*, 2020). Firms should therefore budget for capability-building (data infrastructure, cross-functional teams, analytical skill development) as a core part of technology investment rather than an ancillary cost.

Workforce Readiness

Warehouse automation research frames productivity gains as inseparable from process redesign (de Koster *et al.*, 2007; van Gils *et al.*, 2018), which typically requires retraining and role redesign for affected staff. Firms should plan workforce transition alongside technology deployment rather than treating it as a downstream implementation detail.

Technology Integration Planning

Recent integrative reviews suggest the field is moving toward viewing these technologies as components of a connected ecosystem rather than standalone tools (Winkelhaus & Grosse, 2020; Idrissi *et al.*, 2024). Firms evaluating any single technology should also assess how it will connect to adjacent systems (e.g., IoT sensor data feeding AI forecasting, or blockchain records integrating with existing ERP/WMS platforms) rather than evaluating technologies purely in isolation.

Supply Chain Collaboration

Because blockchain and traceability benefits specifically depend on multi-party participation (Kouhizadeh *et al.*, 2021; Agi & Jha, 2022), firms considering these investments should treat supply chain partner engagement and governance design as a prerequisite workstream, not a downstream rollout task.

Future Research

- U.S.-specific empirical studies: most reviewed studies are not set explicitly in U.S. food and beverage firms; empirical research testing whether the cross-cutting patterns identified here (Section 4) hold under U.S. regulatory and market conditions specifically would strengthen the evidence base substantially.
- Longitudinal research: most reviewed studies examine relatively short post-implementation windows; research tracking technology benefits and organizational capability development over multiple years would clarify whether reported gains persist.
- Comparative research across firm size: the reviewed literature is weighted toward large-enterprise and general supply chain contexts; research examining how resource constraints affect technology selection and benefit realization among small and medium-sized food and beverage firms specifically would support more inclusive practitioner guidance.
- Cross-technology integration studies: given the shift toward ecosystem-level framing in recent reviews (Winkelhaus & Grosse, 2020; Idrissi *et al.*, 2024), empirical research directly comparing integrated multi-technology deployments against single-technology deployments would help quantify the synergy this review's synthesis suggests but cannot itself measure.
- Sustainability outcomes: few reviewed studies directly measure environmental or food-waste outcomes; research linking smart logistics adoption to measured sustainability metrics, rather than operational efficiency alone, would extend this review's scope usefully.
- Workforce impact studies: the reviewed literature treats workforce implications largely as an implementation barrier rather than a primary research question; dedicated research on skill development, job redesign, and workforce outcomes of smart logistics adoption would fill a clear gap.

CONCLUSION

This review synthesized 39 peer-reviewed articles on four smart logistics technologies IoT sensing, blockchain, AI and big-data analytics, and warehouse automation and their contribution to operational efficiency in food and beverage supply chains. The evidence links IoT with visibility and monitoring, blockchain with traceability and food safety, AI and analytics with forecasting and decision support, and automation with throughput and accuracy. Across all four, however, technology alone does not guarantee efficiency gains; successful implementation depends on complementary capabilities, including partner coordination, analytics maturity, and process-design integration.

The review consolidates fragmented technology-specific research into a food and beverage logistics perspective and provides practical guidance for technology prioritization. Managers should therefore align technology investment with the capabilities needed to realize its benefits for example, coordinating partners before blockchain adoption, developing analytics capabilities before AI deployment, and redesigning processes alongside automation.

Finally, this review is not a U.S.-only empirical study. Most evidence comes from broader supply-chain, agri-food, and international contexts, meaning the discussion of U.S. relevance is an interpretation rather than direct evidence from U.S. food and beverage firms. Future research should therefore prioritize U.S.-specific empirical studies to validate these findings.

Conflict of Interest Statement

The author(s) declare no conflict of interest.

Data Availability Statement

No primary dataset was generated for this study. The review is based on published literature cited in the manuscript.

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