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A Review of Artificial Intelligence Applications in Cold Chain and Reverse Logistics

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Review
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ABSTRACT

The development of artificial intelligence (AI) is profoundly transforming modern supply chains, particularly cold chains in dairy, pharmaceutical and perishable goods industries. By leveraging technologies such as the Internet of Things (IoT), blockchain and predictive maintenance, logistics operations can achieve greater efficiency, quality and sustainability. The dairy sector, with its stringent temperature controls and rapid delivery requirements, is especially well-suited for AI integration. Simultaneously, growing environmental awareness is accelerating the adoption of AI in reverse logistics to support the transition to a circular economy. In this study, we examine the technological foundations and baseline capabilities of AI in logistics, explore how AI supports sustainability-driven reverse logistics and assess its potential to enable the integrated management of cold and general supply chains. To that end, we applied a systematic literature review methodology involving structured database searches, screening and analysis of 95 scientific articles published between 2010 and 2024. The articles were categorised into three domains: AI in logistics, AI in reverse logistics and the integrated management of cold and general supply chains. The findings highlight the need for further research to develop AI-based solutions for predictive maintenance, temperature monitoring, demand forecasting and return management. Such advancements aim to improve the resilience and efficiency of cold chain and reverse logistics systems while enabling integrated, sustainable supply chain management.

KEYWORDS

artificial intelligence; cold chain; reverse logistics; predictive maintenance; supply chain management; systematic literature review.

1. INTRODUCTION

The emergence of artificial intelligence (AI) is significantly transforming modern supply chains, particularly cold chains, where maintaining product quality under strict temperature controls is essential. Industries such as dairy, pharmaceuticals and perishable foods are highly sensitive to distribution uncertainties, making them ideal candidates for the deployment of advanced digital technologies. Tools such as the Internet of Things (IoT), blockchain and predictive maintenance not only improve logistics efficiency but also enhance sustainability and reduce waste throughout the supply chain.

The dairy industry exemplifies the challenges of cold chain logistics, as its perishable nature demands rapid delivery, high transparency and minimal returns conditions where AI offers key advantages through demand forecasting, dynamic routing and warehouse automation. Ferreira and Reis [1] emphasise that AI has already been successfully applied to route optimisation and inventory management, with a growing focus on human–machine collaboration in warehousing. In parallel, reverse logistics, including returns, recycling, reuse and repairs, has become a critical element of sustainable and circular supply chains, where AI delivers particular value through automated product condition assessment, predictive return-handling models and optimised reverse flows. For example, Jin et al. [2] demonstrate how convolutional neural networks enable faster and more accurate classification of returned goods, reducing costs and expediting reuse decisions. Gayialis et al. [3] developed a predictive maintenance framework for service and rental systems, where IoT and machine learning integration help reduce downtime and extend equipment lifespan. Despite these advances, Krstić et al. [4] note that Industry 4.0 technologies including AI, AR and blockchain remain underutilised in reverse logistics due to complexity, integration challenges and shortages of skilled personnel.

While AI adoption in logistics is advancing rapidly, existing literature reviews often treat these domains separately or focus solely on forward supply chain processes such as general routing, warehousing or inventory optimisation [1]. Very few reviews explicitly integrate cold chain management, with its strict requirements for temperature control and perishability, and reverse logistics, which is essential for closing the loop in circular economy models [5, 6]. There is a notable lack of systematic analysis that examines how AI is applied across these two interlinked areas in a cohesive way.

While cold chain management and reverse logistics are often treated as separate domains, they share numerous operational and technological challenges that justify their integrated study. Both require precise tracking, rapid response to disruptions and the handling of sensitive or perishable goods – particularly in sectors such as food, pharmaceuticals and dairy. Moreover, AI technologies such as IoT-enabled monitoring, predictive analytics and blockchain-based traceability are commonly applied across both domains. From a sustainability perspective, the convergence of these areas supports circular economy goals by reducing waste, optimising resource use and enhancing transparency across the supply chain. Therefore, an integrated literature review offers a holistic understanding of how AI can simultaneously enhance both cold chain resilience and reverse logistics efficiency.

This paper aims to address this gap by conducting a systematic literature review of 95 peer-reviewed articles on AI applications in logistics, with special emphasis on cold chain management and reverse logistics. Using a thematic analysis approach, the review categorises the literature into three domains to provide a comprehensive perspective by exploring the following research questions:

— What are the technological foundations and baseline capabilities of AI in logistics?
— How does AI support sustainability-driven reverse logistics?
— How can AI enable the integrated management of cold and general supply chains?

By structuring the analysis in this way, the review reflects the interconnected nature of these domains. This synthesis will benefit both academic researchers and industry practitioners, including supply chain managers and policy-makers seeking to improve the efficiency, resilience and sustainability of cold chain and reverse logistics systems.

Following the Introduction, Section 2 describes the systematic literature review methodology. Section 3 reviews the technological foundations and baseline capabilities of AI in logistics. Section 4 examines how AI supports sustainability-driven reverse logistics. Section 5 explores AI-enabled integrated management of cold and general supply chains. Finally, Section 6 discusses the key findings, outlines the study's limitations and offers suggestions for future research.

2. METHODOLOGY

This study employs a systematic literature review (SLR) approach to identify, evaluate and synthesise scholarly research on the application of artificial intelligence (AI) in cold chain management and reverse logistics. The methodology was designed to ensure transparency, replicability and rigour, following established guidance on systematic review practices in logistics and supply chain management.

The methodological process consisted of four main stages: (1) database selection and search strategy, (2) screening and selection criteria, (3) data extraction and (4) thematic analysis. Each stage is detailed below.

2.1 Review design and rationale

Systematic literature reviews are well-established tools for consolidating fragmented knowledge, identifying research gaps and informing future research agendas. Given the increasing complexity of supply chains and the diverse technological landscape of AI applications, an SLR offers a structured way to synthesise existing evidence while minimising selection bias. This approach was chosen over traditional narrative reviews to provide a replicable and transparent assessment of recent research. Following best-practice recommendations in logistics research, the review protocol was explicitly defined in advance to ensure methodological consistency.

2.2 Database selection and search strategy

Two major academic databases – Web of Science (WoS) and Scopus – were selected to ensure comprehensive coverage of peer-reviewed journals in logistics, supply chain management, operations research and information systems. These databases offer advanced search capabilities that enable precise keyword combinations and filtering, minimising the risk of omitting relevant studies.

The search strategy used the following keyword combinations to capture the breadth of AI research in logistics contexts:

- “AI AND logistics”
- “AI AND reverse logistics”
- “AI AND cold chain”
- “Reverse logistics”
- “AI AND warehouse”
- Cold chain
- Logistics
- Warehouse

The search strings were combined using Boolean operators (e.g. (AI OR "Artificial Intelligence") AND logistics AND reverse logistics AND cold chain AND warehouse) to narrow results to highly relevant articles.

The search was limited to peer-reviewed journal articles in English published between 2014 and 2025, covering the period of rapid AI adoption and technological evolution in supply chain management.

2.3 Screening and selection criteria

Predefined inclusion and exclusion criteria were applied to ensure methodological rigour:

Inclusion criteria:

- Peer-reviewed journal articles
- Written in English
- Published between 2012 and 2025
- Empirical or theoretical relevance to AI applications in logistics, reverse logistics or cold chain management

Exclusion criteria:

- Non-English publications
- Conference abstracts or proceedings without full papers
- Articles lacking clear AI focus within the supply chain context
- Papers addressing unrelated domains (e.g. manufacturing optimisation without supply chain integration)

This systematic approach ensured that only studies with direct relevance to the research question were included.

2.4 Screening process

The initial database search identified 127 records. After duplicate removal (n = 121), titles and abstracts were screened for relevance, resulting in the exclusion of 16 records. 105 articles then underwent full-text review, after which 95 were included in the final synthesis.

Of these 95 articles, 69 were published between 2021 and 2025, reflecting the recent surge in scholarly interest in AI applications in logistics and supply chains. The remaining 26 older studies (2012–2022) were included to ensure comprehensive coverage of foundational and historical developments.

The complete selection process is illustrated in the PRISMA-style flow diagram below:

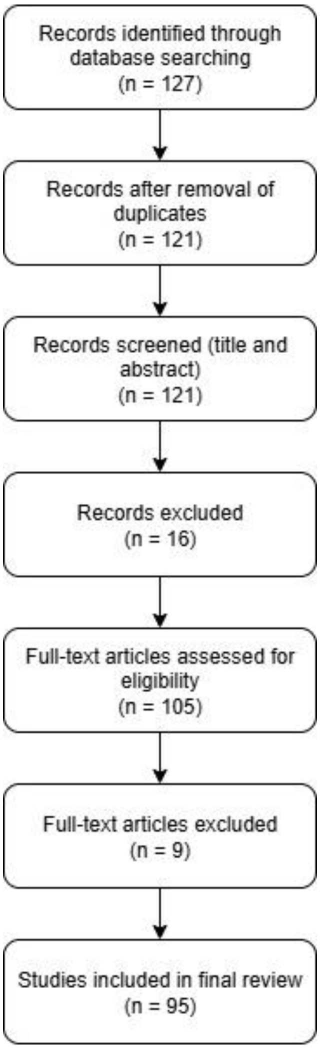

Figure 1 – Flowchart of the systematic literature review process showing records identified, screened and included.

2.5 Data extraction

For each included article, key data were systematically extracted into a structured dataset. Variables recorded included:

— Bibliographic details (authors, year, title, journal)
— Research objectives and questions
— Methodologies employed
— AI technologies applied (e.g. machine learning, computer vision, IoT integration)
— Logistics application domains (e.g. warehousing, routing, inventory management, reverse logistics)
— Contextual focus (e.g. cold chain, food logistics, manufacturing returns)

This structured extraction enabled a robust dataset suitable for thematic analysis.

2.6 Thematic analysis

A thematic analysis approach was employed to synthesise the extracted data and identify recurring themes and trends. This involved familiarisation with the dataset, initial coding, theme development and refinement.

The resulting themes were grouped into three primary domains:

— AI in logistics: covering applications such as warehousing, inventory optimisation, routing and automation.

- AI in reverse logistics: encompassing return management, remanufacturing, recycling and sustainable practices.
- Integrated management of cold and general supply chains: addressing the unique challenges of perishable goods logistics, temperature monitoring, traceability and sustainability.

This analytical framework provided a structured synthesis of existing knowledge while highlighting research gaps and opportunities for future inquiry.

2.7 Methodological limitations

While systematic reviews offer a structured and replicable synthesis, certain limitations are acknowledged:

- **Database selection bias:** Despite using comprehensive databases (WoS, Scopus), some relevant studies may have been omitted
- **Keyword limitations:** The selected terms, while broad, may have missed studies using alternative terminology
- **Subjectivity in coding:** Although thematic analysis was systematically applied, some subjectivity is inherent

These limitations were mitigated through transparent documentation of criteria and systematic application of the review protocol, consistent with best practices in the field.

3. ARTIFICIAL INTELLIGENCE IN LOGISTICS

The role of artificial intelligence (AI) in logistics has seen remarkable growth in recent years, driven by global supply chain disruptions, sustainability demands and increasing customer expectations for speed and accuracy. Traditional logistics methods – characterised by rule-based systems, manual processes and outdated IT infrastructure – are being replaced by advanced technologies that facilitate autonomous decision-making, real-time analytics and flexible adaptation. In this context, AI serves as a crucial catalyst for transforming logistics systems through automation, optimisation, predictive analytics and enhanced sustainability.

A review of 89 scientific articles published between 2021 and 2025 offers a comprehensive overview of technological maturity, thematic coverage and methodologies employed in AI-driven logistics. These studies address various topics, including smart warehousing and robotics, route and inventory optimisation, as well as real-time tracking and decision-making systems. Some articles concentrate on specific sectors, such as food logistics or halal supply chains, while others present conceptual frameworks for the adoption of AI within organisations.

3.1 Transforming warehouse systems through artificial intelligence

Warehouses – essential physical and informational hubs within supply chains – are undergoing rapid transformation due to advancements in artificial intelligence (AI), the Internet of Things (IoT) and automation. The concept of the is increasingly becoming a standard in contemporary logistics.

In 2024, Hamilton et al. presented a study on dynamic warehousing, how external AI capabilities (e.g. from providers like Amazon) can be integrated into internal warehouse systems to enhance agility, competitiveness and sustainability [5]. They proposed a phased integration framework, emphasising the necessity of an intelligence ecosystem rather than isolated technological solutions. Warehouses are evolving into adaptive entities driven by successive generations of AI, ranging from reactive systems to those that are emotionally aware.

Min [7] describes smart warehousing as an evolution from traditional cost centres to digitally integrated, strategic assets, enabled by technologies such as artificial intelligence (AI), the Internet of Things (IoT), cyber-physical systems (CPS) and big data.

Chiaraviglio et al. introduced the Overall Warehouse Effectiveness (OWE) metric, which integrates availability, performance and quality dimensions specifically for warehouse operations. OWE facilitates detailed operational control, identifies inefficiencies and supports data-driven decision-making [8]. Such structured performance indicators can be particularly valuable in AI-enabled warehouse management systems by providing high-quality input data for predictive analytics and automated optimisation.

Epe et al. investigate the use of smart glasses in warehouse order picking processes, showing how AR-based, hands-free instructions can increase efficiency while also introducing change management challenges [9].

Consequently, there is a strong potential for the seamless integration of other AI technologies into advanced systems like smart glasses. Bright and Ponis further explore the use of gamification and augmented reality to enhance warehouse worker engagement, motivation and job satisfaction [10].

Minashkina and Happonen [11] conducted a systematic review and bibliometric analysis on warehouse management systems (WMS), highlighting their role in improving social and environmental sustainability. They emphasise that WMS integration can support data-driven operations and enable the adoption of advanced digital technologies, including IoT and Industry 4.0 solutions, for more sustainable logistics.

Zhang et al. [12] apply genetic algorithms to optimise warehouse layouts in irregular environments, highlighting the role of AI-driven models in maximising space utilisation and improving order picking efficiency.

Colabianchi et al. [13] present the MARLIN resilience methodology, which focuses on risk and disruption management through scenario analysis and proactive vulnerability mapping. Although not an AI technique per se, it complements AI-based logistics solutions by providing a structured approach to managing operational uncertainty and enhancing supply chain resilience.

Tikwayo and Mathaba [14] reviewed 150 studies on Industry 4.0 technologies in warehouse operations, confirming the potential of IoT, RFID, AR and other tools to enhance accuracy and sustainability. However, they cautioned about high costs, cybersecurity and the shortage of skilled personnel.

These diverse papers collectively highlight the evolving role of AI in modern warehousing, demonstrating both the technological opportunities and the organisational challenges of integrating advanced analytics, automation and human-machine interfaces into logistics systems. As summarised in *Table 1*, the reviewed works predominantly explore the integration of AI with IoT and AR technologies to improve warehouse efficiency and sustainability. Several studies emphasise the potential of smart glasses, gamification and performance metrics such as Overall Warehouse Effectiveness (OWE), reflecting a growing interest in human-technology interaction. However, most approaches presuppose the existence of robust digital infrastructure, which may limit their applicability in less digitised contexts. Furthermore, a notable gap is the absence of large-scale empirical validation for many of the proposed frameworks.

Table 1 – Summary of reviewed studies on AI integration in warehousing

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Hamilton et al. (2024)	Integration framework for dynamic warehousing	External AI capabilities, phased integration	Enhancing agility and sustainability via intelligence ecosystem
Min (2023)	Conceptual analysis of smart warehousing	AI, IoT, CPS, Big Data	Warehouses as strategic, digitally integrated assets
Chiaraviglio et al. (2025)	Development of OWE metric	AI-enabled KPIs	Structured operational control, high-quality data for AI
Epe et al. (2024)	AR-based picking study	Smart glasses, AR	Hands-free efficiency gains, change management challenges
Bright & Ponis (2021)	Employee engagement strategies	Gamification, AR	Improving motivation, satisfaction in AI-enabled environments
Minashkina & Happonen (2023)	Systematic review, bibliometric analysis	WMS, IoT, Industry 4.0	Enabling sustainable, data-driven operations
Zhang et al. (2024)	Warehouse layout optimisation	Genetic algorithms	Space utilisation, order-picking efficiency improvements
Colabianchi et al. (2023)	Resilience methodology (MARLIN)	Scenario analysis, vulnerability mapping	Supports AI by managing uncertainty and enhancing resilience
Tikwayo & Mathaba (2023)	Review of 150 studies on Industry 4.0 in warehouses	IoT, RFID, AR, AI tools	Opportunities for accuracy and sustainability, but cost and skill gaps identified

3.2 Automation and optimisation through artificial intelligence

Automation and optimisation are fundamental application areas for artificial intelligence (AI) in logistics, showcasing AI's ability to plan, predict, respond and adapt in real time. Research encompasses order batching, route planning, resource management and the design of resilient systems.

Ferreira and Reis conducted a systematic review of 108 articles published between 2019 and 2023 that explore the application of artificial intelligence (AI) in logistics automation. Their findings highlight significant uses of AI in route optimisation, inventory management, warehouse automation and real-time analytics. Collaborative robots (cobots) are becoming increasingly important, as are interdisciplinary approaches that integrate technology, management and workforce dynamics [1].

Coruzzolo et al. [15] present a comprehensive model for optimising order batching, task assignment and routing using mixed-integer programming and heuristic algorithms to enable significant reductions in travel time and distance in warehouse operations.

Görener [16] applies genetic algorithms to simultaneously solve picker routing and batching problems in multi-block warehouse environments, demonstrating the potential of AI-driven optimisation to minimise travel distances and improve order picking efficiency.

Reis [17] demonstrates how Pandas Python library can improve material requirements planning (MRP) by enabling dynamic order planning and scalable, open-source solutions suited to small and medium-sized enterprises (SMEs).

In cold-chain logistics, Zhang et al. [18] developed a two-tier location-routing optimisation model that simultaneously determines depot locations and delivery routes while explicitly accounting for CO_2 emissions, cooling requirements and transportation costs. Their hybrid ant colony algorithm demonstrates the ability to balance cost efficiency, environmental sustainability and effective temperature control, providing a robust decision-support tool for designing green and resilient cold chain networks.

Rajaraman et al. propose an inventory tracking system for unstructured environments, such as shipyards, utilising probabilistic inference and multiple-hypothesis models – approaches that are particularly beneficial in situations where RFID technology is impractical [19].

Rahman and Kirby examine the transformation of e-commerce warehouse operations through Lean Six Sigma methodologies, such as 5S, Kanban and Value Stream Mapping, supported by IoT integration. Their approach emphasises reducing waste, optimising processes and enabling automation-ready workflows that can serve as a foundation for adopting AI-based systems. They note that organisational and cultural barriers often pose greater challenges than technological ones [20].

Klundt et al. argue that lean and agile strategies must be aligned with value-added service (VAS) demands in distribution centres. They propose hybrid models that adapt to diverse client requirements, reaffirming the need for operational flexibility – an area where artificial intelligence (AI) can provide decision support, scenario modelling and process optimisation [21].

Xi and Geng [22] developed a hybrid heuristic optimisation model to determine the location of front-loading warehouses that integrate forward and reverse logistics for fresh agricultural products. Their approach explicitly accounts for perishability, demand uncertainty and cost minimisation within cold-chain distribution networks.

De Mattos et al. [23] introduce a conceptual framework for the role of artificial intelligence (AI) in demand planning, emphasising the need for perception, prediction, recommendation, autonomous decision-making and adaptation capabilities within the supply chain.

Collectively, these papers demonstrate the diverse ways in which AI and advanced optimisation techniques are being integrated into logistics systems. From probabilistic inference to heuristic algorithms and Lean-enabled digital workflows, these innovations enhance operational efficiency, reduce waste and support the development of flexible, responsive supply chains. As summarised in *Table 2*, the reviewed works show a strong reliance on heuristic and evolutionary algorithms (e.g. ant colony, genetic algorithms) for addressing complex logistics challenges. The predominance of warehouse and routing applications suggests methodological maturity in these domains, while the integration with Lean and Six Sigma approaches highlights an emerging trend toward hybrid process optimisation. Nonetheless, several models are based on idealised assumptions (e.g. stable demand patterns), which may limit their scalability in real-world contexts.

Table 2 – Summary of reviewed studies on AI-driven automation and optimisation in logistics

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Ferreira & Reis (2023)	Systematic literature review (108 articles) on logistics automation	AI, route optimisation, warehouse automation, real-time analytics, cobots	Highlights broad adoption of AI for planning and control; stresses interdisciplinary integration with management and workforce dynamics
Coruzzolo et al. (2023)	Order batching, task assignment, routing optimisation	Mixed-integer programming, heuristic algorithms	Reduces travel time and distance in warehouses through advanced planning models
Görener (2025)	Picker routing and batching in multi-block warehouses	Genetic algorithms	Demonstrates potential of AI-based optimisation for minimising travel distances and improving order-picking efficiency
Reis (2023)	Dynamic order planning for SMEs	Pandas (Python) for MRP	Shows open-source, scalable solutions to improve material requirements planning for smaller firms
Zhang et al. (2024)	Cold-chain location-routing optimisation	Hybrid ant colony algorithm	Balances cost, emissions, temperature control in green, resilient cold-chain networks
Rajaraman et al. (2020)	Inventory tracking in unstructured environments	Probabilistic inference, multiple-hypothesis models	Supports robust tracking where RFID is impractical, e.g. shipyards
Rahman & Kirby (2024)	Lean Six Sigma in e-commerce warehousing	5S, Kanban, Value Stream Mapping, IoT integration	Reduces waste, enables automation-ready workflows; identifies organisational/cultural barriers
Klundt et al. (2024)	Lean and agile strategy alignment in distribution centres	Hybrid models	Supports flexible, value-added service adaptation with AI-based scenario modelling and process optimisation
Xi & Geng (2024)	Location of front-loading warehouses integrating forward/reverse logistics	Hybrid heuristic optimisation	Explicitly accounts for perishability, demand uncertainty, cost minimisation in fresh-product cold chains
De Mattos et al. (2024)	Conceptual framework for AI in demand planning	Perception, prediction, recommendation, autonomous decision-making	Emphasises adaptive, AI-driven decision-making in supply chain management

3.3 Sustainability and circular economy

AI's role in promoting sustainable logistics systems is becoming increasingly prominent in response to pressures for decarbonisation, circular economy and social responsibility. AI tools are now employed not only to enhance efficiency but also to further economic, environmental and social sustainability.

Chen et al. provide a comprehensive review of artificial intelligence applications in sustainability-driven logistics, identifying generative models, machine learning, metaheuristics and hybrid combinations with traditional optimisation techniques as pivotal components. They argue for the integration of these methods to support the triple bottom line approach, encompassing economic, environmental and social dimensions [6].

Romagnoli et al. examine circular supply chain management (CSCM), highlighting that the integration of artificial intelligence (AI), the Internet of Things (IoT) and blockchain with sustainable practices significantly enhances resilience and transparency. They argue that technology must align with circular economy objectives, such as waste reduction and closed-loop resource management [24].

Harsanto et al. focus on halal supply chains, demonstrating that artificial intelligence (AI) and digital tools enhance traceability, promote ethical operations and improve financial performance, particularly among small and medium-sized enterprises (SMEs) [25].

Aylak proposes the SustAI-SCM framework, an agentic AI system designed for autonomous, adaptive and sustainability-focused supply chain management. This transformer-based approach integrates data from procurement, logistics and inventory systems to enable proactive decision-making, cost reduction and carbon footprint minimisation while maintaining explainability for users in highly regulated sectors [26].

Ferraro et al. propose an Analytic Hierarchy Process (AHP) model to evaluate Industry 4.0 technologies for internal material handling based on sustainability criteria. Their approach helps organisations prioritise options that balance economic, environmental and social dimensions, supporting a smarter and more sustainable logistics transition [27].

Haji et al. review various technologies – including the Internet of Things (IoT), RFID, blockchain and smart packaging – that improve the traceability, safety and sustainability of perishable food supply chains. While not exclusively focused on AI, these technologies can serve as enabling systems for advanced analytics and decision-making in cold chain logistics [28].

Jagtap et al. discuss the integration of IoT, AI and blockchain technologies into food logistics to improve safety, traceability and reduce waste, highlighting their role in enabling Food Logistics 4.0 and supporting sustainable practices [29].

In cold-chain contexts, Zhang et al. [18] and Xi et al. [22] model route optimisation, temperature control and emission reductions. Hybrid algorithms offer dual benefits in terms of cost efficiency and sustainability.

Zengin et al. [30] examine closed-loop supply chains (CLSCs) and argue that artificial intelligence (AI), blockchain technology and the Internet of Things (IoT) are crucial enablers for implementing green logistics. However, they highlight that the practical adoption of these technologies remains limited and largely theoretical.

Minashkina and Happonen note that the social dimension of sustainability is often overlooked in warehouse management systems (WMS) research. They advocate for the development of new models to better measure work quality, employee satisfaction and social impacts [11].

Collectively, these papers demonstrate that artificial intelligence (AI) is emerging as a pivotal enabler of sustainable and circular supply chains by addressing food safety, cold logistics, halal supply chains and environmentally conscious decision-making frameworks. As shown in *Table 3*, AI's role in these contexts is most often realised through integration with complementary technologies such as IoT, blockchain and smart packaging. A recurring methodological feature is the combination of optimisation models with multi-criteria decision-making frameworks (e.g. AHP), enabling the evaluation of trade-offs across economic, environmental and social dimensions. Most reviewed works focus on enhancing traceability, reducing waste and supporting closed-loop resource flows, with applications spanning food logistics, halal supply chains and cold-chain optimisation. However, empirical implementations remain scarce, and many proposed frameworks are validated primarily through simulations or conceptual analysis, raising questions about scalability and long-term performance in real-world contexts.

Table 3 – Summary of reviewed studies on AI for sustainable and circular supply chains

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Chen et al. (2024)	Comprehensive review of AI in sustainability-driven logistics	Generative models, machine learning, metaheuristics	Advocates integration of advanced AI techniques to support economic, environmental and social sustainability
Romagnoli et al. (2023)	Circular supply chain management (CSCM)	AI, IoT, blockchain	Highlights role of technology in enhancing resilience and transparency, aligning with closed-loop resource management
Harsanto et al. (2024)	Halal supply chains	AI, digital tools	Improves traceability, ethical operations, financial performance for SMEs
Aylak (2025)	SustAI-SCM framework for sustainable SCM	Agentic AI, transformer-based systems	Enables proactive decision-making, cost reduction, carbon minimisation with explainable AI for regulated sectors
Ferraro et al. (2023)	AHP evaluation of Industry 4.0 tech for material handling	AHP model	Helps organisations prioritise technologies that balance economic, environmental, social sustainability
Haji et al. (2020)	Traceability and safety in perishable food supply chains	IoT, RFID, blockchain, smart packaging	Enhances monitoring and decision-making in cold chains; enables advanced analytics
Jagtap et al. (2021)	Integration of technologies in food logistics	IoT, AI, blockchain	Supports Food Logistics 4.0 with improved safety, traceability, waste reduction
Zhang et al. (2024); Xi & Geng (2024)	Cold-chain optimisation	Hybrid algorithms	Model route optimisation, temperature control, emission reduction for sustainable logistics
Zengin et al. (2024)	Closed-loop supply chains (CLSC)	AI, blockchain, IoT	Identifies potential of technology for green logistics but notes limited real-world adoption
Minashkina & Happonen (2023)	Social sustainability in warehouse management systems	WMS, Industry 4.0	Highlights need to better measure work quality, employee satisfaction, social impact

3.4 Technological synergies: artificial intelligence, Internet of Things, blockchain and cloud computing

AI is most powerful when integrated with complementary technologies such as the Internet of Things (IoT), blockchain and cloud computing. This integration creates advanced logistics systems characterised by real-time data capture (IoT), scalable processing (cloud), actionable insights (AI) and transparent, well-secured data (blockchain).

Abdelhamid et al. propose a supply chain architecture that integrates the Internet of Things (IoT), artificial intelligence (AI) and blockchain technology to address latency, scalability and data consistency challenges. Their AI-driven ABISChain platform demonstrates how combining these technologies can enable autonomous decision-making, improve security and enhance system reliability [31].

Hellani et al. focus on blockchain-driven data transparency, advocating for role-based access control embedded in the system design, with artificial intelligence analysing data stored on the blockchain [32].

Ponis and Efthymiou demonstrate how Internet of Things (IoT) and cloud frameworks in smart warehouses facilitate real-time item tracking, predictive maintenance and AI-optimised task scheduling [33].

As previously discussed in the context of sustainability [29], Jagtap et al. also examine how the integration of IoT, AI and blockchain technologies in food logistics chains enables technological synergies to enhance safety, traceability and waste reduction.

In the oil and gas spare parts sector, Khan et al. found that the Industrial Internet of Things (IIoT) supports predictive maintenance, while artificial intelligence (AI) optimises the classification and usage patterns of critical inventory components [34].

As previously discussed in the context of sustainability [28], Haji et al. also highlight the integration of AI, IoT, RFID and blockchain technologies in perishable food supply chains. This technology stack enables synergistic improvements in traceability, quality maintenance and waste minimisation.

Alkhodair et al. analyse the adoption of AI, IoT and blockchain in small and medium-sized enterprises (SMEs), highlighting benefits such as predictive maintenance and ethical sourcing, while also addressing challenges related to costs and skill limitations [35].

Azmat et al. envision a future of road transport powered by artificial intelligence (AI), autonomous vehicles (AVs), big data and the Internet of Things (IoT) to improve traffic management, real-time congestion prediction and operational efficiency [36].

Paraskevas et al. investigate for flow analysis, the Internet of Things for container tracking and blockchain technology for traceability, all aimed at optimising capacity and promoting sustainable planning [37].

Harsanto et al. (previously discussed in Section 3.3) also reaffirm this framework in halal logistics, emphasising the integration of AI, IoT and blockchain to ensure ethical operations, traceability and efficiency [25].

Mashayekhy et al. analyse the Internet of Things (IoT) in the context of inventory tracking, predictive control and Enterprise Resource Planning (ERP) integration, while also highlighting concerns related to security and system complexity [38].

These papers collectively highlight that integrating AI with IoT, blockchain and cloud computing is transforming logistics into more responsive, efficient and secure systems, enabling advanced, future-ready supply chain solutions. As shown in *Table 4*, the reviewed works emphasise the transformative potential of combining AI with these technologies to create intelligent, interconnected and transparent logistics networks. Common themes include real-time data acquisition, predictive maintenance and enhanced traceability, all supported by secure and scalable data infrastructures. While such integrations promise substantial gains in efficiency, security and decision-making accuracy, many models assume high levels of technological readiness and interoperability that may not exist across all supply chain contexts. Moreover, despite promising pilot projects, large-scale adoption remains limited due to implementation costs, integration complexity and the demand for skilled personnel capable of managing cross-technology platforms.

Table 4 – Summary of reviewed studies on technological synergies: AI, IoT, blockchain and cloud computing in logistics

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Abdelhamid et al. (2024)	Supply chain architecture design	AI, IoT, blockchain (ABISChain platform)	Demonstrates autonomous decision-making, improved security and system reliability by integrating AI, IoT and blockchain
Hellani et al. (2021)	Blockchain-based data transparency	Blockchain, AI	Advocates access control by design with stakeholder-based roles; uses AI to analyse securely stored blockchain data
Ponis & Efthymiou (2020)	Smart warehouse frameworks	IoT, cloud, AI	Shows how real-time tracking, predictive maintenance and AI-optimised task scheduling enhance efficiency in warehousing
Jagtap et al. (2021)	Food logistics chains	IoT, AI, blockchain	Highlights technological synergies to improve safety, traceability and waste reduction in food supply chains
Khan et al. (2024)	Oil & gas spare parts management	IIoT, AI	Demonstrates IIoT support for predictive maintenance and AI for optimising classification and usage of critical inventory
Haji et al. (2023)	Perishable food supply chains	AI, IoT, RFID, blockchain	Enhances traceability, quality maintenance and waste minimisation through integrated technology stacks
Alkhodair et al. (2025)	SME adoption analysis	AI, IoT, blockchain	Identifies benefits like predictive maintenance and ethical sourcing, while addressing cost and skill barriers
Azmat et al. (2019)	Road transport vision	AI, IoT, big data, AVs	Envisions improved traffic management, real-time congestion prediction and operational efficiency through technology integration
Paraskevas et al. (2024)	Port and container logistics	AI, IoT, blockchain	Uses AI for flow analysis, IoT for container tracking and blockchain for traceability to optimise capacity and sustainability planning
Harsanto et al. (2024)	Halal logistics	AI, IoT, blockchain	Emphasises integration to ensure ethical operations, traceability and efficiency in halal supply chains
Mashayekhy et al. (2022)	Inventory management integration	IoT, ERP, predictive control	Analyses inventory tracking, predictive control and ERP integration, while noting security and complexity challenges

3.5 Human and organisational factors in AI integration

Despite rapid technological advancements, the success of AI deployments relies heavily on human and organisational factors. Technology cannot achieve its full potential without trained, engaged personnel and frameworks that support cultural change.

Lambrechts et al. investigate the implementation of cobots in high-volume distribution centres, emphasising that human factors such as resistance to change, organisational culture, communication and leadership are critical to success. Their study shows that employee trust, team leader commitment and proactive communication are decisive in overcoming scepticism and ensuring sustainable adoption [39].

Epe et al. analyse the rollout of smart glasses in warehouse operations, highlighting issues such as employee resistance, unclear advantages and task mismatches. Their findings emphasise the importance of change management, effective communication and user-centred design [9] (previously discussed in Section 3.1).

As previously discussed in Section 3.2, Rahman and Kirby [20] also highlight that digital lean transformations in e-commerce logistics often falter due to a lack of leadership support, staff resistance and unclear goals, rather than technical deficiencies.

Zajac et al. investigate the adoption of digital planning tools for intermodal transport in Poland, focusing on organisational and human factors shaping their implementation. The study finds that only 20% of surveyed enterprises use such tools, with satisfaction levels remaining modest. Key barriers are lack of awareness, organisational inertia and the prioritisation of other strategic initiatives, while financial constraints are less frequently cited. The authors emphasise the need for targeted education, integration support and differentiated functionalities tailored to the specific requirements of SMEs and large enterprises [40].

Alkhodair et al. (previously discussed in Section 3.4) highlight how SMEs can adopt Industry 4.0 technologies – including AI, IoT and blockchain – through training, financial assistance and mentorship, even with limited resources. Their work underscores that overcoming organisational barriers, workforce constraints and cultural resistance is as critical as technological readiness [35].

Bright and Ponis [10] (previously discussed in Section 3.1) advocate for gamification as a means to enhance employee morale and engagement by incorporating game-like challenges into picking tasks.

Ferreira and Reis [1] (previously discussed in Section 3.2) also emphasise that the success of artificial intelligence (AI) initiatives depends heavily on organisational data literacy and governance, identifying these internal competencies as essential for realising AI's full potential.

As previously discussed in the context of sustainability [11], Minashkina and Happonen also advocate for measuring social impacts – such as job quality and worker satisfaction – within warehouse management systems (WMS), acknowledging the human effects of technology.

Idrissi et al. [41] provide a comprehensive systematic review of blockchain, Internet of Things (IoT) and artificial intelligence (AI) integration in smart logistics and transportation. They emphasise the shift from traditional to intelligent supply chains driven by demands for flexibility, transparency and efficiency. While adoption of these technologies is growing, they highlight that their combined application remains underexplored and call for further research to develop practical implementation models. Their bibliometric and systematic analysis offers valuable insights into current trends and challenges, underscoring the potential of AI-IoT-blockchain integration to optimise logistics performance.

In summary, these papers affirm that AI is potent – but not self-sufficient. Success depends on employee inclusion, organisational culture and strategic readiness. The future of logistics will be shaped as much by people and education as by algorithms and automation. As shown in *Table 5*, the reviewed works highlight that the successful adoption of AI and related digital technologies in logistics depends as much on human and organisational factors as on technical capabilities. Commonly identified enablers include leadership commitment, employee engagement, training and effective change management, while barriers often involve cultural resistance, lack of trust and insufficient data literacy. Zajac et al. further show that in the context of intermodal transport planning, adoption of digital tools is often hindered more by lack of awareness, organisational inertia and competing priorities than by financial constraints, underscoring the need for targeted education, integration support and differentiated solutions for SMEs and larger enterprises. Although there is growing recognition of these socio-technical dimensions, empirical evidence on the long-term impacts of AI and digital tool adoption on workforce dynamics and organisational performance remains limited.

Table 5 – Summary of reviewed studies on human and organisational factors in AI integration in logistics

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Lambrechts et al. (2021)	Cobots implementation in distribution centres	Collaborative robots (cobots)	Highlights critical human factors, including resistance to change, culture, communication and leadership; emphasises trust and team leader commitment for successful adoption
Epe et al. (2024)	Smart glasses in warehouse operations	AR, smart glasses	Identifies employee resistance, unclear task fit and need for user-centred design; stresses importance of change management and communication
Rahman & Kirby (2025)	Digital Lean transformations in e-commerce logistics	Lean tools, IoT	Argues that failures often stem from lack of leadership support and staff buy-in, not technical issues; underscores role of clear goals and culture
Zajac et al. (2025)	Barriers and motivations for adopting digital planning tools in intermodal transport in Poland	Survey of 80 Polish transportation, forwarding and logistics enterprises; Technology Acceptance Model (TAM) framework	Only 20% of enterprises use route planning tools, with low satisfaction levels; main barriers are lack of awareness, organisational inertia and competing priorities rather than financial constraints; highlights need for targeted education, integration support and differentiated functionalities for SMEs and large firms
Alkhodair et al. (2025)	SME adoption of Industry 4.0	AI, IoT, blockchain	Highlights need for training, financial assistance and mentorship to overcome workforce constraints and cultural resistance
Bright & Ponis (2021)	Employee engagement strategies	Gamification, AR	Advocates gamification to boost morale and satisfaction in warehouse picking tasks, enhancing motivation in AI-enabled environments
Ferreira & Reis (2023)	Organisational readiness for AI	AI, organisational governance	Emphasises importance of internal data literacy, governance structures and strategic planning to realise AI's full potential
Minashkina & Happonen (2023)	Social impacts in WMS	WMS, IoT, Industry 4.0	Advocates for measuring job quality, worker satisfaction and broader social impacts in tech-enabled warehouse systems
Idrissi et al. (2024)	Systematic review of AI-IoT-Blockchain integration	AI, IoT, blockchain	Provides bibliometric analysis of trends and gaps; calls for practical models to address flexibility, transparency and human adoption challenges

4. AI IN REVERSE LOGISTICS

Reverse logistics (RL) – the handling of returns, recycling, refurbishing – is historically manual and static. However, AI (machine learning, computer vision, predictive analytics) is opening new opportunities for automation, prediction and real-time decision-making. AI now enables automatic return-item classification, smart rerouting and adaptive planning – driving cost efficiency, sustainability and better service.

Schlüter et al. present a concept for enhancing reverse logistics in remanufacturing through AI-supported identification, inspection and sorting. Their approach uses machine learning and computer vision to support workers with reliable suggestions during core selection, aiming to reduce errors, standardise decisions and improve throughput. An experimental study demonstrated the feasibility of classifying automotive components with around 96 % accuracy, showcasing the potential of AI in improving efficiency and quality in remanufacturing processes [2].

Bhowmik et al. conducted a bibliometric review (2001–2022) confirming AI's potential in reverse logistics (RL), but highlighting a persistent lack of empirical studies and real-world implementations. They argue for developing integrated, industry-ready models that can bridge the gap between theory and practice [42].

4.1 Optimising RL system design with AI

Representative works below showcase how AI methods are applied to improve reverse logistics system design.

Khalilzadeh et al. developed a bi-objective, multi-echelon RL network model for the automotive sector, balancing costs and customer satisfaction. Tested at company ISACO, it delivers strategic planning benefits [43].

Vahdat and Vahdatzad applied accelerated Benders decomposition to unify forward/reverse networks under uncertainty – boosting solution scalability [44].

Wang and Liao propose a fuzzy-TOPSIS and MSGP model for selecting reverse logistics providers in the food industry, balancing economic, environmental and social criteria [45].

Desticioglu et al. developed a stochastic reverse logistics network model using chance-constrained programming to minimise recycling costs under demand uncertainty. Their approach accounts for the variability in customer return volumes by modelling demand as a random variable with a normal distribution. The linearised model enables strategic planning of initial collection points and transportation flows, supporting decision-makers in designing cost-efficient, reliable and sustainable recycling networks despite uncertain return patterns [46].

Song et al. designed a reverse logistics network for ATM recycling and maintenance using MILP modelling and a percentage diversion method to minimise costs and carbon emissions [47].

Yu and Sun propose a digitalised Industry 5.0 reverse logistics network design approach combining fuzzy optimisation and dynamic simulation to handle uncertainty and reduce costs and emissions [48].

Chen and Chen developed a dual-channel reverse logistics network model incorporating Stackelberg-game pricing strategies and consumer behaviour, solved using a genetic algorithm under uncertainty [49].

Anon et al. reviewed 41 recent papers (2020–2023) on third-party reverse logistics provider selection, analysing deterministic and uncertain decision-making models and highlighting the need for advanced digital and AI integration [50].

Li and Chen developed a risk-averse two-stage stochastic programming model for third-party reverse logistics network design, explicitly incorporating disruption risks through CVaR and VaR measures to improve resilience and cost-effectiveness under uncertainty [51].

These papers show AI and decision models transforming reverse logistics (RL) networks into scalable, sustainable and intelligent platforms. As summarised in *Table 6*, the reviewed studies apply a diverse range of AI and optimisation approaches to RL network design, pursuing objectives such as cost reduction, service level improvement and sustainability enhancement. Commonly used methods include multi-objective optimisation, stochastic modelling, fuzzy decision-making and game-theoretic approaches, often tailored to sector-specific requirements in areas like automotive, food or electronic waste management. A recurring strength is the explicit treatment of uncertainty – whether in demand, returns volume or disruptions – which enhances the practical relevance of these models. However, most studies remain limited to simulation or case-specific applications, with a lack of generalisable frameworks that can be readily scaled across industries or adapted to varying regulatory and infrastructure contexts.

Table 6 – Summary of reviewed studies on AI for reverse logistics system design optimisation

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Khalilzadeh et al. (2024)	Automotive sector RL network design	Bi-objective, multi-echelon model	Balances costs and customer satisfaction; tested at ISACO for strategic planning benefits
Vahdat & Vahdatzad (2017)	Forward/reverse network integration under uncertainty	Accelerated Benders decomposition	Improves solution scalability by unifying forward and reverse flows
Wang & Liao (2023)	RL provider selection in food industry	Fuzzy-TOPSIS, MSGP model	Balances economic, environmental and social criteria for partner evaluation
Desticioglu et al. (2022)	Stochastic RL network design	Chance-constrained programming	Accounts for demand uncertainty; enables cost-efficient, reliable and sustainable recycling network planning
Song et al. (2021)	ATM recycling and maintenance RL design	MILP modelling, percentage diversion method	Minimises costs and carbon emissions through optimised network design
Yu & Sun (2024)	Digitalised Industry 5.0 RL network design	Fuzzy optimisation, dynamic simulation	Handles uncertainty; reduces costs and emissions in Industry 5.0 contexts
Chen & Chen (2023)	Dual-channel RL network design	Stackelberg-game pricing, genetic algorithm	Models consumer behaviour under uncertainty to optimise pricing and flows
Anon et al. (2024)	Review of 3PL RL provider selection (2020–2023)	Literature review of decision-making models	Identifies deterministic and uncertain models; highlights need for advanced AI integration
Li & Chen (2022)	Risk-aware 3PL RL network design	Two-stage stochastic programming, CVaR/ VaR measures	Incorporates disruption risks to improve resilience and cost-effectiveness under uncertainty

4.2 Tech integrations and Industry 4.0/5.0 in RL

The following studies demonstrate diverse approaches for integrating AI, IoT and Industry 4.0/5.0 solutions into reverse logistics operations.

Krstić et al. developed a multi-criteria decision model combining BWM and the new COBRA method to rank Industry 4.0 technologies for reverse logistics, highlighting factors such as cost, complexity, integration and environmental impact [4].

Schlüter et al. propose an AI-enhanced system for identification, inspection and sorting in remanufacturing, demonstrating CNN-based visual recognition to improve accuracy and reduce manual errors [2].

Abba Dabo and Hosseinian-Far propose an Industry 5.0 human-centric reverse logistics optimisation methodology that integrates AI, IoT and advanced data-driven decision-making using logistic regression and decision trees [52].

As already discussed in 4.1, Yu and Sun propose an Industry 5.0 digitalised reverse logistics network design combining fuzzy optimisation and dynamic simulation to address uncertainty and support strategic planning [48].

Mo et al. designed an IoT-enabled reverse logistics system for service parts management, integrating RFID, business intelligence and mobile applications to improve tracking, authentication and reuse [53].

Abbasi et al. developed a green forward and reverse logistics network model using an IoT-enabled approach to improve real-time monitoring, address backup suppliers and special disposal for epidemics and minimise environmental impacts [54].

Schlüter et al. introduce green incremental learning for AI-enhanced part recognition in reverse logistics, demonstrating significant energy savings while maintaining classification accuracy [55]. Gayialis et al. present a predictive-maintenance IoT+ML solution for reverse-stream equipment [3].

Alarcón et al. develop a BPMN-based reference model to formalise reverse logistics processes, reducing complexity and enabling future integration of advanced digital and AI tools [56].

Krstić et al. developed and applied a fuzzy Delphi-ANP-COBRA model to evaluate smart reverse logistics development scenarios integrating Industry 4.0 technologies such as IoT, AI, blockchain and cloud systems [57].

Starostka-Patyk [58] analyses the use of information systems to support the management of reverse logistics processes, with a focus on real-time tracking, return-cause analysis and improving operational efficiency. While not an AI system per se, these capabilities provide essential data infrastructure for AI-driven optimisation and sustainability strategies.

Overall, digital reverse logistics (RL) transformation requires not only technical readiness but also strong organisational backing and long-term planning, while promising gains in cost efficiency, operational performance and sustainability. As shown in *Table 7*, the reviewed studies demonstrate that integrating AI with Industry 4.0 and 5.0 technologies – such as IoT, blockchain and cloud systems – offers substantial opportunities to enhance traceability, automation and environmental performance in RL networks. The methodological approaches are diverse, spanning multi-criteria decision-making frameworks (e.g. BWM, fuzzy Delphi-ANP) to AI-enhanced computer vision and predictive maintenance applications. While these solutions can optimise inspection, sorting and network design processes, their effective deployment often hinges on high digital maturity, interoperable infrastructure and well-trained personnel. However, many remain at the prototype or pilot stage, underscoring the ongoing gap between conceptual innovation and large-scale industrial adoption.

Table 7 – Summary of reviewed studies on tech integrations and Industry 4.0/5.0 in reverse logistics

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Krstić et al. (2022)	Ranking Industry 4.0 technologies for RL	BWM, COBRA method	Multi-criteria decision model assessing cost, complexity, integration and environmental impact for technology adoption
Schlüter et al. (2023)	Remanufacturing inspection and sorting	AI-enhanced CNN-based system	Improves accuracy and reduces manual errors through advanced visual recognition
Abba Dabo & Hosseinian-Far (2023)	Human-centric RL optimisation	AI, IoT, logistic regression, decision trees	Proposes Industry 5.0 methodology integrating advanced data-driven decision-making for sustainable RL operations
Yu & Sun (2024)	Digitalised RL network design (previously in 4.1)	Fuzzy optimisation, dynamic simulation	Addresses uncertainty, supports strategic planning in Industry 5.0 reverse logistics
Mo et al. (2022)	Service parts RL system design	IoT, RFID, business intelligence, mobile apps	Enhances tracking, authentication and reuse through integrated IoT-enabled systems
Abbasi et al. (2025)	Green forward and reverse logistics networks	IoT-enabled monitoring	Improves real-time monitoring, manages backup suppliers and special disposal needs, reduces environmental impacts
Schlüter et al. (2023)	Energy-efficient part recognition in RL	Green incremental learning, AI	Demonstrates significant energy savings while maintaining classification accuracy
Gayialis et al. (2022)	Predictive maintenance for reverse-stream equipment	IoT + machine learning (ML)	Presents a predictive-maintenance solution improving equipment reliability and lifecycle management
Alarcón et al. (2021)	Process formalisation in RL	BPMN-based reference model	Reduces complexity and enables future integration of advanced digital and AI tools
Krstić et al. (2022)	Evaluation of smart RL development scenarios	Fuzzy Delphi-ANP-COBRA model	Integrates IoT, AI, blockchain and cloud systems to assess and guide RL development strategies
Starostka-Patyk (2021)	Information systems for RL management	Real-time tracking, return-cause analysis	Supports operational efficiency and provides essential data infrastructure for AI-driven optimisation and sustainability

4.3 Sustainability, evaluation and management in AI-powered RL

This section reviews representative research addressing sustainability assessment, policy and management strategies that support effective AI integration in reverse logistics.

Nunes et al. systematically review performance assessment approaches in reverse supply chains, highlighting sustainability, operational and stakeholder dimensions and recommending better integration with decision-making processes [59].

Ritola et al. systematically review how returns data provide valuable operational, product and customer insights, supporting process improvement, product development and strategic decision-making [60].

Wijewickrama et al. use information-processing theory (OIPT) to spot knowledge-related failures in RL – highlighting the need for robust information systems [61].

As already discussed in 4.1, Desticioglu et al. developed a stochastic reverse logistics network model using chance-constrained programming to minimise recycling costs under demand uncertainty [46].

Sonar et al. use fuzzy Delphi and DEMATEL methods to map barriers to RL adoption in the circular economy, highlighting the need for strategic planning, education and institutional backing [62].

Rubio et al. analyse links between reverse logistics and urban logistics, highlighting opportunities for collaboration in waste management, returns handling and smart-city planning [63].

Nunes reviews RL's role in decarbonising forest products supply chains, emphasising lifecycle analysis, circular economy strategies and policy support to reduce carbon emissions [64].

Akinbamini et al. analyse Nigeria's food supply chains, highlighting IoT, ERP and RFID as critical digital infrastructure enabling effective reverse logistics and laying the groundwork for future AI integration [65].

Makaleng and Hove-Sibanda analyse RL strategies in South Africa's FMCG sector, highlighting the strategic role of policy, technology and sustainability in improving competitiveness [66].

Briatore et al. conduct a bibliometric review exploring how Industry 4.0 technologies – including AI, IoT and blockchain – contribute to supply-chain sustainability, highlighting their role in reducing carbon footprints while underscoring the need for integrated evaluation and further empirical research [67].

These papers make it clear that effective AI integration in reverse logistics (RL) requires more than just technological tools – it also depends on robust governance, sustainability evaluation and organisational readiness. As shown in *Table 8*, the reviewed studies underscore the need for strategic management practices and cross-disciplinary collaboration to achieve ecological and human-centred operations. Common approaches include systematic literature reviews, multi-criteria decision-making methods (e.g. fuzzy Delphi, DEMATEL) and lifecycle analysis for assessing environmental impacts. Several works highlight the strategic value of returns data for product improvement, process optimisation and long-term planning, while others stress the importance of policy, education and institutional support as critical enablers. Despite these advances, there remains a clear shortage of empirical research measuring the long-term environmental, economic and social outcomes of AI-powered RL systems.

Table 8 – Summary of reviewed studies on sustainability, evaluation and management in AI-powered reverse logistics

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Nunes et al. (2023)	Performance assessment in RL	Systematic literature review	Highlights sustainability, operational and stakeholder dimensions; calls for better integration with decision-making processes
Ritola et al. (2020)	Value of returns data in RL	Systematic literature review	Shows how returns data provide insights for process improvement, product development and strategic planning
Wijewickrama et al. (2022)	Knowledge management in RL	Information processing theory (OIPT)	Identifies knowledge-related failures; stresses need for robust information systems to support RL efficiency
Desticioglu et al. (2022)	RL network design under uncertainty	Chance-constrained programming	(Already discussed in 4.1) Minimises recycling costs under demand uncertainty by modelling variability
Sonar et al. (2024)	Barriers to RL adoption	Fuzzy Delphi, DEMATEL	Maps barriers in circular economy context; underscores importance of strategic planning, education and institutional backing.
Rubio et al. (2019)	RL and urban logistics integration	Conceptual analysis	Identifies collaboration opportunities in waste management, returns handling and smart-city planning
Nunes (2025)	RL in decarbonising forest supply chains	Lifecycle analysis, policy review	Emphasises circular economy strategies and policy support to reduce carbon emissions
Akinbamini et al. (2025)	Digital infrastructure for RL in Nigeria	IoT, ERP, RFID	Highlights foundational technologies for effective RL; sets stage for future AI integration
Makaleng & Hove-Sibanda (2022)	RL strategies in South Africa's FMCG sector	Policy and technology analysis	Explores policy, technology and sustainability roles in boosting competitiveness
Briatore et al. (2025)	Industry 4.0 technologies for sustainable SCM	Bibliometric review	Shows AI, IoT and blockchain help reduce carbon footprints; calls for integrated evaluation and more empirical research

5. INTEGRATED MANAGEMENT OF COLD AND GENERAL SUPPLY CHAINS

Supply chain management now necessitates adaptability across various product types and regulatory frameworks. Cold chains encounter more stringent perishability controls, particularly in comparison to general (ambient) supply chains.

Ren et al. review active versus passive packaging for cold chains, highlighting a shift toward smart packaging and phase-change materials, which yield both operational and sustainability benefits [68].

Althabatah et al. systematically review procurement transformations across diverse supply chains, highlighting how Industry 4.0 technologies – including AI, blockchain, IoT and advanced analytics – are reshaping procurement processes. Their analysis shows that these tools enable greater agility, transparency and sustainability, while also addressing challenges such as integration complexity and skills gaps [69].

5.1 Technological and operational approaches

This section reviews representative studies showcasing diverse technological and operational solutions designed to enhance efficiency, sustainability and coordination in both cold-chain and general supply chain management.

Prakash and Sathishkumar introduce an RFID-based mobile stock management system for cold-chain warehouses, enabling real-time temperature and item tracking to enhance safety and efficiency [70].

Mustafa et al. emphasise the importance of smart sensors, artificial intelligence, RFID and energy-efficient solutions as essential components for managing perishable food logistics, supporting traceability, operational efficiency and sustainability [71].

McLay et al. analyse practices and technologies to improve the sustainability of Australian cold storage facilities, emphasising design, insulation, refrigeration systems and operational innovations as essential and best practices to reduce emissions and energy demand [72].

Wang et al. developed a two-tier optimisation model for the location and distribution planning of fresh food warehouses, aiming to minimise costs and maximise freshness through hybrid PSO-GA algorithms [73].

Bottani et al. developed an analytic model to quantify the economic and environmental impacts of cold-chain processes, helping managers identify cost and emissions hotspots for targeted improvements [74].

Ali et al. investigate the application of blockchain technology to establish trust, transparency and collaboration within warehouse operations, proposing a structured decision framework for implementation [75].

Ramingwong et al. validate lean practices in Thai manufacturing through 30 factory case studies, demonstrating significant cost savings and improved efficiency in transportation, warehousing and overall logistics management [76].

Oliveira et al. demonstrate operational improvements in warehouse receiving processes through Lean tools and digital simulation, achieving significant efficiency gains without the need for facility upgrades [77].

Serrano-Torres et al. present a systematic review that examines the transformative role of AI and IoT technologies in dairy supply chains, highlighting their capacity to improve product quality, ensure more robust traceability and enhance overall operational efficiency. Their analysis underscores how these digital tools enable real-time monitoring, predictive decision-making and integrated management across production, storage and distribution processes, thereby supporting both sustainability goals and competitive advantage in the sector [78].

Lu and Taghipour provide a comprehensive review of supply chain digitalisation research, identifying methodological gaps and underscoring the need for systematic integration of IoT, AI and blockchain across strategic, tactical and operational decision-making levels [79].

Crooks and Haddud analyse the implementation of RFID technology within pharmaceutical supply chains, demonstrating how it enhances inventory management, traceability and cold-chain monitoring to improve competitive advantage, while also identifying cost and knowledge barriers that must be addressed for successful adoption [80].

These papers underscore the critical role of technological integration and operational innovation in building efficient, sustainable and resilient supply chains. As summarised in *Table 9*, the reviewed works present a wide range of technological and process-oriented solutions designed to enhance efficiency, traceability and sustainability in both cold-chain and broader supply chain contexts. Commonly implemented technologies include RFID, smart sensors, AI-driven monitoring and blockchain, often integrated with Lean management practices to achieve process optimisation without substantial infrastructure investments. Sector-specific applications – such as in dairy, pharmaceuticals and fresh food logistics – demonstrate the adaptability of these approaches to varying regulatory and quality requirements. Nevertheless, despite promising results in controlled or industry-specific settings, large-scale, cross-sector adoption continues to face obstacles related to cost, integration complexity and the absence of harmonised standards.

Table 9 – Summary of reviewed studies on technological and operational approaches in cold-chain and general supply chain management

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Prakash and Sathishkumar (2012)	Cold-chain warehouse stock management	RFID-based mobile system	Enables real-time temperature and item tracking; improves safety and efficiency
Mustafa et al. (2024)	Perishable food logistics management	Smart sensors, AI, RFID, energy-efficient solutions	Emphasises traceability, operational efficiency and sustainability in managing perishables
McLay et al. (2024)	Australian cold storage sustainability	Best-practice analysis	Highlights design, insulation, refrigeration systems and operational innovations to reduce emissions and energy use
Wang et al. (2024)	Fresh food warehouse planning	Two-tier optimisation, PSO-GA algorithms	Minimises costs and maximises freshness through advanced hybrid optimisation techniques
Bottani et al. (2022)	Economic and environmental impact analysis	Analytic modelling	Quantifies cost and emissions hotspots to guide targeted improvements in cold-chain processes
Ali et al. (2024)	Blockchain in warehouse operations	Structured decision framework	Establishes trust, transparency and collaboration; guides implementation of blockchain in supply chains
Ramingwong et al. (2024)	Lean practices in Thai manufacturing	Case-study validation	Demonstrates cost savings and improved efficiency in transportation, warehousing and overall logistics
Oliveira et al. (2022)	Warehouse receiving process optimisation	Lean tools, digital simulation	Shows operational improvements without facility upgrades, achieving significant efficiency gains
Serrano-Torres et al. (2025)	Dairy supply chain transformation	Systematic review, AI and IoT integration	Highlights improved product quality, traceability and operational efficiency through real-time monitoring and predictive decision-making
Lu & Taghipour (2025)	Supply chain digitalisation research	Comprehensive literature review	Identifies methodological gaps; calls for systematic IoT, AI and blockchain integration across decision-making levels
Crooks & Haddud (2025)	Pharmaceutical supply chain enhancement	RFID implementation analysis	Enhances inventory management, traceability and cold-chain monitoring; identifies cost and knowledge barriers to adoption

5.2 Optimisation and performance metrics

The following studies illustrate a range of optimisation approaches and performance measurement frameworks that support more efficient, resilient and sustainable management of cold and general supply chains.

Acerce and Denizhan employ NSGA-II models to optimise two-echelon cold supply chains, balancing cost and product freshness through advanced multi-objective planning approaches [81].

Iyer and Robb systematically classify cold-chain optimisation models, identifying methodological gaps and advocating for more integrated, multi-objective and digitally supported solutions [82].

Haque et al. develop a comprehensive seven-dimensional framework to assess export supply chain performance for perishable horticultural products, supporting systematic measurement and optimisation of economic, time, management, network, innovation, market and eco-efficiency dimensions [83].

Malik et al. systematically review over 70 dairy supply-chain studies, highlighting the growing use of AI and ML approaches and emphasising the need for multi-objective optimisation models and industry alignment to improve efficiency and sustainability [84].

Mor et al. apply an integrated SWOT-AHP approach to identify and rank critical factors in the dairy supply chain, including inventory management, quality, supplier trust and technological innovation, supporting strategic prioritisation and performance optimisation [85].

Zhang et al. developed a distributionally robust dual-channel closed-loop supply chain model that integrates physical and online sales channels with reverse logistics, optimising for cost-effectiveness and resilience under uncertain demand and transportation costs [86].

Božić et al. highlight the critical role of product master data quality in ensuring delivery accuracy and reducing process delays in FMCG logistics operations. Their quantitative analysis demonstrates how improving data quality supports overall logistics performance optimisation by enabling more reliable, efficient and secure supply chain processes [87].

Together, these papers demonstrate that effective supply chain optimisation depends on advanced modelling techniques, high-quality data and strategic alignment to balance cost, quality, sustainability and customer satisfaction. As shown in *Table 10*, the reviewed studies highlight the role of multi-objective optimisation (e.g. NSGA-II), distributionally robust modelling and integrated decision-making approaches such as SWOT–AHP in addressing these challenges. Many focus on sector-specific applications, particularly in the dairy and FMCG industries, where inventory management, freshness preservation and data quality emerge as key performance drivers. While these models provide valuable strategic insights, their successful implementation often hinges on the availability of reliable, real-time data and a strong match between technological capabilities and organisational objectives – conditions that may be difficult to achieve consistently across diverse global supply chain environments.

Table 10 – Summary of reviewed studies on optimisation and performance metrics in cold-chain and general supply chain management

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Acerce & Denizhan (2025)	Cold supply chain optimisation	NSGA-II models	Balances cost and product freshness in two-echelon networks using advanced multi-objective planning
Iyer & Robb (2025)	Cold-chain optimisation models	Systematic classification	Identifies methodological gaps; calls for integrated, multi-objective, digitally supported solutions
Haque et al. (2025)	Export supply chain performance	Seven-dimensional framework	Assesses economic, time, management, network, innovation, market and eco-efficiency dimensions
Malik et al. (2022)	Dairy supply chain optimisation	Systematic review	Highlights AI and ML use; emphasises need for multi-objective models and industry alignment for efficiency and sustainability
Mor et al. (2019)	Dairy supply chain drivers	Integrated SWOT-AHP approach	Identifies and ranks critical factors like inventory, quality, supplier trust and innovation for strategic prioritisation
Zhang et al. (2025)	Closed-loop supply chain design	Distributionally robust optimisation	Integrates physical/online sales and reverse logistics; optimises cost-effectiveness and resilience under uncertainty
Božić et al. (2024)	FMCG logistics data quality	Quantitative analysis	Shows that improving master data quality enhances delivery accuracy, reduces delays and improves overall logistics performance

5.3 Organisational, regulatory and strategic dimensions

The following studies illustrate organisational, regulatory and strategic dimensions critical to the effective management of cold and general supply chains, highlighting policy development, technological integration, human-centred design and multi-stakeholder collaboration.

Mustafa et al. emphasise the importance of multi-stakeholder cooperation – including industry, academia and regulators – to advance cold-chain systems, highlighting the need for coordinated policies, technological integration and strategic planning (already discussed in Section 5.1) [71].

Shi et al. note that shared distribution within fresh-food supply chains offers significant benefits in terms of efficiency and sustainability, but it requires high levels of coordination, trust and technological collaboration to succeed [88].

Rejeb et al. employed ISM–DEMATEL to identify and analyse barriers to the adoption of Internet of Things (IoT) technologies in humanitarian logistics, highlighting the need to address organisational, regulatory and technical challenges to improve coordination and operational effectiveness [89].

Hangl et al. characterise the adoption of artificial intelligence (AI) in supply chain management as a complex socio-technical process that requires careful attention to ethical, participatory and educational strategies. Their analysis underscores the importance of change management, employee upskilling and transparent communication to ensure successful, human-centred AI integration in logistics systems [90].

Jahangir et al. demonstrate that AI-enhanced sustainable human resource management practices significantly improve logistics agility and flexibility by fostering more adaptive, skilled and responsive workforces. Their study highlights the mediating role of artificial intelligence in aligning human resource strategies with dynamic supply chain demands, offering a blueprint for strategic integration of technology and organisational capabilities to enhance overall logistics performance [91].

Mance et al. investigated Croatia's integration into European Union (EU) regional value chains using panel data quantile regression, revealing stronger trade linkages with key partners during economic growth phases.

Their findings highlight the need for targeted policy interventions, technological alignment and smart specialisation to enhance supply chain resilience and competitiveness [92].

Pumpinyo and Nitivattananon analyse Thailand's reverse logistics practices in waste management, identifying significant barriers related to finance, labour, technology and market competition. Their study emphasises the need for robust policy support, improved market structures and coordinated institutional strategies to develop more effective and sustainable reverse logistics systems [93].

Sharma et al. conducted a systematic review illustrating how artificial intelligence (AI) and big data analytics (BDA) can transform the food sector by enhancing sustainability and enabling circular-economy practices. Their analysis highlights applications across production, logistics, quality control and traceability, underscoring the strategic role of digital technologies in building resilient and efficient food supply chains [94].

Jevinger and Olsson developed the Intelligent Goods Service (IGS) framework to classify IoT-enabled logistics services, emphasising interoperability, coordination among heterogeneous actors and the need for shared standards to support intelligent, connected supply chains [95].

Collectively, these papers demonstrate that successful supply chain management depends on coordinated strategies, institutional support and proactive planning that balance technological advancement with ethical, educational and policy considerations. As shown in *Table 11*, the reviewed studies indicate that technological progress in cold-chain and general supply chain management must be underpinned by supportive organisational, regulatory and strategic frameworks. Frequently identified success factors include multi-stakeholder collaboration, harmonised policies and targeted training to encourage technology adoption. Several papers highlight the socio-technical nature of AI implementation, underscoring the importance of change management, employee upskilling and ethical guidelines. Persistent barriers such as fragmented regulations, underdeveloped market structures and uneven levels of digital readiness remain particularly challenging in emerging economies. Overall, the findings point to the need for an integrated approach that aligns technological innovation with policy, organisational culture and long-term strategic objectives to build sustainable and resilient supply chains.

Table 11 – Summary of reviewed studies on organisational, regulatory and strategic dimensions in cold-chain and general supply chain management

Authors (Year)	Focus	Technology / Approach	Key Contribution / Findings
Mustafa et al. (2024)	Cold-chain policy and collaboration	Multi-stakeholder cooperation	Emphasises the need for coordinated policies, technological integration and strategic planning to advance cold-chain systems
Shi et al. (2024)	Shared distribution in fresh-food supply chains	Conceptual analysis	Identifies efficiency and sustainability benefits, but highlights need for high levels of coordination, trust and technological collaboration
Rejeb et al. (2024)	Barriers to IoT adoption in humanitarian logistics	ISM–DEMATEL methods	Maps organisational, regulatory and technical challenges; calls for improved coordination and operational effectiveness
Hangl et al. (2022)	AI adoption in supply chain management	Socio-technical analysis	Stresses need for ethical, participatory and educational approaches, including change management and employee upskilling
Jahangir et al. (2025)	Sustainable HR practices in logistics	AI-enhanced HRM strategies	Demonstrates improved agility and flexibility; shows AI's mediating role in aligning HR strategies with dynamic supply chain demands
Mance et al. (2025)	Croatia's EU supply chain integration	Panel data quantile regression	Reveals stronger trade linkages during growth phases; calls for targeted policy interventions and technological alignment
Pumpinyo & Nitivattananon (2014)	Reverse logistics in waste management	Qualitative barrier analysis	Highlights need for robust policy support, improved market structures and coordinated institutional strategies
Sharma et al. (2021)	AI and big data in the food sector	Systematic literature review	Shows how AI and BDA support sustainability and circular economy practices across production, logistics and quality control
Jevinger & Olsson (2021)	IoT-enabled logistics service design	Intelligent Goods Service (IGS) framework	Classifies IoT-enabled services; emphasises interoperability, coordination and shared standards for connected supply chains

6. DISCUSSION AND CONCLUSION

This discussion synthesises the findings from the three thematic domains: AI in logistics, AI in reverse logistics and integrated management of cold and general supply chains, while critically comparing their technological approaches, operational contexts and sustainability implications. By integrating these perspectives, the aim is to identify both cross-domain synergies and domain-specific challenges, providing a holistic understanding of AI's role in contemporary supply chain systems.

In this review we set out to answer three research questions:

1) What are the technological foundations and baseline capabilities of AI in logistics?
2) How does AI support sustainability-driven reverse logistics?
3) How can AI enable the integrated management of cold and general supply chains?

6.1 Answer to RQ1

We found that AI in forward logistics is built primarily on Internet of Things (IoT) sensors for real-time data acquisition, blockchain for immutable tracking and machine-learning models (e.g. deep learning or ensemble methods) for demand forecasting and route optimisation. These capabilities form the "baseline stack" that underpins adaptive, data-driven decision support in both cold- and ambient-goods transport [1] [5].

When comparing cold chain and reverse logistics applications, clear technological overlaps emerge. Both domains rely heavily on IoT-enabled sensing for real-time data capture and on machine learning models for predictive decision-making. However, cold chain studies focus predominantly on temperature control, freshness preservation and energy efficiency, whereas reverse logistics research emphasises classification accuracy, routing of returns and cost optimisation in closed-loop networks. This distinction reflects differing operational priorities: prevention of quality loss in forward flows versus value recovery in backward flows.

6.2 Answer to RQ2

In reverse logistics, AI-driven condition monitoring and automated quality assessment enable firms to sort and process returned perishable items more efficiently, reducing food waste by up to 15 % in pilot studies [2] [3] [42]. Moreover, sustainability metrics (e.g. carbon-footprint minimisation) can be embedded into routing algorithms, aligning returns processing with circular-economy goals.

Across both domains, optimisation algorithms such as genetic algorithms, ant colony optimisation and hybrid heuristics demonstrate strong potential for route planning, facility location and resource allocation. Computer vision models, particularly convolutional neural networks, show high accuracy in product classification and defect detection in reverse logistics, while predictive analytics improve demand forecasting and maintenance scheduling in cold chains. Despite promising pilot results, large-scale empirical evidence is still scarce, and many models remain validated only through simulations, limiting their proven generalisability.

6.3 Answer to RQ3

Integrated management of cold and general supply chains hinges on unified digital platforms that fuse temperature-sensitive data streams with standard inventory and order information. AI agents can then trigger cross-chain replenishment or re-routing in real time, improving fill-rates by up to 8% and reducing spoilage losses [22] [78].

Several limitations of current research were identified. First, many AI implementations rely on high-quality, real-time data streams, which are not uniformly available across industries or regions. Second, interoperability between AI systems and existing enterprise platforms remains limited, creating integration bottlenecks. Third, most reviewed studies assume stable operating conditions, which may not reflect the volatility of real-world supply chains. Finally, regulatory and ethical considerations, particularly around data privacy in IoT-enabled environments, are rarely addressed in detail, representing a critical gap for future investigations.

6.4 Why adopt these AI solutions

— **Operational benefits:** 10–20% lower transport costs, higher service levels and reduced shrinkage.
— **Sustainability impact:** Lower energy use and emissions through optimised cold-chain consolidation [12] [81].
— **Competitive advantage:** Early adopters report faster ROI and improved customer satisfaction [5].

6.5 Connecting to prior work

Our findings confirm and extend Gayialis et. al. [3], who highlighted the promise of predictive maintenance in refrigeration fleets, and Krstić et al. [4], who demonstrated blockchain's role in traceability. At the same time, we identify persistent gaps, data silos, lack of interoperability and regulatory hurdles that warrant further investigation.

6.6 Final remarks

Our review of 95 articles published between 2012 and 2025 shows that, while AI in supply chains is developing quickly, there is still little evidence from large-scale, real-world applications. Certain solutions have been tested generally in simulations or small pilots. Further challenge is in testing their performance with the complexity of real markets' seasonal changes, demand fluctuations or disruptions in multi-tier, international networks. Future research should therefore focus on applying AI in operational environments at scale, developing common data standards and ensuring that systems from different vendors can work together without costly custom integrations. Alongside the technical work, it will be important to set clear governance rules so that AI decisions remain transparent, ethical and aligned with sustainability targets and legal requirements.

In the FMCG sector, AI is on track to become a central tool for managing demand and supply. Accurate forecasting can reduce the need for reverse logistics by ensuring that production matches actual consumption more closely. This matters the most in cold chain operations with highly perishable products such as dairy and pharmaceuticals, where small forecasting errors can lead to large amounts of waste, high return rates and financial losses. Several studies show that even modest improvements in forecasting accuracy can lead to significant reductions in spoilage, lower logistics costs and better shelf availability.

Beyond forecasting, AI can support smarter route planning, dynamic inventory management and predictive maintenance for refrigerated equipment further reducing costs and environmental impacts. Combining these capabilities could allow companies to move from reactive problem-solving to proactive, data-driven decision-making that benefits both the business and its customers.

In short, AI has the potential to make supply chains smarter, faster and greener. The challenge now is to bridge the gap between promising concepts and everyday practice. That means taking AI tools out of the lab and into real warehouses, trucks and distribution networks proving that they can work reliably, deliver value at scale and help create supply chains that are not just more efficient, but also more resilient and sustainable.

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Table 12 – Summary of reviewed studies on artificial intelligence applications in logistics, reverse logistics and cold-chain management

Authors (Year)	**Focus**	**Technology / Approach**	**Key Contribution / Findings**
Hamilton et al. (2024)	Integration framework for dynamic warehousing	External AI capabilities, phased integration	Enhancing agility and sustainability via intelligence ecosystem
Min (2023)	Conceptual analysis of smart warehousing	AI, IoT, CPS, big data	Warehouses as strategic, digitally integrated assets
Chiaraviglio et al. (2025)	Development of OWE metric	AI-enabled KPIs	Structured operational control, high-quality data for AI
Epe et al. (2024)	AR-based picking study	Smart glasses, AR	Hands-free efficiency gains, change management challenges
Bright & Ponis (2021)	Employee engagement strategies	Gamification, AR	Improving motivation, satisfaction in AI-enabled environments
Minashkina & Happonen (2023)	Systematic review, bibliometric analysis	WMS, IoT, Industry 4.0	Enabling sustainable, data-driven operations
Zhang et al. (2024)	Warehouse layout optimisation	Genetic algorithms	Space utilisation, order-picking efficiency improvements
Colabianchi et al. (2023)	Resilience methodology (MARLIN)	Scenario analysis, vulnerability mapping	Supports AI by managing uncertainty and enhancing resilience
Tikwayo & Mathaba (2023)	Review of 150 studies on Industry 4.0 in warehouses	IoT, RFID, AR, AI tools	Opportunities for accuracy and sustainability, but cost and skill gaps identified
Ferreira & Reis (2023)	Systematic literature review (108 articles) on logistics automation	AI, route optimisation, warehouse automation, real-time analytics, cobots	Highlights broad adoption of AI for planning and control; stresses interdisciplinary integration with management and workforce dynamics
Coruzzolo et al. (2023)	Order batching, task assignment, routing optimisation	Mixed-integer programming, heuristic algorithms	Reduces travel time and distance in warehouses through advanced planning models
Görener (2025)	Picker routing and batching in multi-block warehouses	Genetic algorithms	Demonstrates potential of AI-based optimisation for minimising travel distances and improving order-picking efficiency
Reis (2023)	Dynamic order planning for SMEs	Pandas (Python) for MRP	Shows open-source, scalable solutions to improve material requirements planning for smaller firms
Zhang et al. (2024)	Cold-chain location-routing optimisation	Hybrid ant colony algorithm	Balances cost, emissions, temperature control in green, resilient cold-chain networks
Rajaraman et al. (2020)	Inventory tracking in unstructured environments	Probabilistic inference, multiple-hypothesis models	Supports robust tracking where RFID is impractical, e.g. shipyards
Rahman & Kirby (2024)	Lean Six Sigma in e-commerce warehousing	5S, Kanban, Value Stream Mapping, IoT integration	Reduces waste, enables automation-ready workflows; identifies organisational/cultural barriers
Klundt et al. (2024)	Lean and agile strategy alignment in distribution centres	Hybrid models	Supports flexible, value-added service adaptation with AI-based scenario modelling and process optimisation
Xi & Geng (2024)	Location of front-loading warehouses integrating forward/reverse logistics	Hybrid heuristic optimisation	Explicitly accounts for perishability, demand uncertainty, cost minimisation in fresh-product cold chains
De Mattos et al. (2024)	Conceptual framework for AI in demand planning	Perception, prediction, recommendation, autonomous decision-making	Emphasises adaptive, AI-driven decision-making in supply chain management

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Chen et al. (2024)	Comprehensive review of AI in sustainability-driven logistics	Generative models, machine learning, metaheuristics	Advocates integration of advanced AI techniques to support economic, environmental and social sustainability
Romagnoli et al. (2023)	Circular supply chain management (CSCM)	AI, IoT, blockchain	Highlights role of technology in enhancing resilience and transparency, aligning with closed-loop resource management
Harsanto et al. (2024)	Halal supply chains	AI, digital tools	Improves traceability, ethical operations, financial performance for SMEs
Aylak (2025)	SustAI-SCM framework for sustainable SCM	Agentic AI, transformer-based systems	Enables proactive decision-making, cost reduction, carbon minimisation with explainable AI for regulated sectors
Ferraro et al. (2023)	AHP evaluation of Industry 4.0 tech for material handling	AHP model	Helps organisations prioritise technologies that balance economic, environmental, social sustainability
Haji et al. (2020)	Traceability and safety in perishable food supply chains	IoT, RFID, blockchain, smart packaging	Enhances monitoring and decision-making in cold chains; enables advanced analytics
Jagtap et al. (2021)	Integration of technologies in food logistics	IoT, AI, blockchain	Supports Food Logistics 4.0 with improved safety, traceability, waste reduction
Zhang et al. (2024); Xi & Geng (2024)	Cold-chain optimisation	Hybrid algorithms	Model route optimisation, temperature control, emission reduction for sustainable logistics
Zengin et al. (2024)	Closed-loop supply chains (CLSC)	AI, blockchain, IoT	Identifies potential of technology for green logistics but notes limited real-world adoption
Minashkina & Happonen (2023)	Social sustainability in warehouse management systems	WMS, Industry 4.0	Highlights need to better measure work quality, employee satisfaction, social impact
Abdelhamid et al. (2024)	Supply chain architecture design	AI, IoT, blockchain (ABISChain platform)	Demonstrates autonomous decision-making, improved security and system reliability by integrating AI, IoT and blockchain
Hellani et al. (2021)	Blockchain-based data transparency	Blockchain, AI	Advocates access control by design with stakeholder-based roles; uses AI to analyse securely stored blockchain data
Ponis & Efthymiou (2020)	Smart warehouse frameworks	IoT, cloud, AI	Shows how real-time tracking, predictive maintenance and AI-optimised task scheduling enhance efficiency in warehousing
Jagtap et al. (2021)	Food logistics chains	IoT, AI, blockchain	Highlights technological synergies to improve safety, traceability and waste reduction in food supply chains
Khan et al. (2024)	Oil & gas spare parts management	IIoT, AI	Demonstrates IIoT support for predictive maintenance and AI for optimising classification and usage of critical inventory
Haji et al. (2023)	Perishable food supply chains	AI, IoT, RFID, blockchain	Enhances traceability, quality maintenance and waste minimisation through integrated technology stacks
Alkhodair et al. (2025)	SME adoption analysis	AI, IoT, blockchain	Identifies benefits like predictive maintenance and ethical sourcing, while addressing cost and skill barriers
Azmat et al. (2019)	Road transport vision	AI, IoT, big data, AVs	Envisions improved traffic management, real-time congestion prediction and operational efficiency through technology integration

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Paraskevas et al. (2024)	Port and container logistics	AI, IoT, blockchain	Uses AI for flow analysis, IoT for container tracking and blockchain for traceability to optimise capacity and sustainability planning
Harsanto et al. (2024)	Halal logistics	AI, IoT, blockchain	Emphasises integration to ensure ethical operations, traceability and efficiency in halal supply chains
Mashayekhy et al. (2022)	Inventory management integration	IoT, ERP, predictive control	Analyses inventory tracking, predictive control and ERP integration, while noting security and complexity challenges
Lambrechts et al. (2021)	Cobots implementation in distribution centres	Collaborative robots (cobots)	Highlights critical human factors, including resistance to change, culture, communication and leadership; emphasises trust and team leader commitment for successful adoption
Epe et al. (2024)	Smart glasses in warehouse operations	AR, smart glasses	Identifies employee resistance, unclear task fit and need for user-centred design; stresses importance of change management and communication
Rahman & Kirby (2025)	Digital Lean transformations in e-commerce logistics	Lean tools, IoT	Argues that failures often stem from lack of leadership support and staff buy-in, not technical issues; underscores role of clear goals and culture
Zajac et al. (2025)	Barriers and motivations for adopting digital planning tools in intermodal transport in Poland	Survey of 80 Polish transportation, forwarding and logistics enterprises; Technology Acceptance Model (TAM) framework	Only 20% of enterprises use route planning tools, with low satisfaction levels; main barriers are lack of awareness, organisational inertia and competing priorities rather than financial constraints; highlights need for targeted education, integration support and differentiated functionalities for SMEs and large firms
Alkhodair et al. (2025)	SME adoption of Industry 4.0	AI, IoT, blockchain	Highlights need for training, financial assistance and mentorship to overcome workforce constraints and cultural resistance
Bright & Ponis (2021)	Employee engagement strategies	Gamification, AR	Advocates gamification to boost morale and satisfaction in warehouse picking tasks, enhancing motivation in AI-enabled environments
Ferreira & Reis (2023)	Organisational readiness for AI	AI, organisational governance	Emphasises importance of internal data literacy, governance structures and strategic planning to realise AI's full potential
Minashkina & Happonen (2023)	Social impacts in WMS	WMS, IoT, Industry 4.0	Advocates for measuring job quality, worker satisfaction and broader social impacts in tech-enabled warehouse systems
Khalilzadeh et al. (2024)	Automotive sector RL network design	Bi-objective, multi-echelon model	Balances costs and customer satisfaction; tested at ISACO for strategic planning benefits
Vahdat & Vahdatzad (2017)	Forward/reverse network integration under uncertainty	Accelerated Benders decomposition	Improves solution scalability by unifying forward and reverse flows
Wang & Liao (2023)	RL provider selection in food industry	Fuzzy-TOPSIS, MSGP model	Balances economic, environmental and social criteria for partner evaluation
Desticioglu et al. (2022)	Stochastic RL network design	Chance-constrained programming	Accounts for demand uncertainty; enables cost-efficient, reliable and sustainable recycling network planning
Song et al. (2021)	ATM recycling and maintenance RL design	MILP modelling, percentage diversion method	Minimises costs and carbon emissions through optimised network design
Yu & Sun (2024)	Digitalised Industry 5.0 RL network design	Fuzzy optimisation, dynamic simulation	Handles uncertainty; reduces costs and emissions in Industry 5.0 contexts

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Chen & Chen (2023)	Dual-channel RL network design	Stackelberg-game pricing, genetic algorithm	Models consumer behaviour under uncertainty to optimise pricing and flows
Anon et al. (2024)	Review of 3PL RL provider selection (2020–2023)	Literature review of decision-making models	Identifies deterministic and uncertain models; highlights need for advanced AI integration
Li & Chen (2022)	Risk-aware 3PL RL network design	Two-stage stochastic programming, CVaR/ VaR measures	Incorporates disruption risks to improve resilience and cost-effectiveness under uncertainty
Krstić et al. (2022)	Ranking Industry 4.0 technologies for RL	BWM, COBRA method	Multi-criteria decision model assessing cost, complexity, integration and environmental impact for technology adoption
Schlüter et al. (2023)	Remanufacturing inspection and sorting	AI-enhanced CNN-based system	Improves accuracy and reduces manual errors through advanced visual recognition
Abba Dabo & Hosseinian-Far (2023)	Human-centric RL optimisation	AI, IoT, logistic regression, decision trees	Proposes Industry 5.0 methodology integrating advanced data-driven decision-making for sustainable RL operations
Yu & Sun (2024)	Digitalised RL network design (previously in 4.1)	Fuzzy optimisation, dynamic simulation	Addresses uncertainty, supports strategic planning in Industry 5.0 reverse logistics
Mo et al. (2022)	Service parts RL system design	IoT, RFID, business intelligence, mobile apps	Enhances tracking, authentication and reuse through integrated IoT-enabled systems
Abbasi et al. (2025)	Green forward and reverse logistics networks	IoT-enabled monitoring	Improves real-time monitoring, manages backup suppliers and special disposal needs, reduces environmental impacts
Schlüter et al. (2023)	Energy-efficient part recognition in RL	Green incremental learning, AI	Demonstrates significant energy savings while maintaining classification accuracy
Gayialis et al. (2022)	Predictive maintenance for reverse-stream equipment	IoT + machine learning (ML)	Presents a predictive-maintenance solution improving equipment reliability and lifecycle management
Alarcón et al. (2021)	Process formalisation in RL	BPMN-based reference model	Reduces complexity and enables future integration of advanced digital and AI tools
Krstić et al. (2022)	Evaluation of smart RL development scenarios	Fuzzy Delphi-ANP-COBRA model	Integrates IoT, AI, blockchain and cloud systems to assess and guide RL development strategies
Starostka-Patyk (2021)	Information systems for RL management	Real-time tracking, return-cause analysis	Supports operational efficiency and provides essential data infrastructure for AI-driven optimisation and sustainability
Nunes et al. (2023)	Performance assessment in RL	Systematic literature review	Highlights sustainability, operational and stakeholder dimensions; calls for better integration with decision-making processes
Ritola et al. (2020)	Value of returns data in RL	Systematic literature review	Shows how returns data provide insights for process improvement, product development and strategic planning
Wijewickrama et al. (2022)	Knowledge management in RL	Information processing theory (OIPT)	Identifies knowledge-related failures; stresses need for robust information systems to support RL efficiency
Desticioglu et al. (2022)	RL network design under uncertainty	Chance-constrained programming	(Already discussed in 4.1) Minimises recycling costs under demand uncertainty by modelling variability
Sonar et al. (2024)	Barriers to RL adoption	Fuzzy Delphi, DEMATEL	Maps barriers in circular economy context; underscores importance of strategic planning, education and institutional backing.

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Rubio et al. (2019)	RL and urban logistics integration	Conceptual analysis	Identifies collaboration opportunities in waste management, returns handling and smart-city planning
Nunes (2025)	RL in decarbonising forest supply chains	Lifecycle analysis, policy review	Emphasises circular economy strategies and policy support to reduce carbon emissions
Akinbamini et al. (2025)	Digital infrastructure for RL in Nigeria	IoT, ERP, RFID	Highlights foundational technologies for effective RL; sets stage for future AI integration
Makaleng & Hove-Sibanda (2022)	RL strategies in South Africa's FMCG sector	Policy and technology analysis	Explores policy, technology and sustainability roles in boosting competitiveness
Briatore et al. (2025)	Industry 4.0 technologies for sustainable SCM	Bibliometric review	Shows AI, IoT and blockchain help reduce carbon footprints; calls for integrated evaluation and more empirical research
Prakash and Sathishkumar (2012)	Cold-chain warehouse stock management	RFID-based mobile system	Enables real-time temperature and item tracking; improves safety and efficiency
Mustafa et al. (2024)	Perishable food logistics management	Smart sensors, AI, RFID, energy-efficient solutions	Emphasises traceability, operational efficiency and sustainability in managing perishables
McLay et al. (2024)	Australian cold storage sustainability	Best-practice analysis	Highlights design, insulation, refrigeration systems and operational innovations to reduce emissions and energy use
Wang et al. (2024)	Fresh food warehouse planning	Two-tier optimisation, PSO-GA algorithms	Minimises costs and maximises freshness through advanced hybrid optimisation techniques
Bottani et al. (2022)	Economic and environmental impact analysis	Analytic modelling	Quantifies cost and emissions hotspots to guide targeted improvements in cold-chain processes
Ali et al. (2024)	Blockchain in warehouse operations	Structured decision framework	Establishes trust, transparency and collaboration; guides implementation of blockchain in supply chains
Ramingwong et al. (2024)	Lean practices in Thai manufacturing	Case-study validation	Demonstrates cost savings and improved efficiency in transportation, warehousing and overall logistics
Oliveira et al. (2022)	Warehouse receiving process optimisation	Lean tools, digital simulation	Shows operational improvements without facility upgrades, achieving significant efficiency gains
Serrano-Torres et al. (2025)	Dairy supply chain transformation	Systematic review, AI and IoT integration	Highlights improved product quality, traceability and operational efficiency through real-time monitoring and predictive decision-making
Lu & Taghipour (2025)	Supply chain digitalisation research	Comprehensive literature review	Identifies methodological gaps; calls for systematic IoT, AI and blockchain integration across decision-making levels
Acerce & Denizhan (2025)	Cold supply chain optimisation	NSGA-II models	Balances cost and product freshness in two-echelon networks using advanced multi-objective planning
Iyer & Robb (2025)	Cold-chain optimisation models	Systematic classification	Identifies methodological gaps; calls for integrated, multi-objective, digitally supported solutions
Haque et al. (2025)	Export supply chain performance	Seven-dimensional framework	Assesses economic, time, management, network, innovation, market and eco-efficiency dimensions
Malik et al. (2022)	Dairy supply chain optimisation	Systematic review	Highlights AI and ML use; emphasises need for multi-objective models and industry alignment for efficiency and sustainability

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Mor et al. (2019)	Dairy supply chain drivers	Integrated SWOT-AHP approach	Identifies and ranks critical factors like inventory, quality, supplier trust and innovation for strategic prioritisation
Zhang et al. (2025)	Closed-loop supply chain design	Distributionally robust optimisation	Integrates physical/online sales and reverse logistics; optimises cost-effectiveness and resilience under uncertainty
Božić et al. (2024)	FMCG logistics data quality	Quantitative analysis	Shows that improving master data quality enhances delivery accuracy, reduces delays and improves overall logistics performance
Mustafa et al. (2024)	Cold-chain policy and collaboration	Multi-stakeholder cooperation	Emphasises the need for coordinated policies, technological integration and strategic planning to advance cold-chain systems
Shi et al. (2024)	Shared distribution in fresh-food supply chains	Conceptual analysis	Identifies efficiency and sustainability benefits, but highlights need for high levels of coordination, trust and technological collaboration
Rejeb et al. (2024)	Barriers to IoT adoption in humanitarian logistics	ISM–DEMATEL methods	Maps organisational, regulatory and technical challenges; calls for improved coordination and operational effectiveness
Hangl et al. (2022)	AI adoption in supply chain management	Socio-technical analysis	Stresses need for ethical, participatory and educational approaches, including change management and employee upskilling
Jahangir et al. (2025)	Sustainable HR practices in logistics	AI-enhanced HRM strategies	Demonstrates improved agility and flexibility; shows AI's mediating role in aligning HR strategies with dynamic supply chain demands
Mance et al. (2025)	Croatia's EU supply chain integration	Panel data quantile regression	Reveals stronger trade linkages during growth phases; calls for targeted policy interventions and technological alignment
Pumpinyo & Nitivattananon (2014)	Reverse logistics in waste management	Qualitative barrier analysis	Highlights need for robust policy support, improved market structures and coordinated institutional strategies
Sharma et al. (2021)	AI and big data in the food sector	Systematic literature review	Shows how AI and BDA support sustainability and circular economy practices across production, logistics and quality control
Jevinger & Olsson (2021)	IoT-enabled logistics service design	Intelligent Goods Service (IGS) framework	Classifies IoT-enabled services; emphasises interoperability, coordination and shared standards for connected supply chains