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ARTICLE

Artificial Intelligence Applications in Sustainable Reverse Supply Chains: A Systematic Review, Gap Analysis, and Future Research Agenda

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Abstract

Artificial intelligence (AI) is increasingly reshaping sustainable reverse supply chains (SRSCs) by enhancing product return management, remanufacturing, recycling, recovery, and reintegration processes, while strengthening circular economy implementation and sustainability performance. Escalating regulatory pressures, resource scarcity, climate-related disruptions, and rising reverse logistics complexity have intensified the demand for intelligent, adaptive, and data-driven systems capable of operating effectively under uncertainty. However, despite growing scholarly attention, research on AI-enabled SRSCs remains fragmented across technological, operational, and managerial domains, limiting theoretical integration and a comprehensive understanding of system transformation.

This study presents a systematic literature review of peer-reviewed publications from 2000 to early 2026 to synthesize and critically evaluate the evolution of AI applications in SRSCs. Using a structured review protocol and thematic synthesis, it develops a multidimensional taxonomy and a mechanism-based conceptual framework explaining how AI enhances decision intelligence, coordination efficiency, operational resilience, and sustainability performance across reverse supply chain systems.

Findings reveal a structural shift from cost-centric reverse logistics toward predictive, adaptive, and sustainability-oriented closed-loop systems characterized by real-time visibility, dynamic optimization, and autonomous decision support. AI significantly improves return flow forecasting accuracy, recovery efficiency, waste reduction, and resilience under uncertainty and disruption. However, the literature remains unevenly developed, particularly in relation to governance structures, cross-functional integration, and methodological standardization.

Key research gaps are identified in AI governance, explainability, interoperability, scalability, and social sustainability integration. Importantly, generative AI and large language models (LLMs) emerge as a nascent but largely underexplored frontier with strong potential to transform knowledge-intensive decision-making, coordination mechanisms, and adaptive control in reverse supply chains. In response, the study proposes a future research agenda across six interrelated dimensions to advance intelligent, resilient, and sustainability-oriented closed-loop supply chain systems.

Keywords: Artificial Intelligence; sustainable reverse supply chains; circular economy; reverse logistics; AI governance; sustainable operations.

1. INTRODUCTION

Supply chains are traditionally defined as integrated networks of suppliers, manufacturers, transporters, warehouses, retailers, and customers that convert raw materials into finished products to meet demand [1]. This linear paradigm prioritizes forward flows and cost efficiency but largely neglects

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end-of-life (EoL) product flows, resulting in material leakage, waste accumulation, and resource depletion [2]. As a result, supply chains increasingly operate as complex adaptive systems under uncertainty, interdependence, and resource constraints [3,4].

Reverse Logistics (RL) has emerged as a critical research and practice domain due to its dual potential for value recovery and environmental sustainability. However, the literature remains fragmented, lacking comprehensive synthesis and integrated analytical perspectives to consolidate findings and guide future research [5,6].

Within the Circular Economy (CE) paradigm, RL enables the reintegration of EoL products through reuse, remanufacturing, recycling, and recovery processes [7,8]. Driven by e-commerce expansion, regulatory pressure, and rising return volumes, RL has transitioned from an operational afterthought to a strategic sustainability capability [9,10]. However, inherent uncertainty in return timing, quantity, and quality continues to constrain forecasting, coordination, and capacity planning [11].

Despite extensive research, RL conceptualizations remain heterogeneous, ranging from process-oriented to stage-based and simplified structural models [9,12]. More recent perspectives emphasize systemic integration, cross-functional coordination, and strategic alignment.

A comprehensive RL classification is provided by Alarcón et al. [13], who identify five core decision domains: network design, collection and transportation, inspection and sorting, product disposition, and system monitoring. This framework underpins the present study and is operationalized in Figure 1 and Table 1.

Empirical evidence further highlights that RL systems are highly context-dependent, with performance shaped by industry structure, product characteristics, and recovery complexity, particularly in remanufacturing and industrial applications [14,15].

1.1 Sustainable Reverse Supply Chains (SRSCM)

Sustainability transitions have shifted supply chain paradigms toward circular and regenerative systems. Closed-loop supply chains (CLSCs) integrate forward and reverse flows to enable resource recovery through reuse, remanufacturing, recycling, and disposal optimization. CLSCs constitute a core pillar of Circular Supply Chains [16,17], enabling resource efficiency and decoupling economic growth from environmental degradation [18], while strengthening system resilience and innovation capacity [19].

Reverse logistics is defined as “the process of moving goods from their typical final destination for recapturing value, or proper disposal” [20] and functions as the operational backbone of circular systems [7,21]. However, misaligned incentives among stakeholders and institutional fragmentation result in persistent inefficiencies and leakage of EoL products from circular pathways [22-24].

RL systems are inherently socio-technical and exhibit uncertainty, decentralization, and nonlinear feedback structures, making coordination significantly more complex than forward logistics systems [25]. Despite their strategic importance [26,27], the absence of unified analytical frameworks continues to limit system-level optimization and integration [9].

Sustainable Reverse Supply Chains (SRSCs) integrate environmental, social, and economic objectives across reverse flows, including collection, sorting, disassembly, reuse, remanufacturing, recycling, and disposal [28,29]. Within Sustainable Supply Chain Management (SSCM), SRSC design represents a multi-objective stochastic optimization problem under deep uncertainty, balancing cost, emissions, service performance, and social impact [30-32]. However, classical optimization approaches remain limited in capturing system dynamics, adaptability, and real-time responsiveness. The structural and AI-enabled SRSC architecture is presented in Figure 2.

1.2 Artificial Intelligence and Intelligent SRSC Systems

Artificial intelligence (AI) enables a paradigm shift from static optimization toward adaptive, data-driven, and autonomous decision systems with predictive and prescriptive capabilities [33,34]. In reverse logistics, AI enhances forecasting, return prediction, and recovery optimization, particularly when integrated with IoT and blockchain technologies [35-38].

However, AI applications in RL remain fragmented and lack integrative theoretical grounding [39]. Concurrently, Industry 4.0 technologies improve system visibility and automation [40-42], while waste is increasingly reframed as a recoverable resource within circular systems [43-45].

AI-enabled SRSCs evolve as learning-based socio-technical systems characterized by continuous adaptation and feedback-driven improvement [46,47]. These systems can be conceptualized through predictive, prescriptive, and adaptive intelligence layers (Figure 3), grounded in Dynamic Capabilities Theory, Circular Economy Theory, and Complex Adaptive Systems Theory [48-50].

1.3 Research Gaps, Objectives, and Contributions

Despite growing interest, AI-enabled SRSC research remains fragmented across technological, operational, and managerial domains, with limited theoretical integration explaining governance mechanisms, coordination structures, and decision intelligence. In addition, the social sustainability dimension remains underexplored, particularly in relation to labor impacts and equity in value distribution.

To address these gaps, this study synthesizes AI applications in SRSCs, examines network design under uncertainty, and analyzes sustainability integration in AI-based decision models. A mechanism-based conceptual framework is developed linking AI capabilities, SRSC structures, and sustainability outcomes.

Accordingly, the study addresses the following research questions:
RQ1: How is AI applied in SRSCM and reverse logistics research?
RQ2: How does AI influence SRSCM network design under uncertainty?
RQ3: How is sustainability integrated into AI-driven SRSCM models?
RQ4: What are the key research gaps in AI–SRSCM integration?
RQ5: What future research directions are required to advance theory and practice?

Correspondingly, the study pursues the following research objectives:
RO1: Synthesize AI applications in SRSCM and reverse logistics.
RO2: Analyze AI-driven transformations in network design under uncertainty.
RO3: Examine sustainability integration in AI-enabled SRSCM systems.
RO4: Develop a unified AI–SRSCM–sustainability conceptual framework.
RO5: Identify research gaps and propose future research directions.

The paper is organized as follows: Section 2 presents the methodology; Section 3 provides synthesis and gap analysis; Section 4 develops the conceptual framework and future research agenda; Section 5 concludes the study.

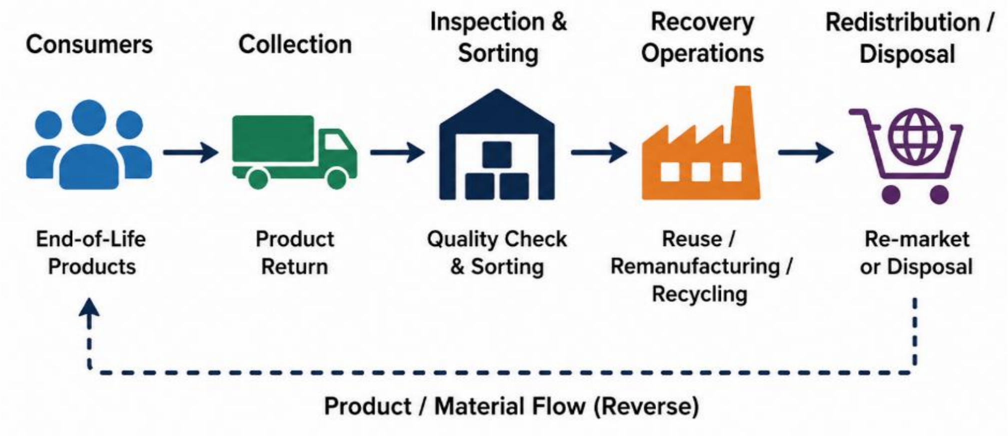

Figure 1. Reverse Supply Chain Network.

Table 1. Structural Elements and Objectives of Sustainable Reverse Supply Chain Networks.

#	Element	System Role	Objective	Key Practices	Impacts
1	Collection Systems	Reverse flow initiation	Maximize product returns	Take-back and collection programs	Improved collection efficiency
2	Inspection & Sorting Systems	Recovery evaluation	Enhance disposition decisions	Inspection and AI-based classification	Higher recovery accuracy
3	Recovery Facilities	Value recovery	Restore product and material value	Repair, remanufacturing, recycling	Resource efficiency
4	Secondary Markets	Product redistribution	Reintegrate recovered products	Resale and reuse channels	Enhanced circularity
5	Information Systems	Digital coordination	Improve visibility and decision-making	IoT, blockchain, AI analytics	Greater transparency
6	Network Design Systems	Logistics optimization	Reduce cost and environmental impact	Optimization models and AI routing	Lower emissions and stronger resilience
7	Regulatory Systems	Governance framework	Ensure compliance and sustainability	EPR and environmental policies	Improved sustainability performance

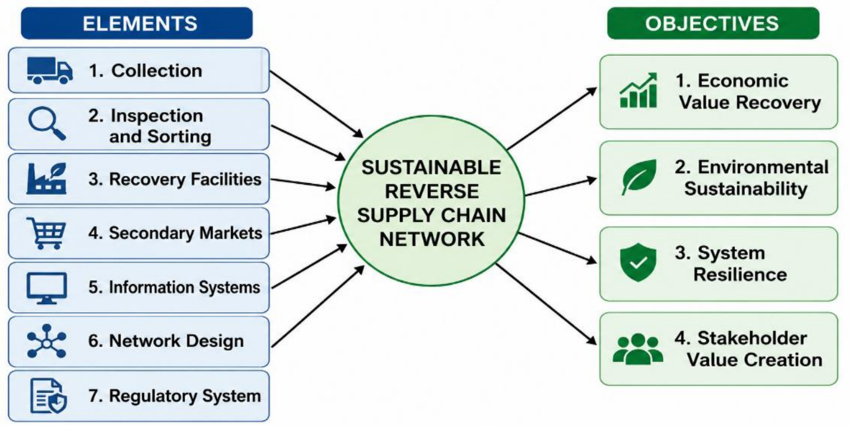

Figure 2. Sustainable Reverse Supply Chain Network: Elements and Objectives.

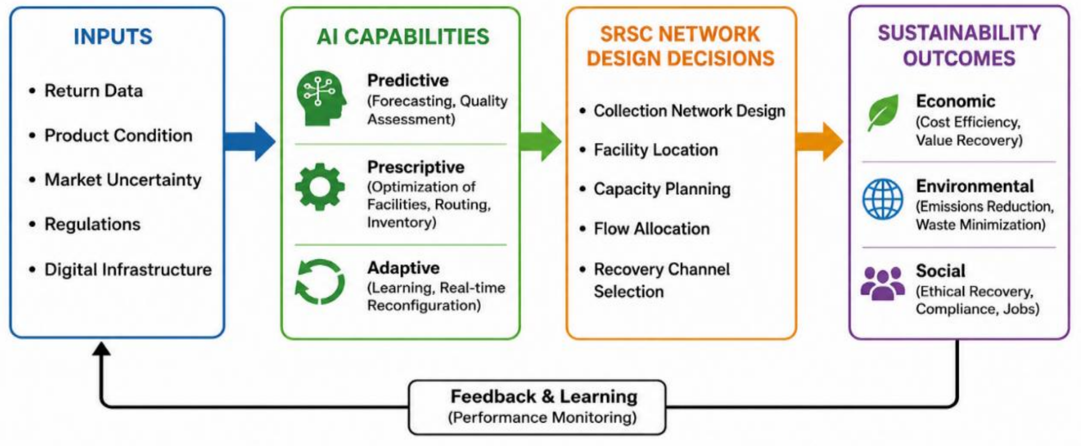

Figure 3. AI-Driven Sustainable Reverse Supply Chain Network Design.

2. LITERATURE REVIEW

This study adopts a PRISMA 2020–compliant systematic literature review (SLR) combined with interpretive thematic synthesis to ensure rigor, transparency, and reproducibility [51]. The review integrates 102 peer-reviewed studies (2000–2026) on artificial intelligence (AI) in sustainable reverse supply chain (SRSC) network design. The PRISMA framework ensures structured identification, screening, eligibility, and inclusion, enabling both systematic mapping and mechanism-based interpretation of AI-enabled transformations in reverse logistics and sustainability integration.

1) Data Sources and Search Strategy: Studies were retrieved from Scopus, Web of Science, and ScienceDirect using Boolean queries combining AI, reverse logistics, network design, and sustainability terms. Only English peer-reviewed journal articles published from 2000 to 2026 were included.
2) Eligibility Criteria: Included studies addressed AI applications in reverse logistics, sustainable reverse supply chains, or closed-loop network design using optimization, simulation, analytics, or decision-support methods. Exclusions comprised non-peer-reviewed, duplicate, conceptual-only, and non-AI studies.
3) Screening Process and PRISMA Workflow: The study follows PRISMA 2020 guidelines [51], with the full process shown in Figure 4. From 412 retrieved records, 98 duplicates were removed, leaving 314 studies. Title and abstract screening excluded 188 studies, and full-text review excluded 24 studies, resulting in 102 final articles. This dataset forms a robust basis for synthesis and framework development.
4) Quality Assessment: A structured assessment evaluated methodological clarity, modeling rigor, relevance to SRSC network design, and sustainability integration. Studies were classified as high, medium, or low quality. Only high- and medium-quality studies were included to ensure analytical robustness and validity.
5) Data Synthesis: A qualitative thematic synthesis using open and axial coding identified cross-study patterns in AI-enabled SRSCs, focusing on optimization, decision-making, and sustainability integration. Key themes include autonomous decision systems, learning-based logistics, explainable AI, and real-time adaptive optimization.
6) Methodological Positioning: This study adopts a hybrid systematic–interpretive design integrating PRISMA rigor with thematic synthesis. The approach combines descriptive mapping, explanatory analysis of AI mechanisms, and conceptual synthesis into a unified framework. It enables understanding of how AI transforms SRSCs into adaptive, intelligent, and sustainability-oriented systems under uncertainty and dynamic conditions.

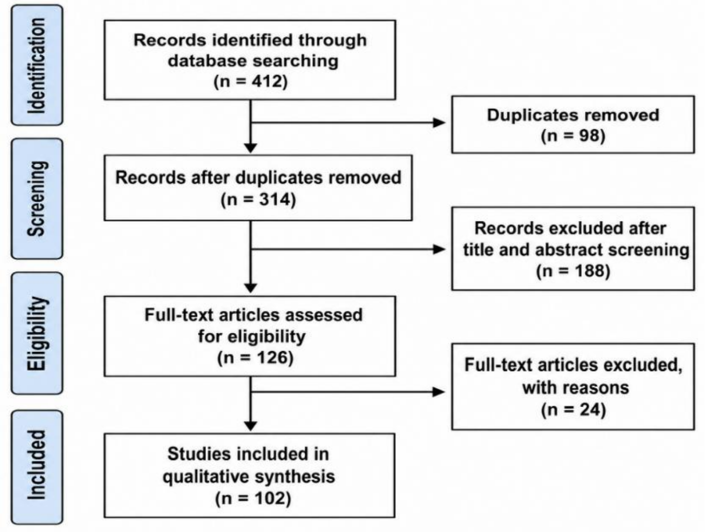

Figure 4. PRISMA flow diagram.

2.1 Foundations and Evolution of Reverse Logistics and Circular Supply Chain Sustainability

The transition toward circular and sustainability-oriented systems has elevated reverse logistics (RL) from an operational function to a strategic enabler of resource efficiency and circular economy implementation [52,53]. Driven by environmental degradation, resource scarcity, and regulatory pressures, RL now supports closed-loop material flows and lifecycle extension. Accordingly, its scope has expanded from cost efficiency to integrated environmental, economic, and social sustainability within circular supply chains (CSCs).

1) Evolution and Conceptual Foundations of Reverse Logistics: Reverse logistics (RL) and reverse supply chains (RSCs) have evolved from deterministic optimization problems into socio-technical systems influenced by institutional, organizational, and technological factors. RL is defined as the flow of products from consumption back to recovery systems for reuse, remanufacturing, recycling, or disposal [54]. Early research emphasized facility location, stochastic modeling, and cost minimization [55,56], while later studies incorporated organizational capabilities, governance structures, and institutional drivers [57,58]. Empirical evidence further confirms that RL systems are highly context-dependent and vary significantly across industries and institutional environments [59,60].
2) Circular Economy and Circular Supply Chain Foundations: The circular economy (CE) promotes regenerative systems that decouple economic growth from resource consumption through closed-loop material cycles [61]. It distinguishes between biological and technical cycles, requiring structured reverse logistics systems to enable recovery and reintegration. Circular supply chains (CSCs) integrate forward and reverse flows to enable lifecycle value retention [62,63]. However, CSCs still suffer from inefficiencies such as material leakage, coordination gaps, and suboptimal recovery performance [64], reinforcing the critical role of RL infrastructures.
3) Theoretical and Sustainability Perspectives: RL is grounded in converging theoretical streams, including closed-loop supply chains (CLSCs), sustainable supply chain management (SSCM), and industrial ecology [65,66]. These perspectives collectively emphasize lifecycle thinking, resource efficiency, and waste minimization. Despite this convergence, RL systems remain constrained by fragmentation, weak coordination, and uncertainty in return flows, particularly in electronics and consumer goods sectors [24]. This reveals a persistent gap between sustainability theory and operational implementation.

2.2 Reverse Logistics Processes, Systems, and Network Structures

Reverse logistics processes convert uncertain return flows into structured recovery outcomes through four interrelated stages: collection, inspection, processing, and redistribution [67].

1) Collection and Redistribution Mechanisms: Collection determines the volume, timing, and quality of returns through take-back systems, recalls, and returns channels. Redistribution allocates recovered products to reuse, remanufacturing, or recycling pathways based on residual value and condition [67].
2) Inspection, Sorting, and Processing: Inspection evaluates product condition and determines recovery routes. Processing includes repair, refurbishment, disassembly, and recycling [7], where disassembly efficiency is critical for cost and recovery performance.
3) Reverse Logistics Networks and Configurations: RL networks integrate facilities and material flows into coordinated systems [68]. Centralized networks improve economies of scale but reduce responsiveness, while decentralized networks enhance flexibility but increase coordination complexity [9,14]. Thus, RL network design reflects trade-offs among efficiency, responsiveness, and resilience.

2.3 Optimization Paradigms and Decision-Making in Reverse Systems

RL network design (RLND) has evolved from deterministic optimization to stochastic, robust, and hybrid decision frameworks capable of handling uncertainty and complexity.

1) Classical Optimization: Mixed-integer linear programming (MILP) dominates RLND for facility location and allocation problems [69]. Stochastic and robust models incorporate uncertainty in return flows and demand [70], while game theory captures strategic interactions among decentralized actors [71].

2) Metaheuristics and Sustainability Integration: Heuristic and metaheuristic approaches address large-scale RL problems while integrating environmental objectives such as emissions and energy consumption [72]. These models support multi-objective closed-loop optimization.
3) Integrated Applications and Digital Transformation (Synthesis): RL optimization spans multiple sectors, including plastics, healthcare, agriculture, and retail using MILP, stochastic, and simulation-based models [73,74]. Vehicle routing and urban logistics incorporate environmental constraints and crowd-based delivery systems [75]. Uncertainty is addressed through fuzzy, bilevel, and grey models in battery and e-commerce systems [76]. Multi-criteria decision-making (AHP, TOPSIS, DEA) supports provider evaluation, while IoT and blockchain enhance real-time traceability (Garrido-Hidalgo et al., 2019). Multi-objective models integrate economic, environmental, and social dimensions [78].

2.4 Sustainability Integration in Reverse Logistics and Circular Systems

The circular economy embeds sustainability into RL through closed-loop systems that enable continuous material circulation [79]. RL has therefore become a structural enabler of sustainability rather than an end-of-pipe solution.

1) Sustainability Evolution: RL generates significant environmental and economic value; however, structural trade-offs and data fragmentation continue to limit full sustainability realization [80,81].
2) Operationalization via 6R Framework: The 6R framework (reduce, reuse, recycle, recover, redesign, remanufacture) operationalizes circular economy principles [82]. Nonetheless, social sustainability remains underrepresented in most RL models [83].
3) WEEE Reverse Logistics: Waste Electrical and Electronic Equipment (WEEE) systems represent a high-impact domain, with global e-waste reaching 53.6 million tons in 2019 and projected to rise sharply [84]. This has driven widespread adoption of stochastic and fuzzy optimization approaches.
4) Advanced CE Integration: Circular economy integration improves recovery efficiency and system coordination, while product-specific modeling enhances realism in RL design [85,86].

2.5 Integrated Closed-Loop Supply Chain Frameworks:

Closed-loop supply chains (CLSCs) integrate forward and reverse flows to enable circular value creation [87]. RL enables physical recovery, product lifecycle management (PLM) provides lifecycle intelligence, and zero-waste strategies define system objectives [88].

1) Structural Pillars: CLSCs are built on RL, PLM, and zero-waste principles, jointly enabling circular system functionality.
2) Feedback Loops: Operational RL data feeds PLM systems to improve design, forecasting, and lifecycle decisions through continuous feedback mechanisms [89].
3) Structural Limitations: Most CLSC models remain static and cost-centric, limiting applicability under real-world uncertainty and dynamic conditions [90].

2.6 AI-Driven Sustainable Reverse Supply Chain Management

Artificial intelligence (AI) has become a critical enabler of sustainable reverse logistics and circular supply chains by enhancing decision-making, automation, and system intelligence across collection, inspection, processing, monitoring, and disposition stages. It facilitates the transition from static, rule-based systems to adaptive, data-driven, and sustainability-oriented reverse logistics. Within circular economy contexts, AI improves traceability, resource efficiency, and recovery performance while enabling continuous learning and system-wide optimization. Overall, AI functions as an integrative mechanism that reduces fragmentation and strengthens coordination in reverse supply chains [91-93].

1) Foundations of AI in Reverse Logistics and Circular Economy Systems: Reverse logistics is a core enabler of closed-loop supply chains, ensuring the reintegration of end-of-life materials instead of landfill disposal. A major operational challenge lies in waste sorting and classification, where AI-based computer vision significantly improves accuracy and efficiency [94]. In circular economy

systems, materials circulate through regenerative loops that preserve value across multiple life cycles [95,96]. In this context, AI enhances reverse logistics by improving classification precision, decision quality, and coordination of multi-actor recovery networks.

2) AI-Driven Capabilities Across Reverse Logistics Processes: AI strengthens reverse logistics performance through predictive analytics, automation, and advanced data processing. Machine learning improves return forecasting and inventory control under uncertainty [8], while deep learning enhances pattern recognition in highly stochastic environments [97,98]. AI also enables the processing of unstructured data, improving defect detection and classification accuracy [99,100]. Operational efficiency is further enhanced through intelligent automation in sorting, routing, and execution processes [36,41,101]. Real-time analytics support adaptive decision-making and continuous system recalibration under uncertainty [102,103].
3) AI in Reverse Logistics Network Design and Sustainable Configuration: AI addresses complexity and uncertainty in reverse logistics network design through metaheuristics, fuzzy systems, and machine learning. Genetic algorithms and swarm intelligence improve facility location and routing efficiency [104,105], while fuzzy logic and MCDM methods enhance robustness under uncertainty [41]. Machine learning improves prediction of return flows and demand variability [106,98]. IoT and blockchain technologies strengthen transparency and traceability [107,108]. Collectively, these approaches enhance sustainability through reduced emissions, improved efficiency, and stronger circular resource utilization [40,109,110].
4) AI in Inspection, Sorting, and Disposition Decisions: AI significantly improves inspection and sorting through computer vision and deep learning. CNN-based models enhance defect detection and classification accuracy [101,8], while neuro-fuzzy systems support decision-making under uncertainty [111,112]. Reinforcement learning optimizes sorting policies in dynamic environments [113], and supervised learning improves condition assessment [108]. For disposition decisions, AI enables accurate classification into reuse, recycling, or disposal pathways [103]. Genetic algorithms further optimize recovery allocation decisions [114], while IoT and blockchain enhance traceability and auditability [107,101].
5) AI in Monitoring, Control, and Management Decisions: AI enables real-time monitoring, predictive control, and intelligent decision-support in reverse logistics systems. Machine learning improves responsiveness under uncertainty [115], while decision-support systems enhance operational visibility and coordination [41]. IoT and blockchain integration strengthen transparency and trust [108,107]. AI also improves sustainability performance by reducing waste generation, optimizing resources, and increasing energy efficiency [113], enabling automated circular operations aligned with circular economy principles [111,116].
6) AI in Robotics and Advanced Waste Processing Systems: AI-enabled robotics enhances waste identification, sorting, and disassembly. Deep learning improves classification accuracy, while robotics increases automation and efficiency in complex waste streams such as plastics and construction materials [117]. In high-complexity applications such as EV battery and construction waste management, robotics improves safety and recovery efficiency [118-120]. However, challenges remain in scalability, robustness, and generalization across heterogeneous environments. Overall, AI is transforming reverse logistics into an adaptive, intelligent, and sustainability-oriented system aligned with circular economy principles, although cross-process integration remains limited.
7) KPIs in AI-Driven Reverse Supply Chain Management: Performance measurement in reverse supply chains is complex due to stochastic returns, heterogeneous product conditions, and multi-stage recovery processes. Traditional KPI systems are static and lagging, limiting real-time decision support. AI transforms KPIs into predictive and adaptive governance tools embedded within decision loops [121]. Foundational studies define lifecycle-based KPIs across collection, processing, and recovery stages, emphasizing economic, environmental, and social dimensions [12,122]. Network-based analyses highlight KPI interdependencies [123], while MCDM and fuzzy

approaches extend KPI structures into multi-dimensional systems [124]. Maturity models further emphasize capability evolution [125].

AI enables a shift from lagging to predictive and autonomous KPIs across four regimes:

- Operational and Economic Performance: AI improves forecasting, routing, and recovery efficiency [101,108].
- Environmental Sustainability: AI reduces emissions through optimized logistics and resource use [126,127].
- Traceability and Risk Governance: IoT and blockchain enhance transparency and risk control [128,107].
- Circular Resource Recovery: AI improves classification and reintegration of recovered materials into production systems [129,40].

Overall, AI transforms KPI systems from static monitoring tools into dynamic, self-learning governance mechanisms embedded within circular supply chain architectures.

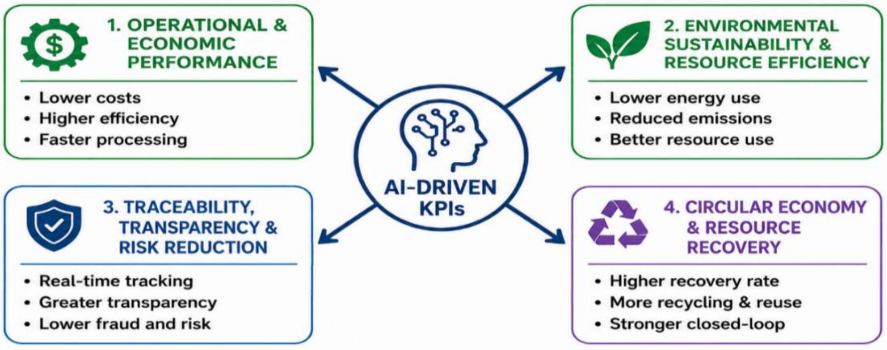

Figure 5. AI–Driven KPIs in Reverse Supply Chain Management.

Table 2. KPIs of AI in Reverse Supply Chain Management.

KPI Category	KPI Area	AI Contribution	Key Outcome
1) Operational & Economic Performance	Cost efficiency	Optimized routing, allocation, and logistics planning	Reduced transport and operational costs
	Operational efficiency	Predictive analytics and optimization for classification and recovery decisions	Improved productivity and decision accuracy
	Process efficiency	Computer vision and digital twins for inspection, sorting, and workflow automation	Faster processing, reduced waste, improved flexibility
2) Environmental Sustainability & Resource Efficiency	Energy efficiency	AI-driven optimization of logistics and operations	Lower energy consumption
	Emissions reduction	Intelligent routing and planning optimization	Reduced carbon emissions
	Resource efficiency	Predictive models for material use and waste reduction	Reduced waste and improved resource utilization
3) Traceability, Transparency & Risk Reduction	Traceability	AI integrated with IoT/blockchain enables real-time tracking and secure data flow	Higher transparency and reduced fraud risk
4) Circular Economy & Resource Recovery	Material recovery	AI-enabled identification, classification, and separation of recoverable materials	Higher recovery and recycling rates
	Circular integration	AI supports the reintegration of recovered materials into production systems	Strengthened closed-loop supply chains

3. CHALLENGES, RESEARCH GAPS, AND STRATEGIC IMPLICATIONS OF AI IN REVERSE SCM

Reverse logistics (RL) is increasingly positioned at the nexus of circular economy transition, digital transformation, and sustainable supply chain redesign. Despite substantial advances in artificial intelligence (AI), closed-loop supply chain (CLSC) theory, and data-driven optimization, RL systems remain structurally fragmented and operationally constrained. These limitations stem from interdependent structural, technological, economic, organizational, sustainability, and theoretical factors that collectively hinder the development of fully integrated and adaptive reverse supply chain systems [69,130,131]. As synthesized in Figure 6 and Table 3, these challenges are organized into six interrelated dimensions: (i) structural and network coordination, (ii) technological infrastructure and data readiness, (iii) economic feasibility and value recovery inefficiencies, (iv) AI adoption barriers, (v) sustainability and circular economy outcomes, and (vi) theoretical and methodological limitations.

1) **Structural and network coordination limitations:** RL systems are constrained by weak integration between forward and reverse flows, limiting lifecycle optimization and circular value recovery. Coordination inefficiencies with third-party logistics providers reduce collection and reintegration effectiveness, while limited cross-functional alignment undermines system responsiveness. Moreover, spatial configuration and network design remain insufficiently incorporated despite their critical impact on cost efficiency, emissions, and resilience [84,90].
2) **Technological and infrastructural constraints:** Digital transformation is constrained by fragmented information systems, limited interoperability, and insufficient real-time data infrastructure. These deficiencies restrict end-to-end visibility, automation, and predictive analytics, particularly in complex and multi-actor industrial environments, thereby constraining scalable AI deployment in RL systems [132,133].
3) **Economic constraints and value recovery inefficiencies:** High upfront investment costs for AI-enabled infrastructure and automation technologies limit adoption, particularly among SMEs. Simultaneously, inefficient return handling and low reintegration rates lead to persistent value leakage across reverse logistics networks.
4) **Barriers to AI adoption in reverse logistics systems:** AI adoption is hindered by high implementation costs, fragmented and non-standardized data, and limited organizational readiness [113,108]. Additional barriers include resistance to change, skill shortages, and managerial capability gaps [41], alongside regulatory uncertainty and interoperability challenges, particularly in AI–blockchain ecosystems [107].
5) **Sustainability and circular economy outcomes:** AI enhances economic efficiency through optimized routing and recovery, improves environmental performance via reduced emissions and higher material recovery rates, and strengthens social outcomes through improved traceability and governance [40,112]. However, these benefits remain uneven due to fragmented implementation and limited system integration.
6) **Theoretical and methodological limitations:** CLSC and RL research remains fragmented, with limited integration between optimization models and theoretical foundations [69]. Behavioral and institutional dimensions remain underexplored, while uncertainty is often modeled exogenously rather than endogenously [135,70]. Sustainability integration remains uneven across environmental, economic, and social dimensions [134,83], and spatial and network effects remain insufficiently modeled. In parallel, AI-enabled adaptive RL frameworks remain conceptually underdeveloped.

Collectively, the evidence demonstrates that AI significantly enhances reverse supply chain performance through improved forecasting accuracy, resource recovery efficiency, transparency, and real-time coordination. This enables a shift from reactive, cost-driven operations to proactive, resilience-oriented, and sustainability-driven reverse logistics under uncertainty. However, the literature remains fragmented across technological, operational, and managerial domains, limiting theoretical consolidation and system-level understanding. Notably, generative AI and large language models (LLMs) represent an emerging yet largely underexplored frontier with strong potential to transform knowledge-intensive decision-making and coordination in reverse supply chains.

Overall, advancing RL requires a next-generation paradigm that is AI-enabled, spatially explicit, behavior-aware, and fully integrated across economic, environmental, and social sustainability dimensions, enabling truly circular, intelligent, and adaptive supply chain ecosystems.

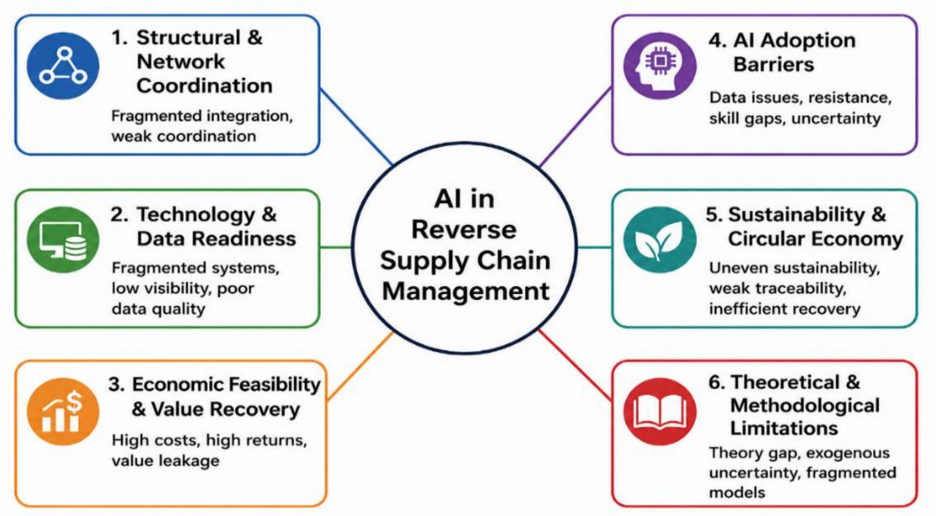

Figure 6. Key Dimensions and Challenges of AI in Reverse SCM.

Table 3. Challenges, Research Gaps, and Strategic Implications of AI in Reverse SCM.

#	Dimension	Key Challenges	Research Gaps	Strategic Implications
1	Structural & Network Coordination	Fragmented forward–reverse integration; weak coordination	Limited CLSC–RL integration; weak network optimization	Integrated closed-loop network design
2	Technological & Data Readiness	Poor interoperability; limited real-time visibility	Lack of end-to-end digital and AI architectures	Interoperable real-time AI systems
3	Economic Feasibility & Value Recovery	High costs; SME constraints; return uncertainty	Limited ROI-based lifecycle value models	Cost-efficient AI and improved value recovery
4	AI Adoption & Governance	Data quality issues, resistance to change, skill gaps	Weak socio-technical governance frameworks	Scalable adoption and strengthened data governance
5	Sustainability & Circular Economy	Weak traceability; inconsistent recovery performance	Limited ESG and circularity metrics	Enhanced sustainability KPIs and tracking
6	Theoretical & Methodological Limits	Fragmented models; weak uncertainty handling	Lack of unified AI–RL frameworks	Integrated adaptive decision models

4. FUTURE RESEARCH DIRECTIONS

Building on the identified challenges and research gaps, Figure 7 and Table 4 develop a forward-looking research agenda by systematically mapping the core limitations of AI-driven Sustainable Reverse Supply Chain Management (SRSCM) into theoretically grounded research directions, methodological advancements, and future research opportunities. The framework organizes the literature into six interrelated and mutually reinforcing dimensions: (i) structural and network coordination, (ii) technological and data readiness, (iii) economic feasibility and value recovery, (iv) AI adoption and governance, (v) sustainability and circular economy outcomes, and (vi) theoretical and methodological foundations. Across these dimensions, Table 4 consolidates fragmented and methodologically heterogeneous research streams into a coherent set of actionable and theory-driven research trajectories, while identifying appropriate AI-enabled, optimization-based, and hybrid analytical methodologies. Simultaneously, it articulates the theoretical extensions required to transition SRSCM from predominantly static, siloed, and optimization-centric formulations toward adaptive, data-driven, and intelligence-augmented circular systems operating under uncertainty. In this regard, the table provides an integrative bridge between dispersed empirical insights and a unified, mechanism-based research architecture grounded in decision intelligence, system resilience, and multi-level governance. Building on this structured roadmap, future research should advance along the following interrelated and theoretically informed directions:

1) **Structural & Network Coordination:** Future research should extend classical closed-loop supply chain models by developing integrated, AI-augmented CLSC–reverse logistics (CLSC–RL) network designs that explicitly co-optimize forward and reverse material flows under deep uncertainty. This requires stochastic, multi-echelon, and spatially explicit optimization frameworks that jointly address facility location–allocation, capacity expansion, inventory positioning, and reverse logistics routing under stochastic demand, return uncertainty, and heterogeneous product quality. A key theoretical advancement lies in embedding AI-enabled predictive and prescriptive analytics within hierarchical decision architectures, enabling dynamic alignment between strategic network design, tactical planning, and operational execution in response to endogenous variability and exogenous disruptions.
2) **Technological & Data Readiness:** Future research should move toward autonomous, AI-native reverse logistics ecosystems underpinned by the convergence of IoT-enabled sensing, blockchain-based traceability, and cloud–edge–AI computing infrastructures. A central research frontier lies in the design of continuously learning data ecosystems that integrate high-velocity, multimodal data streams with online machine learning, deep learning, and reinforcement learning models. Such systems should enable real-time estimation of return probabilities, product condition states, and residual value distributions, while supporting adaptive, closed-loop optimization of reverse logistics operations under non-stationarity, disruption, and information asymmetry.
3) **Economic Feasibility & Value Recovery:** Future research should advance lifecycle-based value intelligence frameworks that explicitly capture uncertainty in product degradation processes, recovery yields, and secondary market price volatility. These frameworks should enable integrated, multi-objective optimization across reuse, repair, refurbishment, remanufacturing, and recycling pathways, thereby shifting decision-making from rule-based and static policies toward adaptive, AI-driven policy optimization. In parallel, research should address the economic scalability of AI adoption by developing lightweight, modular, and energy-efficient AI architectures that enhance computational efficiency and facilitate implementation in SMEs and resource-constrained contexts without compromising predictive accuracy or decision robustness.
4) **AI Adoption & Governance:** Future research should prioritize the development of trustworthy, explainable, and governance-aware AI frameworks tailored to reverse supply chain decision environments. This entails embedding explainability, interpretability, robustness, fairness, and accountability constraints into AI-enabled decision-support systems to strengthen managerial trust, regulatory compliance, and organizational legitimacy. Furthermore, hybrid human–AI decision architectures should be formalized to systematically integrate algorithmic recommendations with managerial expertise across forecasting, inspection, sorting, recovery prioritization, and network coordination. At the inter-organizational level, future studies should examine governance mechanisms governing data sovereignty, incentive alignment, algorithmic accountability, and trust formation within multi-tier circular supply chain ecosystems operating under heterogeneous institutional conditions.
5) **Sustainability & Circular Economy Outcomes:** Future studies should develop next-generation AI-enabled ESG and circularity intelligence systems capable of real-time monitoring, causal inference, and multi-objective optimization of sustainability performance across reverse supply chain networks. This includes the development of standardized, machine-interpretable circularity indicators and dynamic sustainability KPIs that enable cross-firm benchmarking, regulatory alignment, and decision integration within circular economy systems. Particular emphasis should

be placed on strengthening the underdeveloped social sustainability dimension by incorporating labor conditions, equity considerations, informal sector integration, and distributive justice mechanisms into AI-enabled assessment and optimization frameworks.

6) **Theory & Methodological Foundations:** Future research should advance toward a unified AI–CLSC–SRSCM theoretical paradigm that integrates behavioral operations theory, institutional theory, and complexity science to explain emergent, adaptive, and non-linear dynamics in reverse supply chain systems. Methodologically, the field should increasingly leverage digital twins, multi-agent reinforcement learning, system-of-systems modeling, and hybrid AI–optimization approaches to represent SRSCM as a complex adaptive socio-technical system characterized by uncertainty, feedback loops, path dependence, and cross-scale interdependencies.

In conclusion, SRSCM is undergoing a paradigmatic transition from fragmented and optimization-centric approaches toward integrated, intelligence-driven, and sustainability-oriented systems. Advancing this transformation requires not only methodological innovation but also deeper theoretical consolidation and a tighter integration of AI capabilities with economic viability and circular economy imperatives within a unified, multi-level research agenda.

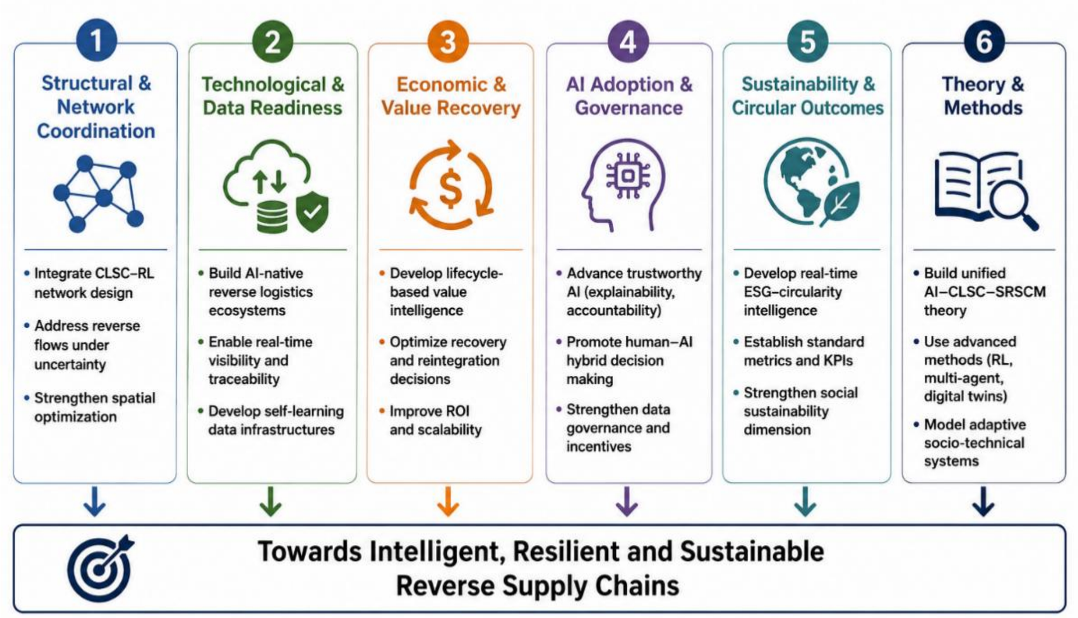

Figure 7. Structured Future Research Agenda for AI-Driven Sustainable Reverse SCM.

Table 4. Future Research Agenda for AI in Sustainable Reverse SCM.

#	Dimension	Research Gaps	Future Directions	Methods	Theoretical Contribution
1	Structural & Network Coordination	Limited CLSC–RL integration; weak network design	Integrate CLSC–RL networks under uncertainty	Stochastic optimization; simulation	AI-enabled network intelligence in CLSC
2	Technological & Data Readiness	Fragmented systems; low real-time visibility	Develop interoperable AI-native ecosystems	Digital twins; edge–cloud AI	Autonomous socio-technical circular systems
3	Economic & Value Recovery	Weak lifecycle value and ROI models	Enable lifecycle value intelligence	Dynamic optimization; lifecycle costing	AI-driven circular value theory
4	AI Adoption & Governance	Low trust; weak governance	Develop trustworthy hybrid AI governance	Behavioral modeling; simulation	Algorithmic governance and hybrid intelligence

5	Sustainability & Circular Outcomes	Weak ESG integration; limited traceability	Build real-time ESG–circular intelligence	MCDA; ML-based KPIs	Dynamic circular performance theory
6	Theory & Methods	Fragmented models; weak uncertainty handling	Develop unified AI–CLSC theory	Reinforcement learning; multi-agent systems	Adaptive socio-technical systems theory

5. CONCLUSION AND FUTURE WORK

This study systematically investigated artificial intelligence (AI) applications in sustainable reverse supply chain management (SRSCM) through a systematic literature review (SLR) of peer-reviewed publications from 2000 to 2026. By synthesizing fragmented and multidisciplinary research streams, it develops a structured taxonomy and a mechanism-based conceptual framework explaining how AI transforms decision intelligence, coordination mechanisms, and governance structures in reverse supply chain ecosystems. The synthesis evidences a clear paradigm shift from conventional cost-driven reverse logistics toward intelligent, adaptive, and multi-objective closed-loop systems enabled by machine learning, predictive analytics, intelligent optimization, and real-time decision support, thereby enhancing responsiveness, resource allocation, and recovery coordination.

The findings demonstrate that AI significantly improves reverse supply chain performance through enhanced return forecasting accuracy, improved resource recovery efficiency, increased operational transparency, and real-time synchronization of reverse logistics activities. This transition enables a shift from reactive, efficiency-oriented operations toward proactive, resilience-oriented, and sustainability-driven supply chain management under uncertainty and disruption. However, despite rapid scholarly progress, the literature remains fragmented across technological, operational, and managerial domains, limiting theoretical integration and holistic system understanding. Notably, generative AI and large language models (LLMs) represent an emerging yet largely unexplored research frontier in reverse supply chains, with current studies remaining scarce and conceptually underdeveloped.

This study proposes a future research agenda across six dimensions: network coordination, technological readiness, economic value recovery, AI governance, sustainability outcomes, and theoretical–methodological advancement. It highlights the need for integrated AI-enabled closed-loop systems, real-time data-driven decision-making, lifecycle-based optimization, trustworthy human–AI collaboration, and scalable deployment strategies. It further emphasizes strengthened ESG and circularity measurement frameworks, alongside advanced analytical approaches such as digital twins, reinforcement learning, and generative AI/LLM-based methods for enhanced reasoning, scenario generation, and decision support.

Theoretical Implications: SRSCM lacks a unified explanatory framework linking AI capabilities with governance structures, coordination logic, and adaptive decision architectures in circular supply chain systems. In particular, autonomy, distributed coordination, and system-level adaptive redesign remain under-theorized, while the social sustainability dimension is still weakly operationalized. Emerging paradigms such as explainable AI, human–AI collaborative governance, and generative AI-driven intelligence remain conceptually fragmented and insufficiently developed.

Practical Implications: This study provides actionable insights for leveraging AI to enhance reverse logistics efficiency, transparency, and sustainability performance through data-driven and adaptive decision systems, supported by structured circular economy strategies.

Managerial Implications: Managers should prioritize investments in AI-enabled infrastructure, strengthen data and analytics capabilities, and foster human–AI collaboration through workforce reskilling and redesign of decision-making processes to ensure effective and responsible adoption.

Study Limitations: This study is limited by its reliance on secondary peer-reviewed data, which may introduce publication bias and underrepresent emerging industrial practices. Additionally, the proposed conceptual framework requires further empirical validation across industries and geographical contexts to strengthen its generalizability and applicability.

Conflicts of Interest: The authors declare no conflicts of interest.

Generative AI Statement: The authors acknowledge that ChatGPT (OpenAI) was used exclusively for language editing and stylistic refinement of the authors' text, including improvements to clarity, grammar, and academic tone. The tool was not used to generate original scholarly content, data, analyses, or references. The authors have carefully reviewed and verified the final manuscript and accept full responsibility for its content.

Data Availability Statement: All data supporting this study are contained within the article.

ABBREVIATION

#	Full Term	Definition
AI	Artificial Intelligence	Systems that learn and support data-driven decision-making
CC	Cognitive Capabilities	AI-enabled perception, learning, and decision-making functions
CE	Circular Economy	System based on reuse, recycling, and regeneration
CF	Cognitive Flexibility	Human ability to adapt and override AI decisions
CSC	Circular Supply Chain	Closed-loop system for continuous resource circulation
CPS	Cyber-Physical Systems	Integrated digital–physical monitoring and control systems
DM	Digital Maturity	Level of digital integration and readiness
DT	Digital Twin	Virtual model of physical systems for simulation
EoL	End-of-Life	Stage of recovery, reuse, or disposal
EI	Environmental Intelligence	Integration of environmental factors into decisions
FL	Forward Logistics	Forward movement of goods in supply chains
IoT	Internet of Things	Connected devices enabling data exchange
KPI	Key Performance Indicator	Metric for performance evaluation
ML	Machine Learning	Algorithms for prediction and pattern recognition
RL	Reverse Logistics	Reverse flow of products for recovery
SC	Supply Chain	Network of production and delivery entities
SP	Sustainable Performance	Combined economic, environmental, and social outcomes
WEEE	Waste Electrical and Electronic Equipment	Discarded electronics for recovery

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