

# Trends and Insights in Integrating Artificial Intelligence with Sustainable Supply Chain Management

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## ABSTRACT

Achieving sustainability in global supply chain management (SCM) presents an ongoing and complex challenge, requiring innovative approaches that align economic goals with environmental and social responsibilities. In this context, Artificial Intelligence (AI) and Machine Learning (ML) are increasingly recognized as transformative technologies for advancing sustainable supply chain management (SSCM) by improving decision-making processes, operational performance, and system responsiveness. This paper presents a systematic literature review (SLR) examining the intersection of AI and SSCM, based on 206 peer-reviewed articles published between 2015 and 2024. Through a comprehensive multi-perspective descriptive and content analysis, the study synthesizes emerging patterns, conceptual developments, and future research trajectories. The review reveals a rapidly expanding academic interest, reflecting a shift from an emerging topic to an established area of investigation. Key themes include the role of AI in supporting circular economy practices, minimizing waste, and enhancing remanufacturing processes, each contributing to overarching sustainability objectives. Moreover, this study identifies significant research gaps, particularly the need for large-scale empirical validation and the integration of ethical and social considerations, offering valuable directions for future inquiry.

**Keywords:** *artificial intelligence, circular economy, supply chain management, sustainability, optimization, systematic literature review*

## 1. INTRODUCTION

In today's globalized and resource-constrained environment, the traditional emphasis in SCM on cost reduction, quality improvement, and delivery speed is no longer sufficient. Emerging pressures, including stricter environmental regulations, heightened societal expectations, and increasing investor scrutiny, have accelerated the evolution toward Sustainable Supply Chain Management (SSCM). This shift compels firms to adopt a more holistic

approach that balances economic efficiency with environmental stewardship and social equity across the entire value chain (Seuring & Müller, 2008; Carter & Rogers, 2008). Far from being just an ethical obligation, this transformation represents a strategic imperative for enhancing long-term competitiveness, strengthening resilience, and mitigating reputational and compliance risks.

Central to environmental sustainability efforts in SSCM is the adoption of the Circular Economy (CE) paradigm. Unlike the conventional "take-make-dispose" model, CE promotes closed-loop systems where resources are retained within the system as long as possible, waste is minimized, and the value of materials is recovered through reuse, remanufacturing, and recycling (Geissdoerfer *et al.*, 2017; Reuter, 2016). However, operationalizing circular and sustainable principles within manufacturing and supply chain routines increases implementation complexity, as it requires integrating closed-loop activities (e.g., reverse logistics, waste valorization, and product-life extension) with enabling organizational and digital capabilities (Setyadi *et al.*, 2025). Supply chain managers must address numerous challenges, such as managing highly variable reverse logistics flows, evaluating the quality of returned products for reuse or remanufacturing, ensuring ethical labor practices across multi-tiered supplier networks, and making trade-offs among competing performance objectives, economic, environmental, and social.

Traditional tools and management approaches, designed for the stable and predictable nature of linear systems, often fall short when applied to today's dynamic, uncertain, and interconnected supply chains, particularly in smart agriculture (Fuentes-Peñailillo *et al.*, 2024). The volume, variety, and velocity of data needed to track resource flows, measure sustainability indicators, and monitor compliance are overwhelming for manual processing or rule-based systems. As a result, organizations face significant information bottlenecks, hindering their ability to act quickly and strategically in a rapidly changing landscape.

It is within this context of complexity, uncertainty, and data intensity that AI and ML have emerged as powerful enablers of SSCM. AI technologies offer advanced

computational capabilities to process massive, diverse datasets and generate actionable insights. ML algorithms can optimize logistics networks to reduce both cost and environmental impact, forecast the remaining useful life of components to support remanufacturing efforts, and detect anomalies in supplier behavior that may signal sustainability or ethical compliance issues (Sadeghi *et al.*, 2024; Govindaraj *et al.*, 2024). These capabilities illustrate how AI can convert high-level sustainability goals into measurable and achievable operational actions. When mapped onto the SCOR framework, AI techniques such as neural networks and reinforcement learning are already delivering cost, service, and efficiency gains across the plan, source, make, and deliver processes of leading firms (Pham & Bris, 2025). At the warehouse level, simulation-based evaluations show that fuzzy-integrated neural architectures can predict multiple key performance indicators simultaneously, supporting more responsive operational decisions (Frikha, 2026).

Despite the clear potential of AI in SSCM, the academic landscape remains fragmented and is evolving rapidly, with an annual publication growth rate surpassing 70%. Several prior reviewers have examined specific aspects of this intersection (Toorajipour *et al.*, 2021; Nishant *et al.*, 2020); however, a comprehensive synthesis that integrates bibliometric mapping with in-depth thematic content analysis remains lacking. Recent bibliometric studies further reveal a persistent gap between conceptual contributions and industrial adoption, both for AI-enabled transparency and accountability in global supply chains (Elghomri *et al.*, 2025) and for digital twins supporting sustainable, low-carbon supply chains (Elghomri & Messaoudi, 2026). This fast-paced development highlights the need for a structured and integrative review to consolidate current knowledge, chart the intellectual landscape, and identify promising but underexplored avenues for future investigation. In response to this need, the present study aims to conduct a bibliometric and thematic analysis to address the following research questions:

- (1) What is the state of research on the integration of AI with sustainable supply chain management?
- (2) What are the research gaps that need to be filled by future studies?

To answer these questions, this study adopts an SLR methodology. This rigorous approach ensures a comprehensive and objective assessment of peer-reviewed studies published between 2015 and 2024. The structure of this paper is as follows:

Section 2 reviews the existing literature to establish the study's conceptual background. Section 3 details the SLR methodology used to guide the data collection and analysis. Section 4 presents both the descriptive and content analyses, outlining the main research trends and thematic insights derived from the selected studies. Section 5 discusses the key findings in light of current developments. Section 6 identifies critical research gaps and suggests future research directions. Finally, Section 7 presents the limitations of this study, and Section 8 concludes the paper by summarizing the core findings and reflecting on their practical and theoretical implications.

## 2. LITERATURE REVIEW

The traditional profit-centric model of supply chain management is increasingly being questioned in light of growing demands for sustainability, environmental responsibility, and social equity. There is a growing scholarly and practical consensus that SSCM is no longer a peripheral consideration but a strategic necessity in contemporary operations (Seuring & Müller, 2008; Carter & Rogers, 2008). SSCM seeks to balance economic viability with ecological and societal responsibilities, encompassing the coordinated flow of materials, information, and capital across a product's lifecycle. This integration mandates collaboration among diverse stakeholders and emphasizes the need for systemic change in how supply chains are designed and managed.

A key conceptual pillar of SSCM is the CE, which promotes closed-loop systems to reduce waste, retain value, and extend product lifecycles (Geissdoerfer *et al.*, 2017; Reuter, 2016). This framework introduces new operational complexities, including the design of reverse logistics networks, the tracking of end-of-life components, and the implementation of material traceability mechanisms. The transition to circularity in supply chains is accompanied by significant barriers, including regulatory fragmentation, limited stakeholder engagement, and informational asymmetries (Govindan & Hasanagic, 2018). Traditional linear SCM models, which operate under stable and predictable assumptions, are often ill-equipped to address these challenges. The multidimensional nature of SSCM demands real-time decision-making and analysis of vast, heterogeneous data sources (Mrad & Boujelbene, 2024).

In response to these evolving demands, AI and ML are increasingly deployed within SSCM. These technologies offer the analytical strength and flexibility required to manage the complexity, dynamism, and volume of sustainability-related data. AI enhances strategic and operational decision-making through predictive analytics, intelligent automation, and optimization techniques (Mrad & Boujelbene, 2019; Narwane *et al.*, 2021). ML algorithms learn from data patterns to continuously improve performance and can be used in diverse applications, from carbon-efficient logistics planning to supplier sustainability assessments and predictive maintenance (Sadeghi *et al.*, 2024; Govindaraj *et al.*, 2024).

The integration of AI into SSCM unfolds along several thematic directions. A notable area is the use of AI-based decision support systems, which assist in making complex trade-offs among cost, environmental impact, and social outcomes. These systems integrate multiple criteria decision analysis and optimization algorithms to support sustainable supplier selection, process improvements, and resource allocation strategies (Kellner *et al.*, 2019; Barrera *et al.*, 2023). AI is also central in advancing circularity via ML-driven models that predict product lifecycles, support remanufacturing, and facilitate intelligent waste management (Debnath *et al.*, 2024; Govindaraj *et al.*, 2024).

Digital infrastructure further strengthens the potential of AI in SSCM. Technologies such as the Internet of Things (IoT) and Blockchain, when combined with AI, improve traceability, enable real-time monitoring, and foster transparency across complex supply chains (Zhong *et al.*, 2017). These tools ensure that timely, accurate, and granular

data support decision-making. The field is also moving toward embracing Industry 5.0 principles, which emphasize human-centric AI, inclusivity, and resilience. This evolution underscores the need to design intelligent systems that not only optimize performance but also align with societal and ethical values (Mourtzis, 2024; Ejjami & Boussalham, 2024).

Given the complexity and interdisciplinarity of the AI-SSCM nexus, there has been a surge in efforts to systematically understand its development. Rather than relying on fragmented observations or anecdotal reviews, researchers increasingly apply quantitative and structured mapping techniques to analyze the evolution of key themes, intellectual influences, and emerging research directions. These approaches allow for a robust and reproducible exploration of knowledge structures and help identify both well-established domains and underexplored frontiers within the field.

A systematic examination of the evolving literature reveals several dominant research trajectories at the intersection of AI and SSCM.

To begin with, a prominent stream of research focuses on the development of AI-driven decision-support systems aimed at fostering resource efficiency and embedding CE principles into supply chain operations. For instance, Sivarajah *et al.* (2024) proposed a Big Data Analytics–AI framework designed to enhance innovation and organizational performance. In a complementary approach, Mardani *et al.* (2015) and Shahidzadeh and Shokouhyar (2023) highlight the application of multi-criteria decision-making (MCDM) techniques in analyzing reverse logistics and supporting closed-loop sustainability strategies in supply chains.

In parallel, ML is increasingly leveraged to optimize waste management and resource recovery. Xia *et al.* (2023) developed ensemble models to forecast the recyclability of end-of-life products, while Nafiz *et al.* (2023) introduced ConvoWaste, a deep learning-based system for real-time waste classification. Similarly, Debnath *et al.* (2024) incorporated financial dimensions into e-waste management through predictive ML modeling, illustrating the dual ecological and economic potential of AI in sustainability contexts.

Another notable line of inquiry highlights the role of digitalization in institutionalizing circularity across supply chains. Technological advancements such as IoT, Blockchain, and AI are utilized to build closed-loop systems, improve traceability, and enhance operational responsiveness (Kushch & Prieto Castrillo, 2017). These tools not only promote transparency but also facilitate inclusive innovation and broaden access to sustainable practices.

Moreover, recent studies frame SSCM transformation through the lens of Industry 5.0, advocating for a more human-centric approach to technological deployment. Research by Ejjami and Boussalham (2024) stresses the importance of designing AI solutions that support occupational safety, worker well-being, and socially responsible innovation, underscoring a shift from automation toward augmentation.

Further, there is a growing emphasis on AI's ability to optimize multi-objective performance within complex supply chain systems. Use cases range from minimizing energy consumption in logistics to enhancing reverse logistics strategies and cost-efficiency. Notably, hybrid models have been proposed to improve sustainability in energy networks (Sadeghi *et al.*, 2024), while Mardani *et al.* (2015) offer a foundational review of MCDM methodologies. Shahidzadeh and Shokouhyar (2023) extend their application by integrating analytics to enhance logistics and sustainability-oriented decision-making.

Lastly, evidence suggests that realizing AI-enabled performance and sustainability gains depends not only on the algorithms themselves, but also on organizational and technological readiness. In the tourism transportation context, digital infrastructure, employee skills, and managerial support have been shown to significantly increase AI adoption, which in turn improves operational efficiency, occupancy rates, customer satisfaction, and profitability in highly uncertain and seasonal environments (Frikha, 2025). These findings highlight the importance of readiness as a practical roadmap for settings that use AI for forecasting and resource-use optimization. Beyond service transport, emerging work also examines AI-supported approaches for improving water and energy management, raw material decisions, and eco-innovative business models, particularly in agriculture, mining, and manufacturing (Ghoreishi & Happonen, 2020; Ramírez-Márquez & Ponce-Ortega, 2023).

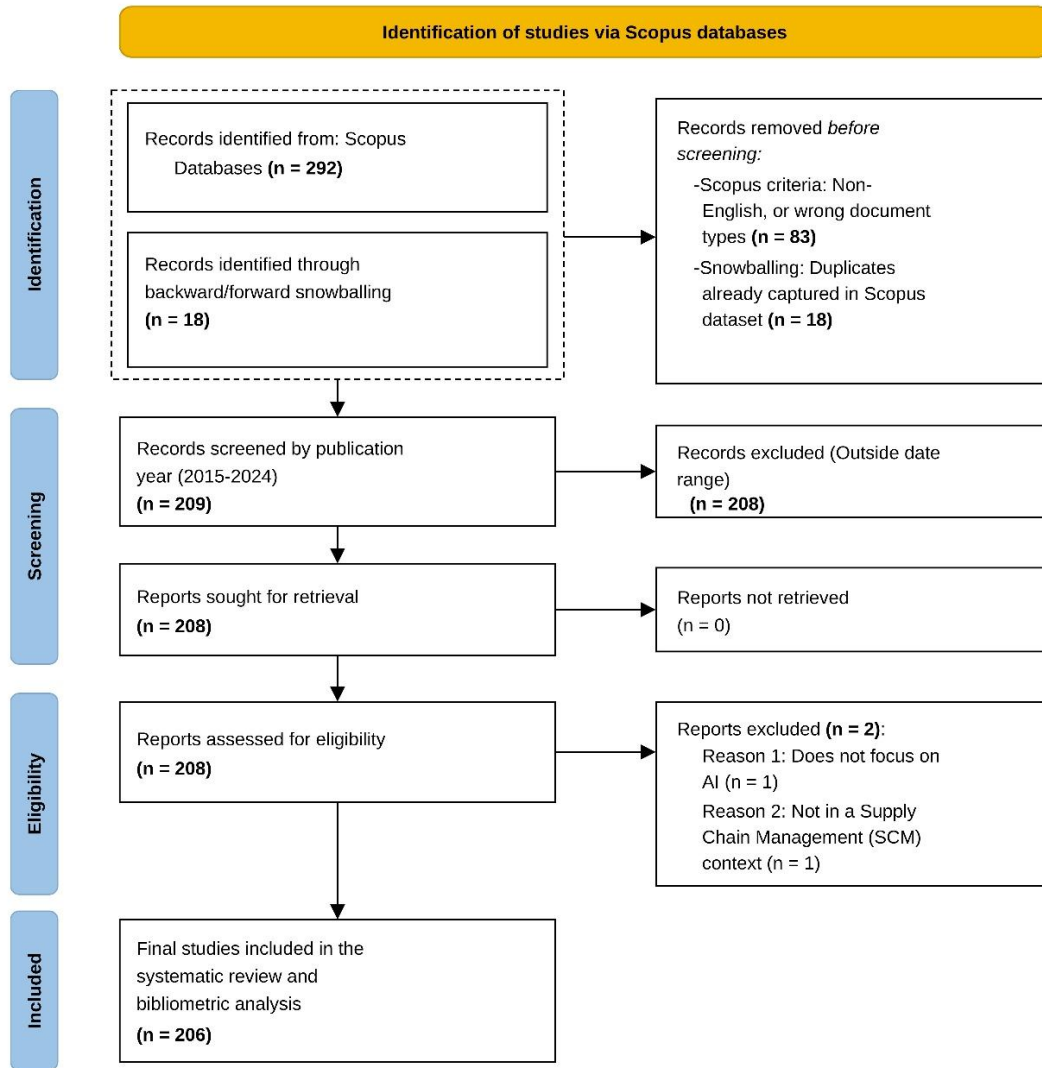
Although the literature has expanded substantially in recent years, it remains fragmented, lacking a unified analytical framework. This paper aims to address this gap by systematically synthesizing the existing body of work, identifying converging research priorities, and outlining future pathways for advancing AI-enabled sustainability in global supply chains.

### 3. METHODOLOGY

Given This study adopts a hybrid methodological framework, combining quantitative bibliometric analysis with a structured thematic review to ensure a rigorous, transparent, and reproducible assessment of the literature on the integration of AI with SSCM. The PRISMA 2020 framework guided the review process to ensure transparency in study identification, screening, eligibility assessment, and inclusion.

The literature search was conducted exclusively using Scopus, which was selected for its broad coverage of peer-reviewed publications in supply chain and environmental management, as well as its suitability for bibliometric analysis. The use of a single database ensured the integrity and standardization of metadata required for bibliometric tools such as Biblioshiny, thereby avoiding the incompatibilities that may arise when merging records from multiple databases.

To enhance the dataset's comprehensiveness, backward and forward snowballing techniques (Wohlin, 2014) were applied to the references and citations of the included studies. Backward snowballing consisted of examining the reference lists of the initially included papers, while forward snowballing involved tracing citing



**Figure 1** PRISMA-Based Filtering of Records for AI and Sustainable Supply Chain Research (2015–2024)

documents through Scopus citation tracking. This complementary procedure identified 18 candidate records. These records were then screened using the same inclusion and exclusion criteria applied to the Scopus dataset. The screening showed that all 18 records had already been captured in the original Scopus search. Consequently, snowballing did not add any new unique studies, and the final dataset retained 206 studies.

The selection and screening process is documented using a PRISMA flow diagram (Figure 1), which reports the number of records excluded at each stage and the reasons for exclusion. In line with systematic literature review principles, the methodological quality of the included studies was assessed using a structured quality appraisal checklist adapted from Kmet *et al.* (2004), as detailed in Section 3.2.

For the qualitative synthesis, a structured content analysis approach inspired by Mayring (2014) was employed. To enhance the reliability of the coding process, inter-coder agreement was ensured through a consensus-based reconciliation procedure among the researchers. This integrated approach enables a coherent synthesis of the literature, facilitating the identification of key themes, emerging trends, and research gaps within the field.

### 3.1 The Selection of Papers

The research questions served as the foundation for the systematic literature review and guided the identification, screening, and selection of relevant studies. To ensure objectivity and reduce bias in the data collection process, a clear set of inclusion and exclusion criteria was implemented before screening. These criteria were designed to retain only studies directly relevant to the scope of AI applications in SSCM. The implemented criteria are the following:

- (1) English-language articles indexed in Scopus.
- (2) Peer-reviewed journal articles and conference papers, while editorials, notes, and book reviews were excluded.
- (3) Published between 2015 and 2024.
- (4) A targeted search strategy based on the following query: ("artificial intelligence" OR "machine learning") AND ("circular economy" OR "circular supply chain" OR "sustainability" OR "waste management" OR "reverse logistics" OR "recycling").
- (5) Studies had to address both an AI-related component and a supply chain, logistics, circular, or sustainability-related context.

The identification and screening process followed the PRISMA 2020 guidelines. The initial Scopus search yielded 292 records after thematic combination. Before formal screening, 83 records were removed because they did not meet the predefined criteria, including duplicates, non-English publications, and document types outside the scope of the review. The remaining 209 records were screened by publication year, and 208 records met the 2015-2024 temporal criterion. These 208 records were then assessed for full-text eligibility. Following the eligibility assessment, 2 records were excluded for substantive reasons: one did not focus on AI, and one was not situated in a supply chain management context. This resulted in 206 studies eligible for inclusion.

As a complementary verification step, backward and forward snowballing were conducted on the included studies, identifying 18 candidate records. However, after applying the same inclusion and exclusion criteria and checking for overlap with the original database retrieval, all 18 records were found to have already been captured in the initial Scopus search. Therefore, no new unique studies were added through snowballing, and the final dataset comprised 206 studies. The detailed selection process is illustrated in Figure 1.

### 3.2 Data Analysis Approach

To ensure methodological rigor, a formal quality appraisal was conducted on the 206 included studies using a 10-point checklist adapted from Kmet *et al.* (2004). Criteria included: (a) clarity of the research objective, (b) justification of the AI methodology, (c) adequacy of data quality description, and (d) robustness of conclusions. Only studies achieving a score greater than 0.7 (on a 0-1 scale) were retained for the final analysis. All 206 studies met this threshold, confirming the overall quality of the included dataset. Thematic coding was carried out independently by two researchers. To assess the reliability of the classification into thematic clusters, Inter-Coder Reliability (ICR) was calculated on a 20% random sample ( $n=41$ ). A Cohen's Kappa coefficient of 0.88 was achieved, indicating almost perfect agreement (Landis & Koch, 1977). Disagreements were resolved through discussion until consensus was reached, after which the agreed coding scheme was applied to the remaining studies.

First, a descriptive bibliometric analysis was performed to map the intellectual structure of the field. This involved using the Biblioshiny tool to explore key quantitative indicators, including annual scientific production, the most influential journals and authors, keyword co-occurrence patterns, and international collaboration networks. Visual outputs such as thematic maps and co-authorship networks were generated to provide a clear representation of the research field's development, highlight influential scholars and institutions, and reveal the interconnections across research domains.

Second, a qualitative content analysis was conducted to identify and synthesize the core themes, methodologies, and findings within the literature. Following the thematic analysis approach described by scholars such as Bryman and Bell (2007), each article was coded and categorized into four broad thematic clusters: (1) AI-driven optimization and decision support, (2) circular economy, waste, and resource management, (3) sustainability performance, risk, and

human-centered transformation, and (4) enabling technologies and data infrastructure. For interpretive clarity, however, the second cluster was subsequently discussed through two related subthemes, (a) waste and resource management, and (b) remanufacturing and circular economy practices, while the third cluster was discussed in relation to the emergence of the industry 5.0 perspective. This analytical subdivision explains why the discussion section is organized into five thematic lenses without altering the underlying four-cluster empirical structure reported in Table 5. This thematic classification helped organize the material into cohesive clusters, enabling a deeper investigation of conceptual trends and patterns. This qualitative step was crucial for moving beyond publication counts to understand how AI is being conceptualized and applied to solve the complex challenges of sustainable supply chain management.

Third, to produce the AI maturity analysis presented in Section 5.6, each of the 206 studies was independently classified along two dimensions: (a) AI maturity level, categorized as predictive, prescriptive, or autonomous, according to the primary analytical function of the AI technique employed; and (b) sustainability dimension addressed, economic, environmental, or social, based on the dominant objective and reported contribution of the study. Descriptive studies were those primarily concerned with monitoring, mapping, or pattern identification; predictive studies focused on forecasting or estimation; prescriptive studies emphasized optimization, recommendation, or decision support; and autonomous studies involved adaptive or self-directing system behavior. Studies addressing multiple dimensions were coded under all applicable categories. This dual-dimension classification was performed by both coders as part of the thematic coding process, with disagreements resolved using the consensus procedure described above. The coding framework was used to support the conceptual interpretation developed in Section 5.6 and to provide a transparent basis for discussing the relative maturity of AI applications across sustainability dimensions. Where quantitative proportions are reported, they are derived from this coding procedure applied to the full set of 206 studies.

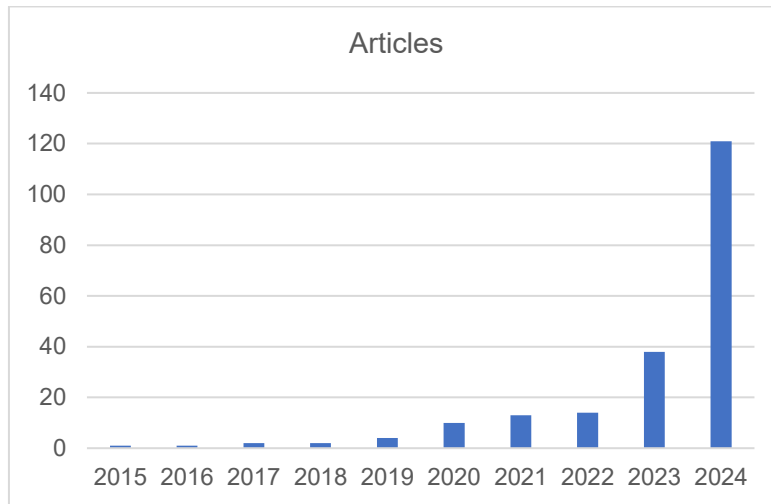
## 4. RESULTS

In this section, we present the descriptive analysis of the findings obtained from the SLR and the categorization of thematic areas of the research on AI in SSCM. The significant contributions across different time periods, journals, and geographical regions are discussed. Furthermore, the selected studies are organized into major areas of focus to highlight recurring themes and provide a solid foundation for identifying existing research gaps.

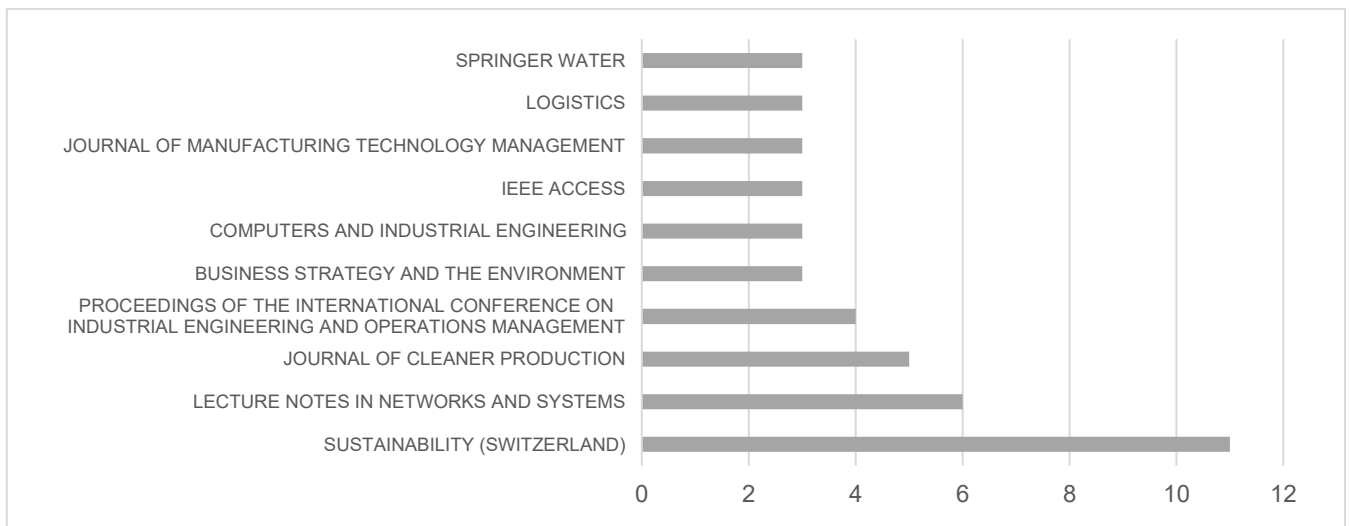
### 4.1 Descriptive Analysis

A descriptive analysis of the 206 papers included in this review was conducted to track the progression of research and to identify the key journals, methodologies, and countries that have contributed significantly to the field. The analysis of the dataset, comprising contributions from 728 authors across 151 distinct sources, reveals a research field undergoing rapid and significant expansion.

The chronological distribution of publications, illustrated in Figure 2, reveals a dramatic and recent surge in academic interest. The field's origins in this review period



**Figure 2** Annual Publication Trend on AI Applications in Circular Supply Chains and Sustainability (2015–2024)



**Figure 3** Most Relevant Sources by Number of Articles

**Table 1** Impact of Key Sources

| Source                                | h-index | g-index | Total Citations (TC) |
|---------------------------------------|---------|---------|----------------------|
| Journal of Cleaner Production         | 5       | 5       | 278                  |
| Sustainability (Switzerland)          | 5       | 11      | 204                  |
| Business Strategy and the Environment | 3       | 3       | 170                  |
| Bioresource Technology                | 2       | 2       | 95                   |
| Computers and Industrial Engineering  | 2       | 3       | 67                   |

are humble, with only a single publication in 2015. Output remained modest until 2019, indicating that the intersection of AI and SSCM was a nascent, exploratory domain. A clear inflection point occurred in 2020, after which research output began to accelerate, coinciding with heightened global awareness of supply chain vulnerabilities and the maturation of accessible AI technologies.

The expansion became exponential in 2023 (38 documents) and culminated in a massive surge to 121 publications in 2024. This trend, representing an impressive 70.38% annual growth rate, signals a definitive shift from a niche topic to a mainstream research priority. This rapid growth is further validated by the citation metrics: with an average document age of just 2.01 years, each paper has

already amassed an average of 12.98 citations, reflecting a high level of scholarly attention and immediate impact within the academic community.

The dissemination of research is concentrated in several key academic venues, as detailed in Figure 3. In terms of sheer volume, *Sustainability* (Switzerland) is the most prolific source with 11 articles, followed by *Lecture Notes in Networks and Systems* (6 articles) and *Journal of Cleaner Production* (5 articles). This indicates a strong interest from journals focused on broad sustainability issues as well as technology-oriented conference proceedings.

However, an analysis of research impact, presented in Table 1, offers a more nuanced picture. *Journal of Cleaner Production* emerges as a leading powerhouse, with its 5

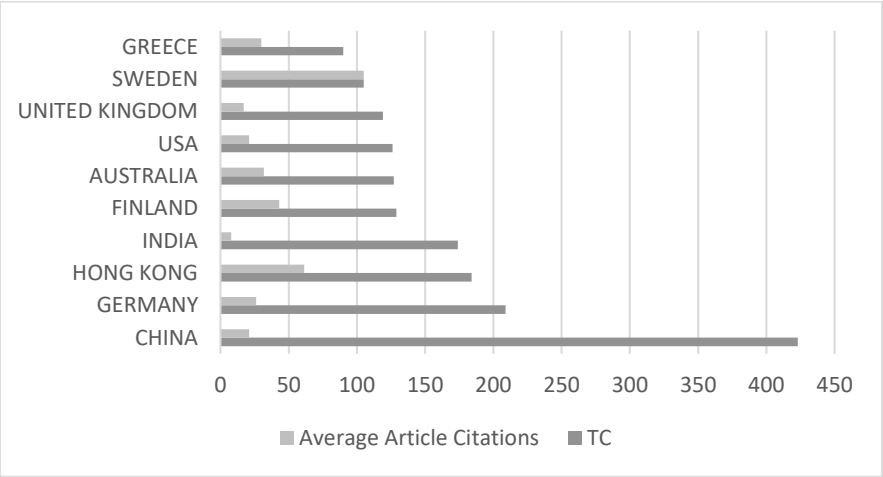


Figure 4 Most Cited Countries

Table 2 Most Relevant Affiliations by Publication Volume

| Affiliation                                                | Articles |
|------------------------------------------------------------|----------|
| Jilin University                                           | 9        |
| Amity University                                           | 8        |
| University of Nevada-Reno                                  | 8        |
| De La Salle University                                     | 7        |
| Shahid Beheshti University                                 | 7        |
| Chitkara University                                        | 6        |
| Helmholtz Institute Freiberg for Resource Technology (HIF) | 6        |
| Information Technologies Institute                         | 6        |
| SRM University AP                                          | 6        |
| The Hong Kong University of Science and Technology         | 6        |

articles accumulating 278 total citations. Similarly, *Business Strategy and the Environment* demonstrates exceptional citation efficiency, gathering 170 citations from only 3 articles, suggesting it publishes foundational or highly resonant work. The high h-index and g-index scores for these top journals confirm their central role in shaping the discourse. The presence of specialized journals such as *Computers and Industrial Engineering and Logistics* further underscores the field’s interdisciplinary nature, blending operations research, computer science, and environmental management.

The research landscape is decidedly global, reflecting the international nature of modern supply chains. This is evidenced by a high international co-authorship rate of 31.07%. However, certain nations have established themselves as epicenters of research impact. As shown in Figure 4, China leads significantly in influence, with its publications amassing 423 total citations. This dominance highlights the intense research activity within China aimed at addressing its vast manufacturing and logistics sectors through a sustainability lens.

Following China are prominent European and Asian research hubs, including Germany (209 citations), Hong Kong (184), and India (174). This geographical distribution suggests that research is most active in regions with either major industrial economies facing sustainability pressures (China, Germany, India) or significant academic and financial centers driving technological innovation (Hong Kong, USA, UK). The collaborative map underscores a global effort to tackle shared challenges in building resilient and sustainable supply networks.

The examination of research methodologies reveals a strong orientation toward developing and applying new models. Quantitative methods, particularly optimization and simulation, are the most employed approaches, reflecting an emphasis on providing practical, data-driven solutions. The field is characterized by a vibrant and increasingly collaborative scholarly community. With an average of 3.68 co-authors per document and only 20 out of 206 articles being single-authored, the findings suggest that interdisciplinary and multi-authored research is the prevailing norm. This collaborative tendency reflects the complexity of sustainability challenges, which often require cross-domain expertise.

An analysis of institutional affiliations (Table 2) highlights the most active contributors to this research area. Jilin University (China), Amity University (India), and the University of Nevada-Reno (USA) emerge as the most prolific institutions, mirroring the broader geographical trends observed in the dataset. Notably, the involvement of specialized research centers, such as the Helmholtz Institute Freiberg for Resource Technology, illustrates the field’s emphasis on resource efficiency and technological innovation.

In terms of individual contributions, leading scholars such as Sharma P. and Kumari S. stand out for their research productivity, particularly in recent years. Citation analysis (Table 3) further underscores the increasing impact of their work; for instance, Sharma P. has accrued 80 citations across four publications in 2023 alone, signaling both relevance and early influence within the academic community.

**Table 3** Author Production Over Time

| Author         | Year | Freq | TC | TCpY   |
|----------------|------|------|----|--------|
| Ahmed SR       | 2024 | 2    | 16 | 8      |
| Al-Sharify TA  | 2024 | 2    | 16 | 8      |
| Ali I          | 2024 | 2    | 1  | 0,5    |
| Bolaji AL      | 2024 | 2    | 1  | 0,5    |
| Eswaran V      | 2024 | 2    | 0  | 0      |
| Garg H         | 2024 | 2    | 1  | 0,5    |
| Kumari S       | 2024 | 3    | 9  | 4,5    |
| Shahidzadeh MH | 2022 | 1    | 25 | 6,25   |
| Shahidzadeh MH | 2024 | 2    | 1  | 0,5    |
| Sharma P       | 2023 | 4    | 80 | 26,667 |

**Table 4** Synthesis of Key Research on AI, Sustainability, and Supply Chain Management (2015–2024)

| Author & Year                        | Domain/Focus                                    | Problem Statement                                                            | Proposed Solution / Technology                                                   | Key Benefits                                                                                   | Research Gaps / Future Directions                                                                                                        |
|--------------------------------------|-------------------------------------------------|------------------------------------------------------------------------------|----------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Debnath, B., <i>et al.</i> , 2024    | E-Waste Management, Circular Economy            | Uncertainty in sustainable e-waste material recovery                         | ML-based AHP-PCA optimization model                                              | Identifies key sustainability drivers; enables probabilistic decision-making                   | Data-intensive modeling; roadmap development for future e-waste flows                                                                    |
| Barrera, F., <i>et al.</i> , 2023    | SCM, Customer Segmentation                      | Difficulty in effective B2B marketing segmentation                           | Sorting outranking-based multi-criteria decision system                          | Automates segmentation; enables robust group formation                                         | Scalability for large datasets; handling massive alternatives                                                                            |
| Centobelli <i>et al.</i> , 2022      | Circular supply chain, blockchain, traceability | Lack of trust, transparency, and traceability in circular supply chains      | Blockchain-enabled framework for trust and transparency                          | Enhanced traceability, transparency, and stakeholder trust                                     | Integration with broader AI-enabled analytics and empirical validation across industries                                                 |
| Govindaraj, M., <i>et al.</i> , 2024 | Waste Management, Digital Circular Economy      | Low efficiency in waste-to-value extraction                                  | ML techniques (K-Means, Regression, Deep RL)                                     | High prediction accuracy; optimized routing; real-time decisions                               | Method integration; full lifecycle modeling                                                                                              |
| Lipu <i>et al.</i> , 2021            | Battery Management                              | Poor end-of-life evaluation of EV batteries                                  | Onboard ML with EIS for State of Health prediction                               | Real-time diagnostics; better reuse; waste minimization                                        | Cloud integration; remote monitoring systems                                                                                             |
| Ejjami, R., <i>et al.</i> , 2024     | Manufacturing, Industry 5.0                     | Challenges in achieving resilience and responsibility in smart manufacturing | AI-driven predictive maintenance, quality control, and supply chain optimization | Enhanced manufacturing resilience; improved product quality                                    | Ethics, security, and governance of AI in Industry 5.0 contexts                                                                          |
| Sadeghi, R. K., <i>et al.</i> , 2024 | Renewable Energy, Circular Economy              | Integration of socio-environmental metrics into energy modeling              | Hybrid ML with multi-objective logistic-optimization model                       | Cost parity with fossil fuels; reduced emissions                                               | Empirical validation; large-scale applicability                                                                                          |
| Mrad, M., <i>et al.</i> , 2025       | SCM, Sustainability                             | Fragmented research on combined AI & robotics for low-carbon supply chains   | Systematic scoping review; evidence-based implementation framework               | AI-driven logistics optimization; robotic energy-efficient warehousing; practical SCM guidance | High AI energy demands; data integration challenges; need for standardized validation benchmarks; limited combined AI + robotics studies |

**Table 4** Synthesis of Key Research on AI, Sustainability, and Supply Chain Management (2015–2024) (Cont'd)

| Author & Year                       | Domain/Focus                                                    | Problem Statement                                                                           | Proposed Solution / Technology                                                                                       | Key Benefits                                                                                   | Research Gaps / Future Directions                                                                     |
|-------------------------------------|-----------------------------------------------------------------|---------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------|
| Said, Z., <i>et al.</i> , 2023      | Food Waste, Sustainability                                      | Low valorization of food waste via circular practices                                       | IoT + AI-based bioprocess monitoring system                                                                          | Improved food security; sustainability enhancement                                             | Governmental integration; CE model maturity                                                           |
| Yogarajan, L., <i>et al.</i> , 2023 | Agri-food supply chain, blockchain adoption                     | Lack of clarity on drivers, impacts, and implementation of blockchain in agri-food systems  | Systematic literature review identifying adoption factors and thematic areas                                         | Improved traceability, transparency, food safety, waste reduction, and supply chain efficiency | Need for policy frameworks, quantitative evaluation, and deeper integration with digital technologies |
| Sun, X., <i>et al.</i> , 2022       | Logistics, Operations Research                                  | Lack of novel risk-aware logistics strategies                                               | Review of MCDM, game theory, and ML techniques                                                                       | Advanced modeling methods; new OR applications                                                 | Integration of quantitative and qualitative metrics                                                   |
| Kellner <i>et al.</i> , 2019        | Supplier Selection, SCM                                         | Trade-off management in sustainable supplier selection                                      | Multi-objective optimization + ANP approach                                                                          | Balanced criteria selection; informed decision-making                                          | Complex real-world constraints                                                                        |
| Narwane <i>et al.</i> , 2021        | SCM, Big Data                                                   | Inability to leverage data for strategic decisions                                          | AI-enabled Big Data Analytics framework                                                                              | Operational insights; innovation enablement; competitiveness                                   | Data quality impact on decisions                                                                      |
| Despoudi, S., <i>et al.</i> , 2021  | Agri-SCM, Industry 4.0                                          | Low transparency and inefficiency in traditional farming                                    | IoT, Robotics, AI and Big Data integration                                                                           | Efficiency boost; sustainability compliance                                                    | Conceptual clarity; real-case validation                                                              |
| Bentalha, B., <i>et al.</i> , 2023  | Smart SCM                                                       | Misalignment between sustainability and logistics intelligence                              | Theoretical framework for smart-sustainable SCM                                                                      | Integration of ecological thinking; industrial decision support                                | Empirical grounding; interdisciplinary methods                                                        |
| Yadav <i>et al.</i> (2024)          | Sustainable supply chain management; AI; information management | Lack of a comprehensive understanding of AI applications for information management in SSCM | Systematic literature review with bibliometric analysis and AI-based framework proposal                              | Improved decision-making, data management, operational efficiency, and sustainability          | Limited empirical validation; need for real-world implementation and advanced AI integration          |
| Özsoy, 2023                         | Circular economy, AI                                            | Challenges in implementing circular practices and the need to leverage AI                   | Literature review on AI's role in enabling CE (resource optimization, waste/emissions reduction, recovery/recycling) | Clarifies AI opportunities; guidance for firms and policymakers                                | Needs empirical validation; governance/ethical risks and implementation roadmaps by sector            |
| Mourtzis, 2024                      | Industry 4.0/5.0, AI                                            | Unclear AI pathways for sustainable Industry 5.0                                            | Review of AI techniques for personalization + CE                                                                     | Human-centered AI; process optimization                                                        | Ethics, security, and sustainability concerns                                                         |
| Ghoreishi, M., & Happonen, A., 2020 | Product Design, Circular Economy                                | Weak AI integration in circular product innovation                                          | Conceptual AI framework for repair/restoration designs                                                               | Real-time design feedback; productivity boost                                                  | Few optimization studies for repair and restoration                                                   |

**Table 4** Synthesis of Key Research on AI, Sustainability, and Supply Chain Management (2015–2024) (Cont'd)

| Author & Year                             | Domain/Focus                                                                                | Problem Statement                                                                                                                            | Proposed Solution / Technology                                                                                     | Key Benefits                                                                                                                                     | Research Gaps / Future Directions                                                                                      |
|-------------------------------------------|---------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------|
| Reuter, M. A., 2016                       | Metallurgy, Circular Economy                                                                | Digitalization gap in global resource processing                                                                                             | Metallurgical Internet of Things (m-IoT)                                                                           | Resource quantification; eco-boundaries definition                                                                                               | Smart tool integration; CE engineering                                                                                 |
| Öztürk, B. A., 2014                       | Green Supply Chain                                                                          | Lacking an environmental supplier selection framework                                                                                        | Fuzzy multi-criteria decision-making (MCDM) model                                                                  | Intelligent supplier evaluation under uncertainty and multi-dimensional sustainability criteria                                                  | Application across industries and further validation with broader sustainability criteria                              |
| Iacovidou & Voulvoulis (2018)             | Food waste management (UK region), Resource recovery, and sustainability assessment         | Selecting the more sustainable food-waste management option under multi-dimensional trade-offs                                               | Computational multi-criteria decision-support framework based on weighted aggregation                              | Transparent sustainability comparison and decision support under multiple sustainability dimensions; sensitivity analysis identifies key drivers | Needs stakeholder-derived weights, broader criteria, stronger data, uncertainty treatment, and multi-region validation |
| Gan, V. J. L., <i>et al.</i> , 2020       | Green Buildings, Energy Optimization                                                        | Suboptimal energy usage across the building lifecycle                                                                                        | Optimization review for energy-carbon performance                                                                  | Design-phase energy awareness; digital twin possibilities                                                                                        | Human-centered design integration                                                                                      |
| Boonsothonsatit, G., <i>et al.</i> , 2015 | SME SCM Performance                                                                         | Lack of trade-off tools for SME supply chains                                                                                                | Fuzzy logic-based decision-support system combined with multi-objective optimization                               | Intelligent decision support for cost–time trade-offs and Pareto-optimal solutions                                                               | Cross-sector testing; sustainability extension                                                                         |
| Balashanmugam, 2021                       | Additive Manufacturing (AM) in Industry 4.0, digital manufacturing ecosystems               | Limited integration of AM with I4.0 technologies                                                                                             | Review of AM with AI, IIoT, big data, and cloud across the lifecycle                                               | Automation, flexibility, sustainability                                                                                                          | Lacks implementation frameworks and empirical validation; limited advanced AI integration                              |
| Leng, J., <i>et al.</i> , 2023            | Automotive manufacturing systems, resequencing scheduling, and multi-objective optimization | Conflict between minimizing color change costs in paint shops and maintaining high sequence adherence (reducing tardiness) in assembly lines | Multi-objective Deep Q-Network (DQN) with reward shaping and 2D folded-normal distribution for preference sampling | Better convergence, efficiency, and Pareto solutions                                                                                             | Limited to static/single-machine; lacks real-time scalability                                                          |
| Zhong, R. Y., <i>et al.</i> , 2017        | Industry 4.0, intelligent manufacturing                                                     | Need for flexible, high-quality, customized production in smart environments                                                                 | Review of intelligent manufacturing enabled by IoT, CPS, cloud computing, big data, and ICT                        | Enhanced flexibility, productivity, and mass customization                                                                                       | Lack of unified frameworks; integration challenges; need for real-world implementation and standardization             |

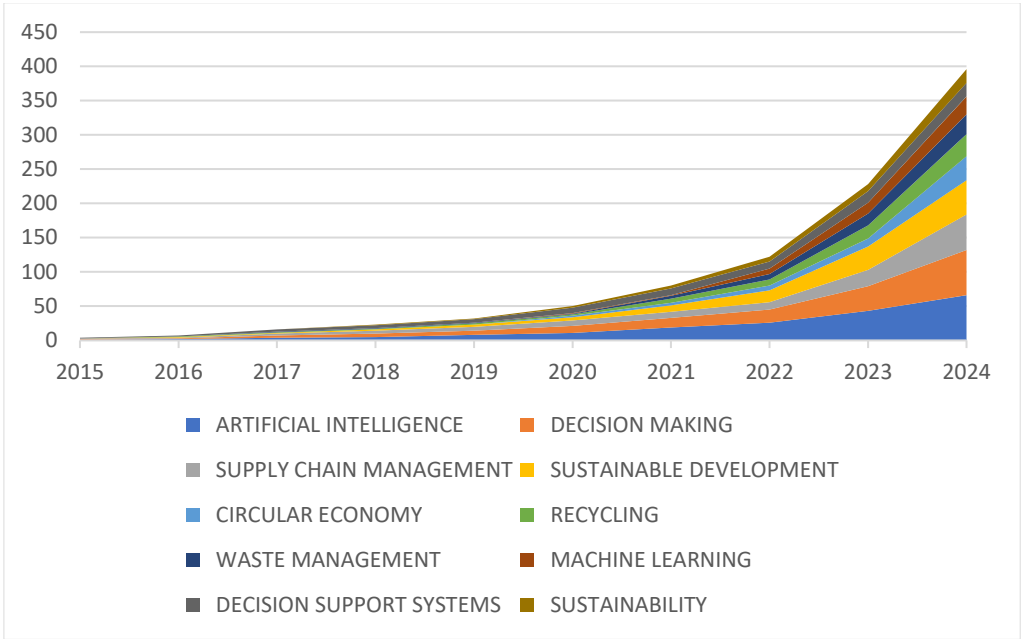


Figure 5 Word Cloud of High-Frequency Keywords

4.2 Content Analysis and Thematic Discussion

The This section presents a dual-layered content analysis of the selected literature, focusing on the intersection of AI, sustainability, and SCM. The analysis integrates descriptive synthesis and conceptual thematization, thereby enabling a structured understanding of research developments from 2015 to 2024.

4.2.1 Descriptive Analysis of Core Contributions

To complement the bibliometric mapping, we conducted a structured review of 28 representative articles based on high citation impact and methodological diversity. Table 4 summarizes the synthesized findings of 28 highly relevant articles. This subset was selected through a purposive sampling strategy based on two criteria: (1) high citation impact, defined as the top 10% most-cited papers within the dataset, and (2) methodological diversity, ensuring representation of distinctive approaches such as hybrid ML-MCDM models, IoT-enabled frameworks, and deep learning architectures. Although this subset represents approximately 14% of the full 206-paper dataset, it was deliberately curated to provide an in-depth qualitative synthesis that complements the broader quantitative bibliometric mapping presented in Section 4.1. Accordingly, the subset is intended to deepen the interpretation of the full corpus rather than to replace the analysis of the entire dataset.

4.2.2 Keyword-Based Content Analysis

To further understand the intellectual structure of the field, a keyword co-occurrence analysis was conducted using author-defined terms and Keywords Plus. As illustrated in the word cloud (Figure 5), high-frequency terms include "Artificial Intelligence", "Circular Economy", "Supply Chain Management", "Decision Making", and "Optimization". These terms not only indicate the central focus areas but also demonstrate the convergence between digital innovation and sustainability imperatives.

4.2.3 Thematic Cluster Identification

Building on the descriptive synthesis and keyword analysis, we identified four major thematic clusters that capture the conceptual trajectories of AI applications in sustainable supply chains. These clusters were derived by grouping papers with shared objectives, solution architectures, and sustainability outcomes. The clusters reflect distinct, however interrelated, areas of scholarly focus.

Table 5 reports four empirical thematic clusters identified in the dataset. In the subsequent discussion, the second cluster is unpacked into two related subthemes for interpretive depth; accordingly, the discussion is presented through five thematic lenses while the empirical structure remains fourfold.

The clusters are detailed as follows:

- **Cluster 1: AI-Driven Optimization and Decision Support**  
This group focuses on algorithmic solutions to optimize logistics, production planning, and inventory control. Representative works such as Gan *et al.* (2020) and Kellner *et al.* (2019) utilize multi-objective models to balance cost, environmental impact, and operational performance.
- **Cluster 2: Circular Economy Enablement**  
Studies in this category examine the role of AI and decision-support methods in enabling circular economy practices through improved resource allocation, end-of-life product management, and sustainable supplier selection (Reuter, 2016; Centobelli *et al.*, 2022).
- **Cluster 3: Sustainability Performance and Risk Management**  
This cluster addresses sustainability metrics, ESG integration, and predictive risk modeling using AI. Agrawal *et al.* (2022) exemplify this stream with frameworks that quantify environmental and social outcomes.

**Table 5** Major Thematic Clusters in AI for SSCM Research

| Thematic Cluster                               | Description                                                                                                                    | Associated Keywords                                                    | Representative Highly Cited Work                          |
|------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------|-----------------------------------------------------------|
| AI-Driven Optimization and Decision Support    | AI and ML applications for optimizing logistics, inventory, and production to reduce waste, cost, and environmental impact.    | Optimization, Decision Making, Forecasting, Logistics                  | Gan <i>et al.</i> (2020), Kellner <i>et al.</i> (2019)    |
| Circular Economy Enablement                    | AI-supported strategies for reverse logistics, remanufacturing, recycling, and end-of-life product management.                 | Circular Economy, Waste Management, Reverse Logistics, Product Design  | Reuter (2016)                                             |
| Sustainability Performance and Risk Management | Predictive models for carbon footprint monitoring, performance metrics, and risk assessment in global supply chains.           | Sustainability, Risk Management, Transparency, Performance Measurement | Agrawal <i>et al.</i> (2022), Sjödin <i>et al.</i> (2023) |
| Enabling Technologies and Data Infrastructure  | Foundational digital enablers such as IoT, blockchain, and big data analytics for transparency, traceability, and scalability. | IoT, Blockchain, Big Data, Traceability, Digital Twin                  | Balashanmugam (2021), Kurniawan and Fernando (2023)       |

#### • Cluster 4: Enabling Technologies and Data Infrastructure

Papers in this theme explore the foundational digital enablers, IoT, blockchain, and big data, that facilitate AI deployment in complex supply networks. Studies such as Balashanmugam (2021) and Yogarajan *et al.* (2023) fall into this category.

##### 4.2.4 Cross-Cutting Insights and Research Implications

The two-level analysis reveals several unifying patterns. First, decision-making enhancement emerges as a common objective across all thematic areas. Whether through predictive analytics, simulation, or hybrid optimization, AI is consistently deployed to support real-time, informed decisions under uncertainty.

Second, the integration of AI with sustainability is maturing, moving from conceptual frameworks to practical tools with real-world deployment potential. For instance, models addressing e-waste management (Debnath *et al.*, 2024) and food waste valorization (Said *et al.*, 2023) demonstrate how AI can directly contribute to circularity and waste reduction.

Third, the social dimension of sustainability, often underrepresented, is gaining attention, particularly in the context of Industry 5.0. Human-centric AI systems that support local livelihoods, workforce resilience, and ethical technology deployment are beginning to appear in the literature.

Finally, the reviewed studies highlight ongoing research gaps, including:

- The need for scalable and interoperable AI systems
- Ethical and governance frameworks for AI deployment
- Empirical validation of conceptual models in industrial contexts
- Deeper integration of AI with circular economy principles and social sustainability

## 5. DISCUSSION

The purpose of this work was to address two research questions by conducting a systematic literature review: (RQ1) What is the state of the art of research on AI in Sustainable Supply Chain Management? and (RQ2) What are the gaps in current research that should be addressed? The thematic analysis yielded four core empirical clusters, as reported in Table 5. However, for interpretive clarity, the

cluster related to circular economy, waste, and resource management is discussed through two closely related subthemes. Accordingly, this section is organized into five thematic lenses: (1) AI-Driven Optimization and Decision Support; (2) Machine Learning for Waste and Resource Management; (3) AI in Remanufacturing and the Circular Economy; (4) Digital Integration for Sustainable Supply Chains; and (5) Human-Centric Sustainability and Industry 5.0. This structure does not alter the underlying four-cluster empirical framework, but rather provides a more fine-grained interpretation of the findings. These five thematic lenses summarize the current state of research and provide a starting basis for a more detailed examination of the opportunities and challenges in each area, in order to further theory and practice.

### 5.1 AI-Driven Optimization and Decision Support

First, it is imperative to emphasize that the integration of AI into SSCM entails developing sophisticated systems capable of navigating the complex trade-offs inherent in the triple bottom line. The literature shows a strong focus on creating decision support systems that move beyond single-objective optimization (e.g., cost reduction) to incorporate multiple, often conflicting, criteria. As seen in the work of Sadeghi *et al.* (2024), hybrid models combining ML and multi-objective optimization are being developed to balance economic viability with environmental and social indicators. Similarly, Kellner *et al.* (2019) demonstrate the use of multi-criteria decision support for sustainable supplier selection, allowing managers to visualize and weigh different sustainability outcomes. The challenge, as noted in the research gaps, remains the integration of complex, real-world constraints and the validation of these models at an industrial scale.

### 5.2 Machine Learning for Waste and Resource Management

Representing the first specific lens of the broader circular economy cluster, the results demonstrate a significant concentration of research on applying ML to address core challenges in environmental sustainability, particularly waste and resource management. This theme represents a direct application of AI to operationalize the principles of the Circular Economy. Numerous studies in the reviewed literature show how ML can transform waste from

**Table 6** Conceptual Classification of AI Maturity in Sustainable Supply Chain Management

| AI Maturity Level                     | Environmental Dimension                               | Social Dimension                                     | Economic Dimension                              |
|---------------------------------------|-------------------------------------------------------|------------------------------------------------------|-------------------------------------------------|
| Predictive (What will happen?)        | Carbon footprint forecasting; Waste volume prediction | Labor risk forecasting; Sentiment analysis on ethics | Demand forecasting; Price volatility modeling   |
| Prescriptive (How to make it happen?) | Multi-objective optimization for CE; Green routing    | Fair labor allocation; Diversity-aware hiring        | Inventory optimization; Cost-benefit trade-offs |
| Autonomous (Self-adapting)            | Self-healing circular loops; AI-driven sorting        | Ethics-governed autonomous agents                    | Decentralized autonomous SC (Blockchain-AI)     |

an environmental liability into a valuable resource. For example, Govindaraj *et al.* (2024) use a suite of ML models, including regression and deep learning, to optimize the routing of waste collection and improve the efficiency of material valorization. In the high-stakes area of e-waste, Debnath *et al.* (2024) developed a model that uses ML to make probabilistic predictions about material recovery, thereby informing investment and policy decisions. The practical, problem-solving nature of this research cluster underscores the tangible benefits AI can bring to sustainability performance by improving resource efficiency and minimizing environmental footprints.

**5.3 AI in Remanufacturing and the Circular Economy**

Most studies investigating circular strategies focus on the role of AI in enabling product life extension through remanufacturing, repair, and reuse. This theme is critical, as keeping products and materials in use for as long as possible is a cornerstone of the circular economy. The literature highlights two key application areas. First, AI is used for the assessment of end-of-life products. For instance, Lipu *et al.* (2021) reviewed how intelligent algorithms and onboard ML strategies can evaluate the state of health of electric vehicle batteries in real-time. This allows for quick and accurate decisions on whether a battery should be reused, remanufactured, or recycled. Second, AI is applied to the design process itself. As reviewed by Balashanmugam (2021), AI techniques can be used to optimize product designs specifically for automated repair and restoration using technologies like additive manufacturing. This research is crucial for overcoming the technical and economic barriers that have traditionally made remanufacturing a costly and complex process.

**5.4 Digital Integration for Sustainable Supply Chains**

A significant portion of the contemporary literature focuses on the foundational role of digital technologies in creating the transparent and accountable networks required for credible SSCM. A recurring challenge in sustainability is the lack of end-to-end visibility, which makes it difficult to verify claims about ethical sourcing or recycled content. The integration of AI with technologies such as the IoT and Blockchain is presented as a solution to this problem. Rather than functioning in isolation, AI is typically embedded in wider digital infrastructures that support traceability, monitoring, and data sharing across supply chains. Furthermore, the conceptual framework proposed by Narwane *et al.* (2021) illustrates how a combination of Big Data and AI can be leveraged to generate the data-driven insights necessary for monitoring, reporting, and continuously improving sustainability performance across the entire supply chain.

**5.5 Human-Centric Sustainability and Industry 5.0**

Finally, an emerging but increasingly important theme considers the social pillar of sustainability through the lens of Industry 5.0. This perspective argues that the goal of technological integration should not be to simply replace human labor but to augment human capabilities and enhance overall well-being. According to Mourtzis (2024), AI applications in an Industry 5.0 context can support human skills in complex tasks, optimize processes in a way that improves working conditions, and cater to personalized consumer demands for sustainable products. This approach is vital for ensuring that the transition to technologically advanced, sustainable supply chains is also socially equitable and beneficial for the workforce. However, as the authors note, this human-centric vision also brings to the forefront critical challenges related to data security, algorithmic bias, and the ethical governance of AI, all of which represent significant areas for future research.

**5.6 A Proposed Conceptual Framework for AI-SSCM Integration**

Based on the critical synthesis of the 206 reviewed papers, a conceptual framework is proposed (Table 6) to map the maturity of AI capabilities across the dimensions of sustainability (environmental, social, and economic) and different levels of supply chain management. This framework extends beyond descriptive analysis by providing a typology to guide future research and theory development.

The coding results indicate a clear maturity imbalance across sustainability dimensions. Applications classified as predictive and prescriptive are substantially more prevalent in studies focused on economic and environmental performance, whereas socially oriented applications remain comparatively limited and are rarely developed beyond early-stage analytical support. Autonomous AI applications, in particular, remain scarce across the dataset and are especially underrepresented in studies addressing social sustainability. Rather than treating these differences as absolute claims, the framework should be interpreted as evidence-based conceptual mapping of current tendencies in the literature derived from the coding of the 206 reviewed studies.

This pattern suggests that the field has advanced more rapidly in efficiency and optimization-oriented domains than in areas related to labor conditions, inclusion, ethics, and social outcomes. Accordingly, the proposed framework highlights not only the current maturity of AI use in SSCM, but also the unevenness of that maturity across the three pillars of sustainability.

The analysis also points to a potential “AI rebound effect”. While AI can enhance energy efficiency, support resource optimization, and improve sustainability-related decision-making, the computational intensity associated with training and deploying advanced models may itself generate environmental costs. This tension underscores the importance of considering the sustainability of AI systems themselves and supports recent calls for integrating Green AI principles into future SSCM research and practice.

## 6. RESEARCH GAPS AND FUTURE DIRECTIONS

Regarding the second research question on research gaps, our analysis of the 206 reviewed studies reveals dataset-grounded and specific avenues for future research. From a theoretical perspective, the review highlights the need for a holistic and integrated approach to SSCM that simultaneously considers economic, environmental, and social performance. While environmental optimization dominates the literature (approximately 68% of the coded studies), the social dimension, particularly labor ethics, worker well-being, and diversity, is addressed in only about 12% of the dataset. This indicates a critical need for theoretical frameworks that examine the paradoxical relationship between AI-driven operational efficiency and social equity within global supply chains.

From a practical perspective, several gaps emerge. First, a methodological imbalance is evident: the majority of prior studies rely on conceptual modeling or simulations, with only a small proportion of studies (approximately 4%) employing longitudinal empirical designs. Future research should embrace diverse empirical methodologies, such as large-scale surveys, in-depth longitudinal case studies, and controlled experiments, to capture the real-world complexities of AI implementation in SSCM.

Second, a geographical concentration is observed. Approximately 55% of studies originate from China, Germany, and India, while less than 5% come from Africa, Latin America, and the Middle East, according to the bibliometric mapping. Future work should address this imbalance by exploring AI-enabled SSCM in underrepresented regions, considering local regulatory, infrastructural, and socio-cultural factors that shape sustainability outcomes.

Third, a technological gap persists. While optimization and predictive analytics dominate, the application of advanced AI techniques, such as deep reinforcement learning, generative AI for sustainable product design, and digital twins for circular ecosystems, is minimal (representing less than 2% of the reviewed studies). Future research should investigate how these technologies can support autonomous, self-adaptive, and resilient supply chain systems.

Finally, the human-centric and ethical dimension of AI remains underexplored. Despite recognition of Industry 5.0 principles, there is limited guidance on designing AI systems that augment human capabilities, ensure workforce inclusion, and promote ethical governance. Research is needed to evaluate the impact of AI on labor dynamics, develop training programs for human–AI collaboration, and create robust frameworks for socially responsible AI deployment.

In summary, future research should prioritize: (i) methodological diversification beyond simulations, (ii) global expansion into underrepresented regions, (iii) exploration of advanced and autonomous AI technologies, and (iv) a deeper engagement with social and ethical sustainability. Taken together, these datasets provide a more comprehensive and actionable basis for understanding how AI can advance sustainable supply chains across varied contexts and levels of maturity.

## 7. LIMITATIONS

This study has several limitations. First, the review exclusively utilized the Scopus database, which, although extensive, may have excluded relevant literature indexed elsewhere or in grey literature, including preprints and technical reports. Second, the quality appraisal process, while structured, involves subjective judgment, which may influence scoring outcomes. Third, the thematic clustering represents a single interpretive approach; alternative frameworks could yield different perspectives. Finally, although 206 articles were analyzed, expanding to additional databases could provide a more comprehensive view of AI applications in SSCM.

## 8. CONCLUSION

This paper provides a comprehensive investigation into the current state of research on the integration of Artificial Intelligence with Sustainable Supply Chain Management, offering an extensive overview of the field, identifying critical gaps in the literature, and highlighting emerging areas for further exploration. Through a systematic literature review of 206 studies published between 2015 and 2024, this paper employs a multi-perspective descriptive and content analysis approach to deliver a well-structured examination of the research at this intersection. This review examines the multifaceted challenges of SSCM and evaluates the AI-driven tools and strategies being developed to address them. The findings illustrate how, over the past decade, the application of AI to SSCM has matured from an emerging concept into a well-established field, with recent developments emphasizing practical, data-driven solutions to complex sustainability problems.

The analysis identifies five major themes as central to the existing body of work: AI-driven optimization and decision support, machine learning for waste and resource management, AI’s role in remanufacturing and the circular economy, digital integration for transparency, and the shift toward human-centric sustainability. The research highlights the importance of AI in enabling circular strategies, optimizing resource flows, and providing the analytical power needed to balance the triple bottom line. Furthermore, the findings emphasize the growing recognition of AI’s role in enhancing the efficiency, transparency, and accountability of sustainable supply chains.

Despite the contributions of this study, several limitations and areas for future research remain. First, there is a need to move beyond the current dominance of conceptual and modeling studies. The majority of the methodological approaches used have been restricted to simulations and literature reviews, which provide valuable but often static views. Future studies should incorporate

experimental designs and longitudinal analyses to provide deeper and more dynamic insights into the real-world impact of AI implementation. Second, the geographical distribution of research has been heavily focused on regions in Asia and Europe, highlighting the need to explore underrepresented contexts, including Africa, South America, and the Middle East, to understand how regional factors shape the application of AI in SSCM. Third, while this study analyzed 206 articles, future research could include data from additional databases to provide an even broader and richer perspective on the field.

The findings not only confirm prior research but also expand the current understanding of how AI can be leveraged as a critical enabler for sustainable supply chains, offering critical insights into the evolving dimensions of this field. This paper serves as a foundational resource for scholars and practitioners, providing a roadmap for addressing the identified gaps and advancing research in this vital area. By following these recommendations, future studies can contribute to the development of more robust, intelligent, and truly sustainable supply chain management practices.

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## CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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