

Intelligent Supply Chain Management: A Systematic Literature Review on Artificial Intelligence Contributions

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Abstract: This systematic literature review investigates the recent applications of artificial intelligence (AI) in supply chain management (SCM), particularly in the domains of resilience, process optimization, sustainability, and implementation challenges. The study is motivated by gaps identified in previous reviews, which often exclude literature published after 2020 and lack an integrated analysis of AI's contributions across multiple supply chain phases. The review aims to provide an updated synthesis of AI technologies—such as machine learning, deep learning, and generative AI—and their practical implementation between 2021 and 2024. Following the PRISMA framework, a rigorous methodology was applied using the Scopus database, complemented by bibliometric and content analyses. A total of 66 studies were selected based on predefined inclusion criteria and evaluated for methodological quality and thematic relevance. The findings reveal a diverse classification of AI applications across strategic and operational SCM phases and highlight emerging techniques like explainable AI, neurosymbolic systems, and federated learning. The review also identifies persistent barriers such as data governance, ethical concerns, and scalability. Future research should focus on hybrid AI–human collaboration, transparency through explainable models, and integration with technologies such as IoT and blockchain. This review contributes to the literature by offering a structured synthesis of AI's transformative impact on SCM and by outlining key research directions to guide future investigations and managerial practice.

Keywords: artificial intelligence; supply chain management; sustainability; systematic literature review; PRISMA methodology



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1. Introduction

1.1. Research Territory

The increasing complexity, globalization, and vulnerability of supply chains have driven organizations to seek innovative solutions for enhancing their operational resilience, efficiency, and sustainability. In this context, artificial intelligence (AI) has emerged as a transformative force, enabling data-driven decision-making and intelligent automation across multiple supply chain functions. The proliferation of AI applications—ranging from predictive analytics to autonomous systems—has reshaped supply chain management (SCM), particularly in sectors where responsiveness and adaptability are critical [1–3].

AI technologies have demonstrated significant potential in optimizing key supply chain functions, including supplier selection, inventory management, and logistics plan-

ning. The use of advanced AI algorithms facilitates precise demand forecasting, reduces stockouts, and enhances decision-making under conditions of uncertainty [3,4]. In addition to AI, the integration of complementary digital technologies—such as the Internet of Things (IoT) and Augmented Reality (AR)—has also contributed to improved organizational performance by enhancing real-time visibility and collaboration across supply chain networks [5].

In the context of sustainability, AI-based models have demonstrated significant potential in addressing economic, environmental, and social dimensions within supply chains. By integrating technologies such as machine learning and optimization algorithms, businesses can minimize costs, reduce environmental impacts, and enhance the reliability of operations. These capabilities were particularly vital during the COVID-19 pandemic, where sustainable supply chain networks for essential goods became a priority [6].

Moreover, the ongoing digital transformation in supply chain operations underscores the critical role of AI as part of a broader technological ecosystem, including blockchain, IoT, and big data. Such technologies not only enable better information exchange and responsiveness but also drive sustainable supply chain performance [7]. Despite these advancements, there are persistent challenges, including data governance, workforce upskilling, and the equitable adoption of AI technologies. Addressing these issues is essential to unlocking the full potential of AI in SCM and achieving both operational excellence and long-term resilience [8]. The scalability of AI solutions, the ethical implications of data-driven technologies, and the integration of these systems into existing frameworks remain significant hurdles [2]. However, as demonstrated in bibliometric and content analyses of AI applications in various industries, including manufacturing and retail, the benefits often outweigh the challenges, particularly when AI is used strategically to address critical issues such as sustainability and operational efficiency [2,9].

1.2. Previous Research

The application of artificial intelligence in supply chain management has increasingly become a pertinent topic, as evidenced by the abrupt rise in the number of documents on the subject in Scopus (Figure 1), reflecting the growing academic and industrial interest in leveraging this technology to optimize processes and enhance efficiency within supply chains.

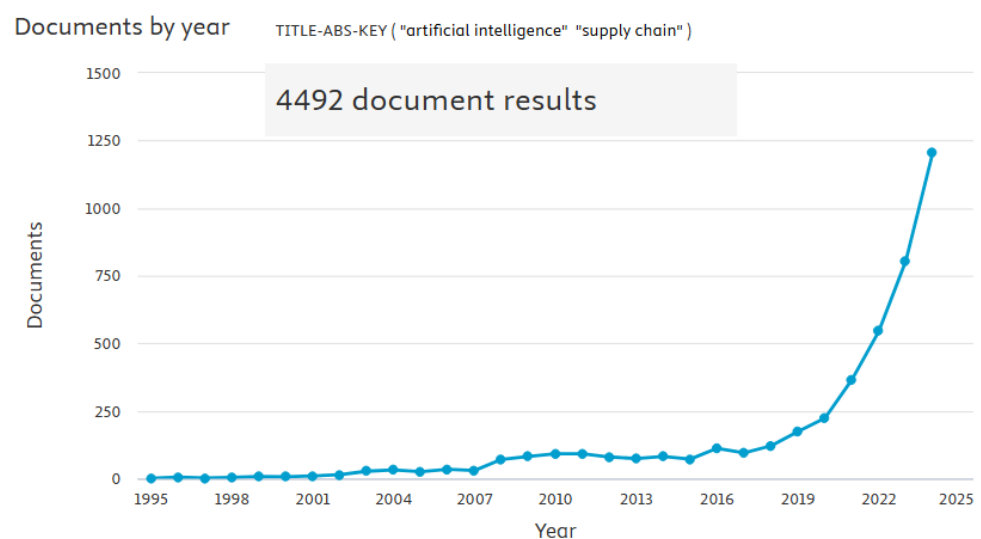


Figure 1. Growth of research on artificial intelligence in supply chain management.

Despite the growing interest in artificial intelligence (AI) within supply chain management (SCM), several prior literature reviews reveal important gaps that limit a comprehensive understanding of the field. Toorajipour et al. (2021) [10] conducted one of the earliest systematic reviews but focused mainly on identifying the prevalent AI techniques and their potential without an in-depth analysis of adoption barriers or emerging trends such as generative AI. Smyth et al. (2024) [11] expanded the scope by exploring prescriptive analytics and resilience, yet their study was fragmented by the diversity of AI tools and lacked a structured categorization of supply chain functions. Similarly, Rolf et al. (2023) [12] focused exclusively on reinforcement learning in SCM, identifying the dominance of Q-learning and highlighting a reliance on simulated rather than real-world data. Jahin et al. (2025) [13] provided a combined bibliometric and content analysis for AI in risk assessment but did not explore cross-phase integration in SCM or broader managerial implications. Finally, Hao and Demir (2024) [14] analyzed adoption through an ESG framework, yet their emphasis on governance and inhibitors overlooks the functional and technological evolution of AI tools. These limitations—such as limited focus on recent developments, lack of integrated phase-wise supply chain analysis, insufficient discussion of emerging AI techniques (e.g., generative AI, explainable AI), and absence of structured future research directions—justify the need for a comprehensive and updated review. This study aims to bridge these gaps by systematically reviewing recent literature (2021–2024), classifying the use of AI across SCM phases, analyzing technological trends, identifying adoption challenges, and outlining future research avenues.

1.3. Research Objectives

This review aims to synthesize recent advancements in AI applications in SCM, spanning 2021 to 2024, to provide a comprehensive understanding of emerging trends, challenges, and opportunities. The insights gained will contribute to both academic discourse and practical strategies for leveraging AI in achieving efficient and sustainable supply chains. By combining bibliometric and content analysis, this review classifies AI use across SCM phases, identifies technological trends, discusses barriers to implementation, and proposes future research avenues.

Specifically, the study aims to do the following:

1. Examine the role of AI in enhancing supply chain resilience: Investigate how AI technologies contribute to improving the adaptability and recovery of supply chains in response to disruptions, including the optimization of risk management strategies and operational efficiency.
2. Identify key AI-driven solutions for supply chain optimization: Analyze the specific AI techniques, such as machine learning, predictive analytics, and real-time data processing, that are currently being used to optimize critical functions in supply chain management, such as demand forecasting, inventory control, and logistics planning.
3. Assess the impact of AI on sustainability in supply chains: Explore how the integration of AI in supply chains contributes to achieving sustainability goals, including economic, environmental, and social dimensions, with a particular focus on the fashion, manufacturing, and retail sectors.
4. Investigate the challenges and barriers to AI implementation in supply chains: Identify the key challenges, such as scalability, ethical concerns, and integration with existing systems, that organizations face when adopting AI solutions in supply chain management.
5. Outline future research directions: Identify and structure key gaps in the existing literature to propose future avenues for investigation.

These objectives will guide research in offering a deep understanding of how AI can reshape supply chain management, as well as the critical factors influencing its successful implementation and long-term impact on business performance.

The article is structured as follows:

- Section 2 outlines the materials and methods used in this study, including the systematic review protocol based on the PRISMA framework, the use of tools such as StArt 2.3.4.2, Zotero 7.9.11, RStudio 4.4.2, and VOSviewer 1.6.20, the search strategy, inclusion and exclusion criteria, and the bibliometric approach adopted.
- Section 3 presents the results of the systematic literature review, offering a state-of-the-art analysis through a detailed synthesis of 66 selected articles. It includes a bibliometric overview and a classification of AI applications across various supply chain management functions and phases.
- Section 4 provides a comprehensive discussion of the main thematic findings—namely resilience, process optimization, sustainability, and implementation barriers—while also examining the role of emerging AI techniques, identifying research gaps, proposing future research directions, and discussing the theoretical and managerial implications.
- Section 5 outlines the limitations of the study, particularly regarding the scope of the databases, the dynamic evolution of the field, and the subjective nature of article selection and categorization.
- Section 6 presents the conclusion, summarizing the review and reinforcing the contribution of AI to intelligent supply chain management.

2. Materials and Methods

This chapter provides an overview of the tools and methodologies employed to conduct the literature review for this study. A rigorous and systematic approach was adopted, incorporating a range of specialized tools to enhance both the quality and structure of the review process. The Global Literature Review was conducted using StArt 2.3.4.2, while the Systematic Literature Review followed the PRISMA framework. Bibliographic reference management was handled through Zotero 7.9.11, and VOSviewer 1.6.20 was utilized for constructing and visualizing bibliometric networks. Qualitative data analysis was performed using R Scripts developed in RStudio 4.4.2, alongside quantitative data analysis. Although some of these tools offer overlapping functionalities, each tool was carefully selected for its specific suitability at each stage of the review process, ensuring a comprehensive and coherent analysis.

In Appendix A, Table A1 presents a detailed version of the PRISMA 2020 checklist, providing a comprehensive overview of the reporting items.

This study followed predefined methodological guidelines to ensure transparency and reproducibility.

2.1. PRISMA Framework and StArt 2.3.4.2

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework is a widely recognized methodology for conducting and reporting systematic reviews and meta-analyses. It aims to improve the transparency, consistency, and reproducibility of systematic review findings, thereby enhancing the quality of research [15,16]. By providing a structured approach, PRISMA guides researchers through the process of identifying, selecting, evaluating, and synthesizing research studies. This ensures that all relevant information is considered, and that the review methodology is rigorous, clear, and reproducible [15,16].

The PRISMA framework consists of 27 essential items that span the entire process of a systematic review, from planning to reporting. These items are divided into various sections,

each addressing different aspects of the review process. The framework emphasizes not only the importance of a comprehensive search strategy and clear data synthesis but also the necessity of transparency in reporting. The following sections outline the main components of PRISMA [15,16].

By adhering to the PRISMA framework, researchers ensure methodological rigor, making their systematic reviews not only reproducible but also relevant in the evolving landscape of AI applications in industries like supply chain management.

To support the systematic review process, the StArt 2.3.4.2 (State of the Art through Systematic Review) tool was employed for managing and organizing the retrieved studies. StArt 2.3.4.2 is a software application specifically developed to facilitate systematic literature reviews, enabling researchers to structure the inclusion and exclusion process in a transparent and replicable manner. It provides functionalities for importing search results, applying screening criteria, and extracting relevant data, contributing to the methodological rigor of the review. Regarding the study selection process, an initial filtering criterion was applied to ensure relevance, wherein studies were required to include references to both “artificial intelligence” and “supply chain” within the title, abstract, or keywords. While it is acknowledged that such terms may appear infrequently in some relevant studies, this approach served as a preliminary filter to manage the volume of retrieved articles and focus the analysis. This criterion has been used in previous systematic reviews [17], where keyword-based thresholds were employed to ensure thematic alignment with the research objectives. Nevertheless, all selected papers were subsequently assessed manually to confirm their relevance beyond simple keyword occurrence.

To enhance the clarity and transparency of the methodological process, Figure 2 presents a detailed flowchart summarizing the systematic review workflow. The diagram outlines the main stages—from literature search to bibliometric and content analysis—highlighting the specific inputs, tools and software employed (e.g., StArt 2.3.4.2, Zotero 7.9.11, RStudio 4.4.2, VOSviewer 1.6.20), and the corresponding outputs at each step. This visualization supports a clearer understanding of how data were collected, processed, and synthesized to ensure methodological rigor and reproducibility.

2.2. Search Strategy

The search was limited to studies published between 2021 and 2024 to ensure an updated and focused review aligned with recent technological advances and post-pandemic shifts in supply chain dynamics. This timeframe also reflects a research gap identified in prior reviews that do not incorporate the latest literature, particularly regarding emerging technologies such as generative AI and explainable AI.

Two reputable databases were selected for this review: Scopus, due to its broad coverage of high-impact journals and its compatibility with bibliometric tools such as VOSviewer 1.6.20; and ScienceDirect, for its extensive repository of peer-reviewed articles in both business and technical disciplines. These platforms were chosen to ensure a comprehensive, high-quality, and multidisciplinary dataset relevant to AI applications in supply chain management.

The search focused on the Business, Management, and Accounting (BUSI) subject area to ensure relevance to managerial and operational perspectives on AI implementation in supply chain contexts. While other fields such as engineering and environmental science are relevant, studies with cross-disciplinary insights often appear in business-indexed journals. This focus aligns with the scope of the study, which seeks to assess not only technical contributions but also strategic, organizational, and sustainability implications within business-oriented supply chains.

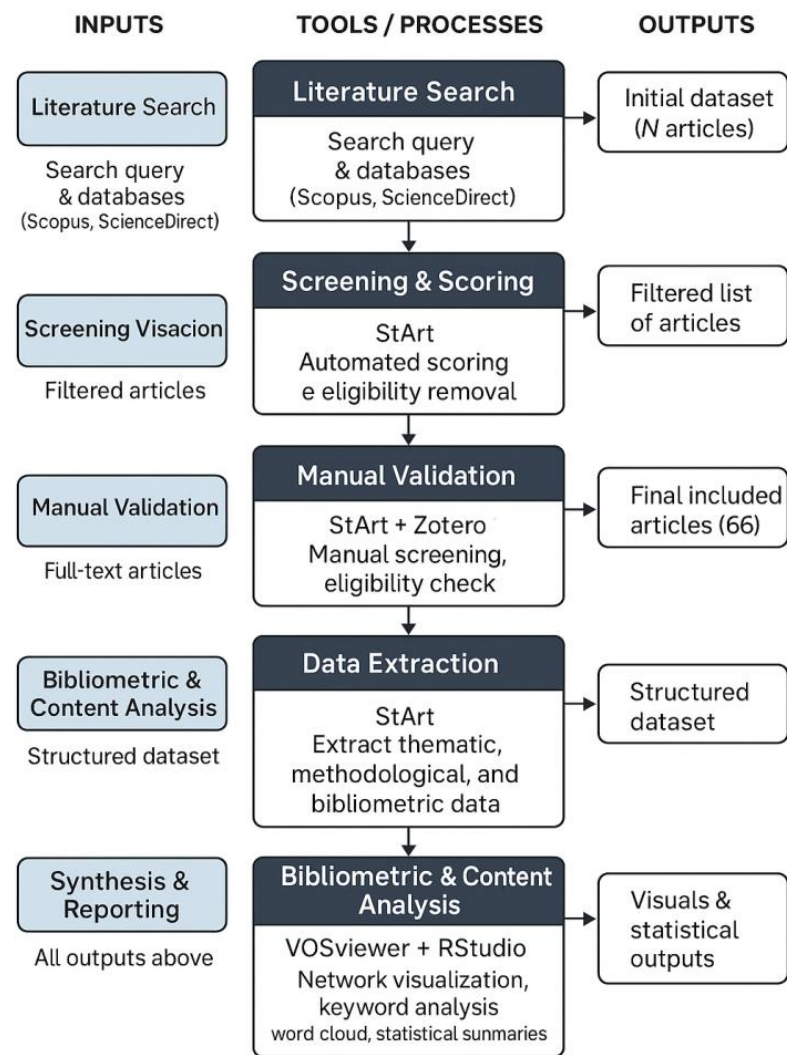


Figure 2. Systematic review workflow.

Due to the high volume of articles retrieved, a score threshold of ≥ 40 was applied to ensure that only articles with meaningful thematic alignment were considered. This threshold was based on default parameters of the StArt 2.3.4.2 software, widely used in systematic literature reviews. The threshold reflects a balance between inclusivity and relevance, filtering out studies with only superficial references to AI or supply chain terms, while retaining a manageable and thematically coherent set of sources. A lower threshold (e.g., 10 or 30) was tested and led to the inclusion of numerous marginally relevant studies; a higher threshold (e.g., 50) risked excluding articles of significant value but with less keyword repetition.

The application of this threshold was performed automatically within the StArt 2.3.4.2 software, which scored each article by assigning 5 points for each keyword occurrence in the title, 3 points in the abstract, and 2 points in the list of keywords. This quantitative filter was used in the initial screening stage to rank the thematic relevance of studies before manual validation. The scoring system has been employed in previous systematic reviews to ensure transparency and replicability of the selection process.

Summarized search strategy parameters are as follows:

- Keywords: (("artificial intelligence" OR "AI") AND ("supply chain" OR "SCM")).
- Publication period: Studies published between 2021 and 2024.
- Subject area: Restricted to the Business, Management, and Accounting (BUSI) subject area.

- Document type: Limited to articles (ar) and reports (re).
- Language: Only English-language studies were included.
- Open Access: Open access articles available through the University of Aveiro library's affiliation.

Search query: TITLE-ABS-KEY ((“artificial intelligence” OR “AI”) AND (“supply chain” OR “SCM”)) AND PUBYEAR > 2020 AND PUBYEAR < 2025 AND (LIMIT-TO (SUBJAREA, “BUSI”)) AND (LIMIT-TO (LANGUAGE, “English”)) AND (LIMIT-TO (OA, “all”)) AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “re”)).

These search criteria were designed to identify relevant literature on the application of artificial intelligence in supply chains, with a focus on the quality and academic impact of the selected studies. A PRISMA (2020) [11] flowchart was used to display the process of study selection (Figure 3).

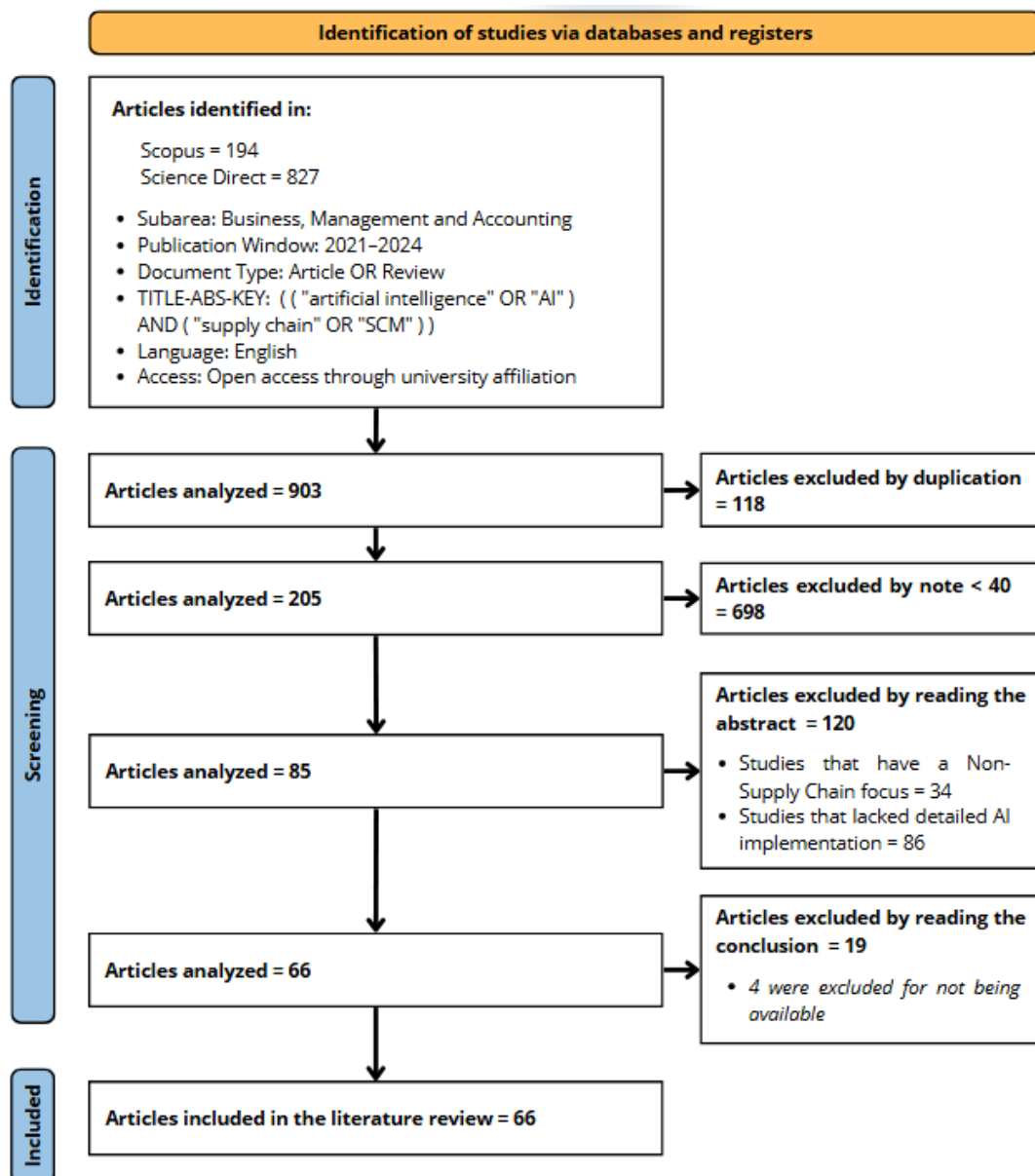


Figure 3. PRISMA flowchart.

2.3. Eligibility Criteria and Data Extraction

The selection of studies for this systematic review followed a two-step approach to ensure a comprehensive and rigorous selection process.

Step 1 Title and Abstract Screening: Initially, the titles and abstracts of all identified articles were screened to determine their relevance to the research topic. This step aimed to identify studies that specifically focused on artificial intelligence applications in supply chain management. Only studies that met the criteria presented in Table 1 were included in the review.

Step 2: Conclusion Review: Following the initial screening, a thorough conclusion review was conducted to assess the eligibility of each study in a more detailed and comprehensive manner.

Table 1. Eligibility criteria and research opportunities.

Inclusion Criteria (I)	Exclusion Criteria (E)	Potential Research Questions for Future Studies
Studies that explicitly explored AI technologies in SCM, including machine learning, deep learning, neural networks, etc.	Studies with a non-supply chain focus	How can machine learning models be adapted to handle real-time disruptions across multiple supply chain phases?
Studies that investigated AI implementation across different supply chain phases (Plan, Source, Make, Deliver, Return, Enable)	Studies lacking detailed analysis of AI implementation	What AI techniques are most effective in integrating circular economy principles in the ‘Return’ phase of supply chains?
Studies that provided insights into resilience, optimization, or sustainability through AI	Studies focusing solely on conceptual frameworks without empirical validation	How can digital twins and reinforcement learning be combined to enhance operational resilience in dynamic supply networks?
Studies presenting real-world applications or case-based validation of AI in SCM	Studies using purely simulated data with no discussion of real-world feasibility	What are the barriers and enablers to implementing explainable AI frameworks in sustainable supply chain decision-making?

The included studies were assessed for potential methodological biases to ensure a balanced evaluation of the findings.

Studies from various sources were considered to minimize potential publication bias.

2.4. Definitions of Key AI Technologies

To improve accessibility and support a clearer understanding of the analysis, this subsection presents brief definitions of the main AI technologies referenced throughout this review:

- **Machine Learning (ML):** A subset of AI that enables systems to learn patterns from data and improve performance without being explicitly programmed. Common ML techniques include decision trees, support vector machines, and ensemble learning.
- **Deep Learning (DL):** A specialized form of machine learning that uses multilayered neural networks to process complex patterns in large datasets. It is particularly effective in image recognition, natural language processing, and time-series forecasting.
- **Reinforcement Learning (RL):** A learning paradigm where agents learn optimal actions through trial-and-error interactions with their environment, guided by reward signals. RL is widely used in dynamic and real-time optimization tasks.

- **Generative AI (GAI):** Refers to AI systems capable of generating new content—such as text, images, or simulations—by learning from existing data. Examples include language models like ChatGPT and generative adversarial networks (GANs).
- **Explainable AI (XAI):** A class of AI methods that aim to make model decisions transparent and interpretable to human users, addressing concerns related to algorithmic opacity and accountability.
- **Neurosymbolic AI:** An emerging hybrid approach that integrates neural networks with symbolic reasoning to combine learning capabilities with logical inference and explainability.
- **Graph Neural Networks (GNNs):** A type of neural network designed to operate on graph-structured data, enabling the modeling of relationships and dependencies, such as those found in complex supply networks.
- **Federated Learning:** A decentralized machine learning technique where models are trained across multiple devices or organizations without centralizing data, thereby enhancing privacy and data security.
- **Digital Twins:** Virtual replicas of physical supply chain systems that integrate real-time data and AI to simulate, predict, and optimize operations under various conditions.

3. Results—State of the Art

To synthesize the contributions of the selected studies, a structured classification framework was adopted. This framework is based on multiple dimensions that capture the technological, functional, and managerial aspects of AI implementation in supply chain management. The classification criteria were as follows:

- **AI Technique:** Identifies the specific artificial intelligence methods used in each study (e.g., machine learning, deep learning, reinforcement learning, generative AI, explainable AI, neurosymbolic AI).
- **SCM Application:** Describes the functional objective within the supply chain, such as demand forecasting, risk management, logistics planning, inventory optimization, or sustainability enhancement.
- **SCM Phase:** Indicates the specific phase(s) of the supply chain addressed by the AI application, using the extended SCOR model (Plan, Source, Make, Deliver, Return, and Enable).
- **Reported Benefits:** Summarizes the main operational, strategic, or environmental advantages observed in each study.
- **Limitations:** Highlights key constraints, including methodological weaknesses, narrow contexts, or absence of real-world validation.
- **Potential Biases:** Notes possible distortions, such as survey self-reporting, limited geographic scope, or reliance on simulated data.

This multidimensional classification enables a more granular understanding of how AI is being applied across different supply chain contexts. It also facilitates the identification of recurring challenges and research gaps across industries and technologies.

Table 2 presents the results of this classification. It offers a comprehensive overview of the 66 articles included in this systematic literature review, serving as the foundation for the thematic synthesis and discussion.

To enhance clarity and usability, the comprehensive Table 2 has been reorganized into four distinct thematic tables. This division reflects the primary focus areas identified in the reviewed literature: (A) supply chain resilience, highlighting AI applications that strengthen risk management, agility, and disruption recovery; (B) optimization and operational efficiency, encompassing studies centered on improving forecasting, planning, logistics, and process performance; (C) sustainability and environmental, social, and gov-

ernance (ESG), which consolidates research on environmentally and socially responsible supply chain initiatives; and (D) implementation challenges and technological integration, capturing works that address adoption barriers, enablers, explainability, and strategic alignment of AI in SCM contexts. This structured approach allows readers to navigate the diverse applications of AI in supply chains more effectively, providing a clearer view of methodological trends, thematic concentrations, and research gaps.

Table 2. (A) Supply chain resilience. (B) Optimization and operational efficiency. (C) Sustainability and ESG. (D) Implementation challenges and technological integration.

(A)							
N°	Reference	AI Technique	SCM Application	SCM Phase	Reported Benefits	Limitations	Potential Biases
[3]	Riad et al. (2024)	Multiple (ML, Predictive Analytics, NLP, RPA, etc.)	Resilience: forecasting, risk mitigation, optimization	End-to-end (Plan, Source, Make, Deliver, Monitor)	Improved forecasting, risk anticipation, automation, visibility	Single case study; context-specific; needs legacy integration	Conceptual assumptions; simulation-based; digital readiness
[11]	Smyth et al. (2024)	ML, RL, NLP, ANN, Hybrid Models	Resilience via prescriptive analytics	Planning, Risk, Visibility, Inventory	Enhanced visibility, optimization, decision automation	Conceptual synthesis; fragmented validation	Past literature focus; no unified empirical framework
[18]	Ali et al. (2024)	AI (ML, Predictive Analytics, BDA, Automation)	SC resilience through collaboration and AI integration	Resilience, Planning, Coordination	Enhanced collaboration, agility, real-time decisions	Jordanian sector; survey-based; perception-driven	Regional focus; lacks deployment data
[19]	Kosasih & Brintrup (2024)	Neurosymbolic AI (GNN + Knowledge Graph Reasoning)	Supply chain link prediction for risk mapping	Risk Management/Network Visibility	High accuracy, explainability, scalable reasoning	Requires structured ontologies; complex implementation	Manual ontology design; limited adaptability to dynamic data
[20]	Hirsch et al. (2024)	AI + Info Systems	Resilience: planning, monitoring, automation	Planning, Sourcing, Risk Management	Faster decisions, improved integration, operational efficiency	FMCG sector focus; 12 interviews only	Perception-based; developing economies' challenges
[21]	Gupta et al. (2024)	AI-enabled RIS (ML, NLP, Digital Twins, Blockchain)	Risk mitigation, disruption mgmt, scenario simulation	Risk Management, Planning, Crisis Response	Faster recovery, predictive capabilities, trust restoration	Qualitative; India-based manufacturing	Context-specific; expert-driven
[22]	Barhmi et al. (2024)	SCDA with AI (dashboards, decision tools)	Flexibility, resilience, responsiveness	Operational and Risk/Performance Mgmt	Enhanced flexibility, resilience, responsiveness, decision-making	Cross-sectional; Morocco focus; no longitudinal data	Regional; survey-based; excludes financial metrics

Table 2. Cont.

(A)							
N°	Reference	AI Technique	SCM Application	SCM Phase	Reported Benefits	Limitations	Potential Biases
[23]	Dubey et al. (2022)	AI-BDAC (ML, NLP, cognitive computing)	Agility and resilience in humanitarian SCs	Risk, Agility, Crisis Response	Improved agility, disaster response, data-driven decisions	Humanitarian NGOs; survey-based; no tracking	Self-report; geopolitical specificity
[24]	Isaid et al. (2024)	AI (ML, planning, automation)	Agility, collaboration, performance (healthcare)	Planning, Resilience, Performance Mgmt	Strengthened agility and collaboration; responsiveness	Qatar healthcare; survey; no system deployment	Self-report; social desirability bias
[25]	Wong et al. (2024)	ANN and PLS-SEM	Risk and agility for SMEs	Risk Mgmt/Agility Enhancement	Faster decisions, predictive risk response, visibility	Malaysian SMEs; survey; no real-world testing	Self-report; geographic limitation
[26]	Dey et al. (2024)	AI Decision Support (conceptual + SEM)	Resilience via circular economy and agility (SMEs)	Strategic and Operational Resilience	Agility, risk mitigation, CE adoption	Vietnam SMEs; cross-sectional; no longitudinal validation	Managerial perception; lack of diversification
[27]	Modgil et al. (2022)	AI (ML, BDA, NLP, agent-based)	Resilience post-COVID (forecasting, delivery)	End-to-end SCM (Plan, Source, Deliver)	Transparency, agile procurement, disruption mitigation	India-centric; interviews; qualitative coding	Perception-based; lacks real-time validation
[28]	Dubey et al. (2021)	AI-SCAC (Cognitive Tech)	Performance via alliance mgmt in crises	Strategic and Operational Planning	SC agility, better decisions, performance under uncertainty	Indian auto industry; survey; no longitudinal analysis	Industry-specific; self-report bias
[29]	Naz et al. (2021)	Multiple (ML, DL, Fuzzy Logic, STM, etc.)	Risk mgmt and resilience post-COVID	Risk, Strategic Resilience, Recovery	Preparedness, forecasting, resilience modeling	Review-based; no empirical deployment	Keyword bias; COVID-19 focus
[30]	Sadeghi et al. (2024)	XAI (LIME, LRP, DeepLIFT)	Cyber resilience and agile decision-making	Risk/Cyber Resilience/Decision Support	Transparency, fast decisions, enhanced cyber response	Experimental; US sample; simulation-based	Survey design; no operational deployment
[31]	Wang et al. (2024)	Hybrid AI-Human Integration (CSF-DEMATEL-MARCOS)	Enabler assessment in humanitarian SCM	Preparedness, Response, Recovery	Better decision support, coordination, efficiency	Expert judgment; no operational validation	Cognitive bias; regional variation
[32]	Kosasih et al. (2024)	Neurosymbolic AI (Graph Neural Networks + Knowledge Graphs)	Risk management via link prediction and hidden relationship discovery	Risk Monitoring/Visibility	Enhanced visibility, hidden risk detection, explainability	Needs structured data; manual ontology	Dataset-dependent; limited dynamic adaptability

Table 2. Cont.

(A)							
N°	Reference	AI Technique	SCM Application	SCM Phase	Reported Benefits	Limitations	Potential Biases
[33]	Pereira & Shafique (2024)	AI-BDAC	Agility and collaboration in humanitarian SCM	Disaster Relief/Agility	Improved agility, coordination, responsiveness	NGOs in Pakistan; survey-based	Perception-based; lacks generalizability
[34]	Ghourri et al. (2023)	ML (LSTM, RF, CART, k-NN, Transfer Learning)	Omnichannel blood SC optimization	Humanitarian Logistics/Emergency Response	Forecast accuracy, better inventory and response	Four hospitals in Pakistan; time-intensive retraining	Context-specific; operational constraints
[35]	Zheng et al. (2023)	Federated Machine Learning	Risk prediction (delivery delays)	Risk Management/Resilience	Enhanced prediction with data privacy	Complex coordination; data quality dependency	May underperform with imbalanced data
[36]	Shamout et al. (2022)	Autonomous Robots	Adoption of autonomous robots	Strategic and Logistics Operations	Resource allocation, cost-efficiency, operational autonomy	MENA-focused; survey-based; no longitudinal data	Self-reporting bias; regional context
[37]	Damoah et al. (2021)	AI-Enhanced Medical Drones	Delivery of medical supplies to remote areas	Logistics and Last-Mile (Healthcare SCM)	Reduced mortality, faster response, emissions reduction	Ghana-focused; qualitative; no control group	Context-specific; lacks quantitative data
[38]	Kosasih & Brintrup (2022)	Graph Neural Networks (GNN)	Prediction of hidden supply chain links	Network Design/Visibility	Better visibility, hidden risk detection	Automotive data only; limited GNN explainability	Data incompleteness; narrow sector focus
[39]	Allahham et al. (2024)	AI and Big Data Analytics	Risk alert tools for SCM	Risk Monitoring/Resilience	Enhanced responsiveness, predictive risk management	US-focused; managerial only	Self-reporting bias; excludes lower-level views
[40]	Brintrup et al. (2024)	NLP, GNNs, Neurosymbolic AI, BERT	Digital SC surveillance (risk, ESG, finance)	Cross-phase (Visibility, Risk, Finance)	Real-time risk detection, ESG monitoring, supplier mapping	UK-based; no longitudinal deployment	Black-box concerns; privacy; explainability issues
(B)							
N°	Reference	AI Technique	SCM Application	SCM Phase	Reported Benefits	Limitations	Potential Biases
[5]	Aburayya (2024)	AR + ANN + PLS-SEM	Warehousing, logistics, HR	Cross-functional	Efficiency, better training, reduced errors	Furniture sector; self-reported data	Regional focus; subjective perception

Table 2. Cont.

(B)							
N°	Reference	AI Technique	SCM Application	SCM Phase	Reported Benefits	Limitations	Potential Biases
[10]	Toorajipour et al. (2021)	Multiple (ANN, Fuzzy Logic, GA, SVM, etc.)	Broad SCM: marketing, logistics, production	Forecasting, Scheduling, Risk, Sustainability	Performance improvements; roadmap	Literature review only (64 articles); 2008–2018	Selection bias; limited generalizability
[12]	Rolf et al. (2023)	Reinforcement Learning (Q-learning, DQN, etc.)	Inventory, transportation, supplier selection	Inventory, Sourcing, Risk, Pricing	Adaptive decision-making; real-time learning	Simulation-based; lacks empirical studies	Artificial data; underrepresentation of real-world cases
[41]	Jackson et al. (2024)	ML (Facebook Prophet) + SARIMA	Cold chain: demand forecasting and capacity planning	Planning and Operations	Optimized planning, risk reduction, tailored forecasts	Single-site case; models not always superior	Site-specific focus; overfitting risks
[42]	Nguyen (2023)	Multiple (ANN, SVM, LSTM, BiLSTM, GAN, CNN)	Demand Forecasting (energy, water, fashion)	Planning and Demand Management	Forecast accuracy; operational cost reduction	Review-based; lacks empirical validation	Database selection bias; limited KPI assessment
[43]	Jackson et al. (2024)	Generative AI (GANs, Transformers)	Forecasting, inventory, sourcing, logistics, etc.	End-to-end SCM	Learning, adaptability, scenario simulation, agility	Conceptual; no empirical testing	Exploratory; functional focus; interpretation bias
[44]	Lin et al. (2022)	CGAN and BP Neural Networks	Partner selection, inventory, transportation optimization	Strategic Sourcing and Operational Logistics	Improved prediction, clustering, SCM integration	Simulated data; no real-world validation	Limited generalizability beyond tested datasets
[45]	Cannas et al. (2024)	Multiple (ML, ANN, Visual Inspection, Cobot-AI, NLP)	Planning, scheduling, maintenance, inventory, customer service	Planning, Make, Deliver	Cost/time reduction, quality, safety, sustainability	Six Italian firms; qualitative only	Country/sector-specific; expert interpretation
[46]	Abdelhamid et al. (2024)	AI + Blockchain (BDI Agents, Swarm Intelligence)	Data storage/processing in IoT-based SCM	Monitoring, Traceability, Infrastructure	Scalability, traceability, latency reduction	Simulation-based; no real-world pilot	Simulation limits; lacks real-time complexity validation
[47]	Dalal et al. (2024)	Hybrid CNN + BiLSTM (Bayesian Optimization)	Forecasting, inventory, transport planning	Planning, Procurement, Distribution	High prediction accuracy, reduced carbon footprint	Cosmetic sector data; simulation only	Domain-specific; overfitting risk
[48]	Hejazi et al. (2022)	AI-based product rec. and social media analysis	Operational performance via demand stimulation and risk mgmt.	Demand and Risk Mgmt/Customer Interface	Better performance, engagement, disruption resilience	Five e-commerce firms; weak factor loadings	Regional specificity; survey bias

Table 2. Cont.

(B)							
N°	Reference	AI Technique	SCM Application	SCM Phase	Reported Benefits	Limitations	Potential Biases
[49]	Xu et al. (2021)	Agent-Based and Multi-Agent Systems	Automation (procurement, coordination, negotiation)	Cross-phase	Distributed decisions, scalability, flexibility	Review-based; lacks empirical validation	Literature bias; under-represents ML-driven systems
[50]	Alnadi & Altahat (2024)	Expert Systems and Neural Networks	AI-driven ops and decision support in e-commerce	Strategic and Operational (SCM agility mediation)	Improved performance, precision, agility-supported excellence	Jordan-focused; self-reported; cross-sectional	Social desirability bias; regional scope
[51]	Sharabati et al. (2024)	AI (ML, robotics, automation) + DOI and TOE frameworks	Digital transformation and operational efficiency	Strategic and Operational Transformation	Enhanced scalability, responsiveness, conceptual integration	Jordanian industry; survey-based; lacks real-time deployment	Theoretical dependency; perception-based
[52]	Frederico (2023)	Generative AI (ChatGPT)	Communication, optimization, data analysis, reporting	Cross-phase	Process efficiency, improved communication, waste reduction	Industry blogs only; no empirical validation	Secondary source bias; early-stage insights
[53]	Helo & Hao (2022)	Multiple (Rule-based, GA, Deep Learning, etc.)	Sales configuration, production planning, maintenance	Planning, Make, Deliver, Service	Faster quotations, optimized production, predictive maintenance	Four cases; qualitative; early-stage implementations	Interviewee bias; no longitudinal outcomes
[54]	Olan et al. (2024)	XAI (SHAP, CBR, Genetic Algorithms, MAS)	Decision support in uncertain scenarios	Strategic and Tactical Decision-Making	Transparency, trust, better scenario planning	Simulation-based; no real-world deployment	Dataset-dependent; oversimplification risk
[55]	Zhao et al. (2022)	Evolutionary Game Theory + AI	Contract performance and compliance modeling	Governance/Legal Oversight	Better understanding of AI's influence on compliance	Conceptual only; China-specific	Assumption bias; lacks real-world validation
[56]	Salhab et al. (2023)	AI-Powered Decision Support	Quality improvement under digital marketing influence	Strategic and Operational Quality Management	Enhanced quality, improved decision-making	US-focused; survey-based; cross-sectional	Response bias; limited generalizability
(C)							
N°	Reference	AI Technique	SCM Application	SCM Phase	Reported Benefits	Limitations	Potential Biases
[14]	Hao & Demir (2024)	Multiple (ML, DL, GA, ANN, MAS, IDSS, NLP)	ESG: AI adoption triggers/inhibitors	Strategic/ESG Integration	Emissions reduction, risk management, quality improvement	Literature-based; no empirical deployment	Database and coding bias; English-only focus

Table 2. Cont.

(C)							
N°	Reference	AI Technique	SCM Application	SCM Phase	Reported Benefits	Limitations	Potential Biases
[57]	Olan et al. (2024)	AI-Enabled Systems (ANNs, Fuzzy Logic, AI-driven SCF)	Sustainable supply chain finance (SCF)	Finance, Network Integration	Improved financing, resource allocation, sustainability	Survey-based; no system validation	Self-reported; regional skew
[58]	Bhattacharya et al. (2024)	Multiple (GA, ANN, RL, CNN, etc.)	Reverse logistics, remanufacturing, CLSC design	Reverse Logistics/Circular Ops	Cost reduction, sustainability, CLSC optimization	Conceptual; no empirical validation	Literature selection bias
[59]	Virmani et al. (2024)	Fuzzy–Delphi, F-DEMATEL, Graph Theory	Enabler prioritization in healthcare SCM	Strategic Adoption and Responsiveness	Traceability, readiness, strategic alignment	India-focused; qualitative; no empirical implementation	Expert subjectivity; limited generalizability
[60]	Nozari (2024)	AIoE (AI, IoE, IoT, Big Data, ML, etc.)	Smart green supply chain	End-to-end (Green Procurement, Production, Recycling)	Energy efficiency, green sourcing, sustainability	Conceptual only; expert validation	Overgeneralization; early-stage
[61]	Li & Donta (2023)	XGBoost + SNN-Stacking	Demand forecasting in green supply chains	Strategic Planning/Sustainability	High accuracy, reduced environmental risk, better resource use	China-based; domain-specific; no external validation	Regional focus; model complexity
[62]	Dohale et al. (2024)	Bayesian Network and VAHP (MCDM)	Carbon Neutrality Index prediction (clothing industry)	Sustainability/Strategic Ops	Identifies key determinants, prioritizes actions	India-focused; perception-based	Regional bias; expert subjectivity
[63]	Naz et al. (2022)	GA, Fuzzy Logic, ML, ANN, NLP, Metaheuristics	Sustainable SC development (reverse logistics, transport)	Cross-phase (Sustainability, Planning)	Carbon reduction, optimized operations, sustainability	Theoretical only; no empirical data	Scopus-based selection bias
[64]	Benzidia et al. (2021)	BDA-AI (Big Data + AI tools)	Green SC process integration (hospital logistics)	Integration and Collaboration	Emission reduction, supplier alignment, decision efficiency	French hospitals; perception-based	Regional; no multi-stakeholder validation
[65]	Jamwal et al. (2022)	Deep Learning (CNN, RNN, LSTM, AE, RBM)	Sustainability in manufacturing (predictive maintenance)	Operational and Strategic Sustainability	Less downtime, higher quality, predictive capacity	Conceptual; no empirical validation	Literature bias; limited generalization

Table 2. Cont.

(D)							
N°	Reference	AI Technique	SCM Application	SCM Phase	Reported Benefits	Limitations	Potential Biases
[66]	Hatamlah et al. (2023)	AI Supply Chain Analytics	Alliance mgmt during pandemic	Strategic and Operational Planning	Better decisions, agility, alliance coordination	Indian auto industry; survey; no longitudinal validation	Regional; self-report bias
[67]	Rana & Daultani (2023)	Multiple (ML, ANN, CNN, RL, Hybrid Models)	Broad AI/ML applications overview	Cross-phase	Trends, research gaps, leading techniques	Bibliometric; no empirical validation	Publication and keyword bias
[68]	Ronchini et al. (2024)	Multiple (ML, NLP, RPA, Chatbots)	SC Finance innovation	Implementation Processes	Faster processes, cost savings, risk reduction	Ten SCF providers; qualitative only	Provider sampling bias
[69]	Georgiev et al. (2024)	Multiple (ML, DL, NLP, RPA, GenAI)	Project management in SCM	Strategic and Operational PM	Planning, automation, risk analysis	Survey-based; cross-industry; limited generalisability	Respondent bias; no longitudinal data
[70]	Purnama et al. (2023)	Deep Learning + Case-Based Reasoning	Decision support in tele-dermatology services	Service Supply Chain/Healthcare Logistics	Diagnostic accuracy, service reach, patient access	Design-focused; lacks empirical performance metrics	Healthcare-specific; no clinical validation
[71]	Singh et al. (2023)	AI, ML, DL, Robotics, Fuzzy DEMATEL	Critical issues in AI adoption (construction SCM)	Strategic Adoption and Digital Transformation	Roadmap for adoption, barrier prioritization	India-focused; qualitative	Expert subjectivity; no empirical implementation
[72]	Raman et al. (2024)	Generative AI (ChatGPT and Bard—LLMs)	SC education and certification (CSCP simulation)	Training and Knowledge Management	Personalized feedback, improved educational outcomes	Simulation only; scored by experts	AI version variability; subjective scoring
[73]	Shrivastav (2022)	Cross-cutting AI (ML, DL, IoT-AI, Recommender Systems)	Barriers to AI adoption across SCM	Strategic and Operational Transformation	Framework of 10 AI barriers; guidance for alignment	Conceptual; US-focused; no empirical testing	Expert-based; limited generalization
[74]	Cadden et al. (2022)	AI + Business Analytics (ML, RPA, CRM-AI)	Cultural, technical, business enablers of AI/BA adoption	Strategic Integration and Performance Improvement	Highlights cultural enablers; improved alignment and performance	UK manufacturing; survey-based; cross-sectional	Buyer-side focus; absence of multi-tier view
[75]	Hendriksen (2023)	Generative AI (GPT-4) + AII Framework	Theoretical/strate integration and disruption assessment	Strategy, Risk, Coordination	Conceptualizat of AI's role; AII framework	Theoretical; lacks empirical validation	Subjective projections; metaphor-based modeling

Table 2. Cont.

(D)							
N°	Reference	AI Technique	SCM Application	SCM Phase	Reported Benefits	Limitations	Potential Biases
[76]	Kosasih et al. (2024)	Neurosymbolic AI (ANFIS, GNN + Knowledge Graphs, etc.)	Explainability in SCM decision support	Cross-phase (Planning, Sourcing, Risk, Monitoring)	Enhanced transparency, human–AI trust, regulatory potential	Focused on ANFIS; limited real-world deployment	Overrepresentation of neuro-fuzzy; few sector validations
[77]	Hangl et al. (2022)	Cross-cutting (meta-SLR on AI: ML, DL, NLP, etc.)	Barriers, drivers, human/social factors in AI adoption	Cross-phase (Strategic, Operational, Sustainability)	Synthesis of 44 SLRs; roadmap for AI readiness	No empirical data; secondary/tertiary focus	Dependent on quality of prior SLRs

3.1. Bibliometric Analysis

For the 66 articles selected in this systematic literature review (SLR), the theme is highly contemporary, reflecting the growing interest and rapid advancements in the field. The majority of the articles included in the review were published in the last few years, specifically between 2021 and 2024. This recent publication trend highlights the ongoing relevance and increasing volume of research in this area, with a substantial contribution from numerous scholars. As shown in Figure 4, the articles selected for this review are largely concentrated within this narrow time window, emphasizing the current nature of the research landscape.

A visualization created using VOSviewer 1.6.20 highlights the key authors contributing to the research theme in the selected literature (Figure 5). Among the most prominent authors, Allahham, Madmoud emerge as leading figure in the field. His substantial contributions are reflected in the high number of publications and their central positions in the research network. Additionally, Sharabati, Abdel-Aziz Ahmad has also made significant strides, positioning himself as a crucial author in the exploration of artificial intelligence applications in supply chain management.

Among the journals selected, the *International Journal of Production Research* stands out with 14 articles (Figure 6). This journal is widely recognized for its focus on production management, operations research, and industrial engineering. With a CiteScore of 19.2 (2023) and an SJR of 2.668, the *International Journal of Production Research* ranks highly within its subject areas, including Decision Sciences and Industrial Engineering. It ranks #3 in Decision Sciences (Management Science and Operations Research), placing it in the 98th percentile, and #10 in Business, Management and Accounting (Strategy and Management), also within the 98th percentile. This reflects its significant influence and relevance to the research topics explored in this review.

The *Uncertain Supply Chain Management* journal, with seven articles in the selected set, also plays a crucial role in the field of supply chain research. Despite being indexed in Scopus from 2013 to 2024, its coverage was discontinued after 2024. This journal primarily addresses the areas of statistics, probability, and uncertainty, which are vital for understanding the complexities of modern supply chains, especially in the context of artificial intelligence and machine learning applications. It holds a CiteScore of 5.6 (2023) and an SJR of 0.436. In terms of its CiteScore Rank 2023, it is ranked #21/168 in Decision Sciences (Statistics, Probability and Uncertainty), placing it in the 87th percentile.



Figure 4. Included articles per year.

The journal *Logistics* contributed five articles to the review. Published by the Multi-disciplinary Digital Publishing Institute (MDPI) and covering topics such as Management Information Systems and Management Science and Operations Research, *Logistics* has gained attention for its open access format and broad reach in the academic community. In 2023, it achieved a CiteScore of 6.6 and an SJR of 0.740. In terms of its CiteScore Rank 2023, it ranks #31/131 in Business, Management, and Accounting (Management Information Systems), in the 76th percentile, and #50/207 in Decision Sciences (Management Science and Operations Research), also in the 76th percentile.

These journals not only contribute to the theoretical foundations but also shape the practical applications of AI in the sector, providing valuable insights for both academia and industry.

To better understand the thematic structure and research trends in the field, two complementary techniques were employed: a word cloud (Figure 7) and a keyword co-occurrence network (Figure 8). While both approaches derive from text-mining processes, they serve distinct analytical purposes and provide different levels of insight.

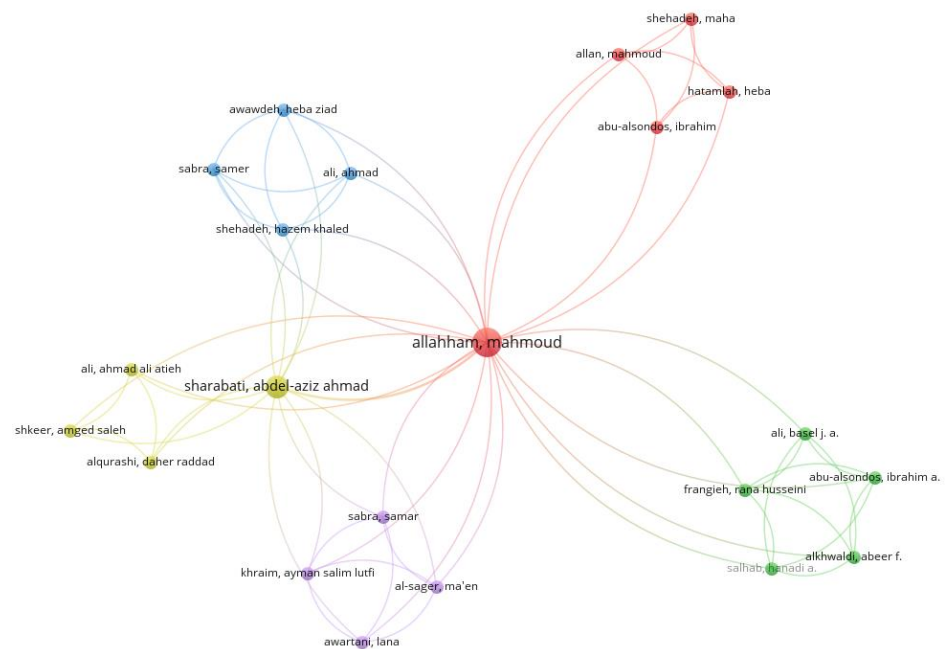


Figure 5. Co-authorship analysis.



Figure 6. Journal of publication of the selected articles.

The word cloud (Figure 7) was generated using a custom R script in RStudio 4.4.2, which analyzed the frequency of terms in the titles, abstracts, and keywords of the selected corpus. Prior to visualization, extensive preprocessing was conducted, including the removal of stopwords, normalization of plural and singular forms, and the manual exclusion of non-informative terms. The word cloud offers a high-level overview of dominant terms across the dataset, with “supply chain”, “data”, “management”, and “information” emerging as the most salient. However, as highlighted in Wuni and Shen (2019) [78], word clouds, while visually intuitive, lack the ability to represent relationships between terms or cluster thematic areas.



Figure 7. Word cloud.

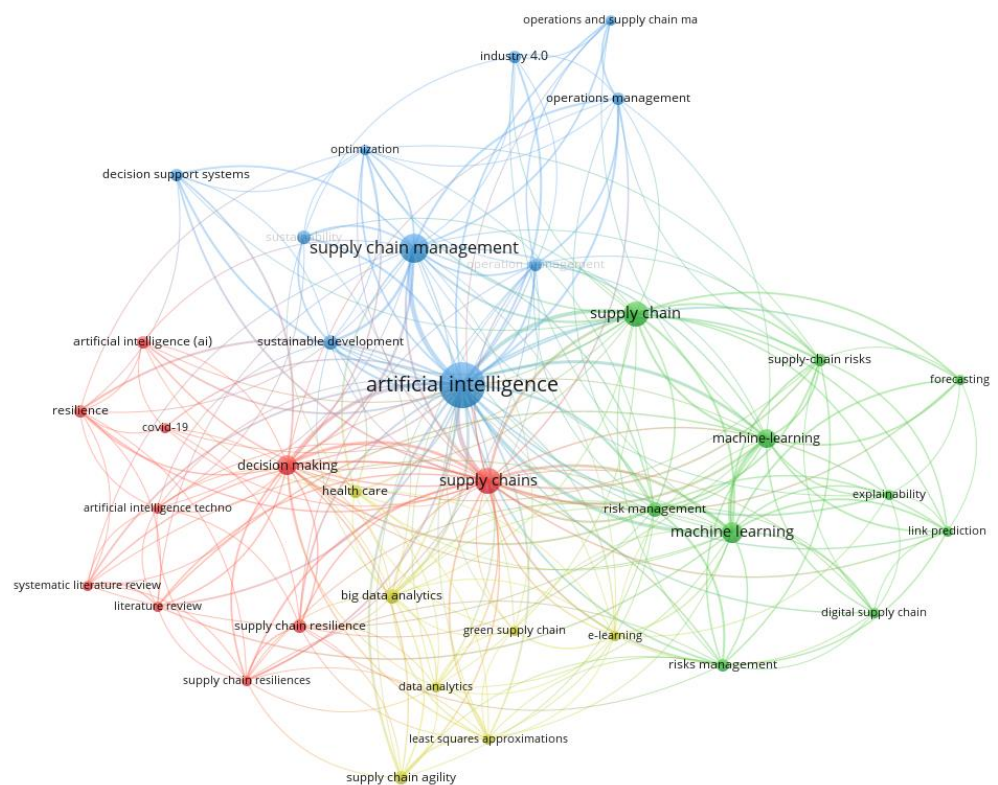


Figure 8. Co-occurrence of all keywords.

Therefore, to complement this analysis, a co-occurrence network was constructed using VOSviewer 1.6.20 (Figure 8), based on author keywords. Only keywords with a minimum occurrence threshold (e.g., two or more appearances) were included to ensure the robustness of the visualization. VOSviewer 1.6.20 applied fractional counting and association strength normalization to build the network, in line with the methodology adopted by Zhang et al. (2023) [79].

This network visualization enables the identification of conceptual clusters and thematic proximities, with the following examples:

- The blue cluster centers around “supply chain management”, “decision support systems”, and “optimization”, indicating a stream of research concerned with operational performance and planning.
- The green cluster highlights “machine learning”, “forecasting”, and “risk management”, pointing to predictive analytics and data-driven risk mitigation approaches.
- The red cluster links “resilience”, “COVID-19”, and “decision making”, suggesting a focus on adaptive strategies under uncertainty and disruption.
- The yellow cluster includes terms such as “big data analytics”, “green supply chain”, and “sustainability”, showing intersections between digital transformation and environmental objectives.

This structured mapping reveals how different research streams are interconnected and identifies gaps or emerging trends that are less evident in the word cloud. For instance, the presence of keywords like “health care” and “e-learning” within the network suggests the diffusion of supply chain AI applications into sector-specific contexts.

In contrast to the word cloud, the co-occurrence network facilitates a more rigorous bibliometric interpretation. Following the principles in Zhang et al. (2023) [79], this enables researchers to move beyond simple frequency counts and begin exploring thematic evolution, conceptual influence, and future research trajectories. The density, clustering, and centrality of nodes in Figure 8 thus provide key insights that can inform the formulation of research questions and the development of analytical frameworks.

In summary, while the word cloud (Figure 7) serves as an accessible entry point for identifying prominent terms, it is the co-occurrence network (Figure 8) that delivers substantive value in identifying intellectual structures and interrelationships within the field. This justifies the inclusion of both figures in the analysis, as each offers complementary perspectives for understanding the literature landscape on artificial intelligence in supply chains.

To provide a structured and analytically rigorous synthesis of the selected literature, the results of this systematic review are organized into distinct yet interrelated thematic dimensions. This structure was designed to reflect the most recurrent and impactful application areas of AI within SCM, as well as to enable a clearer articulation of emerging trends, research gaps, and practical implications.

The first four thematic sections were developed based on the dominant axes identified during the content analysis, and their scope was cross-validated against the bibliometric structures—particularly the keyword co-occurrence network. This integration ensures that the thematic synthesis is not presented in isolation but is grounded in the structural patterns of the literature. Specifically, each thematic axis corresponds closely to clusters within the co-occurrence network, reinforcing the analytical continuity between publication trends and the substantive content of AI applications in SCM.

- Section 3.2—Enhancing Supply Chain Resilience examines how AI technologies contribute to risk mitigation, agility, and recovery capabilities across supply chains. This theme is strongly aligned with a co-occurrence cluster centered on keywords such as “machine learning”, “forecasting”, and “risk management”, reflecting the field’s focus on predictive analytics and resilience-building.
- Section 3.3—Optimizing Supply Chain Processes explores the role of AI in improving forecasting accuracy, inventory control, logistics planning, and automation. This section connects directly to the cluster dominated by terms like “supply chain management”, “decision support systems”, and “optimization”, highlighting the operational and strategic performance dimensions emphasized in the literature.

- Section 3.4—Applications in Sustainability addresses the intersection between AI and environmental, social, and governance (ESG) objectives, and is mapped to a distinct cluster featuring “big data analytics”, “green supply chain”, and “sustainability”, underscoring the growing importance of AI in supporting eco-efficiency and ethical practices.
- Section 3.5—Challenges and Barriers identifies critical obstacles to AI adoption, which, although thematically transversal, are also reflected in overlapping clusters that address explainability, data integration, and implementation constraints—issues that pervade multiple research streams.

During the peer review process, a gap was identified regarding the limited exploration of AI applications in managing supply chain dynamics and disruptions. To address this, Section 3.6—Managing Supply Chain Dynamics and Disruptions was added, deepening the discussion on AI’s role in dynamic decision-making and disruption management. This section draws on pivotal studies that extend the thematic coverage and ensure the review reflects critical dimensions of modern SCM challenges.

To offer a broader contextual understanding, two additional sections complement the thematic synthesis:

- Section 3.7—Geographical and Industry-Specific Differences in AI Adoption synthesizes how regional and sectoral factors influence AI implementation, providing insights into the contextual diversity of adoption patterns.
- Section 3.8—Emerging Techniques and Future Directions outlines novel AI approaches and articulates future research needs, integrating both thematic gaps and evolving technological trajectories identified through the literature.

By explicitly aligning the thematic axes with the bibliometric clusters, this revised structure ensures a coherent narrative that bridges publication trends with substantive research themes. This approach not only strengthens the analytical depth of the manuscript but also demonstrates the continuity between the structural and content-based dimensions of AI applications in supply chain management.

3.2. Enhancing Supply Chain Resilience

Numerous studies have explored the role of artificial intelligence (AI) in enhancing supply chain resilience, highlighting its contributions to risk management, agility, and operational performance in response to disruptions [3,11,18–32,41–44,66].

AI has emerged as a crucial tool for improving resilience by enabling real-time decision-making, enhancing information-sharing mechanisms, and optimizing risk management strategies. AI-driven supply chain collaboration fosters trust and transparency among partners, allowing timely responses to market fluctuations and uncertainties [18]. Digital supply chain surveillance (DSCS), using AI-based link prediction, proactively monitors risks, uncovers hidden vulnerabilities, and enhances network stability [19]. Neurosymbolic reasoning approaches address concerns about the explainability of AI-driven risk assessments [19].

Predictive analytics powered by AI mitigates the impact of unforeseen disruptions. Advanced forecasting models, such as machine learning (ML), LSTM, and SARIMA, have been applied in cold chain logistics and FMCG sectors to address capacity shortages and improve planning accuracy [20,41,42]. AI-based information systems facilitate real-time data acquisition and decision-making, improving adaptability and responsiveness to supply chain disturbances [21–23].

AI also enhances agility and collaboration, especially in critical sectors such as healthcare, where real-time insights can improve outcomes [24]. Prescriptive analytics and AI-driven risk management frameworks strengthen supply chain reengineering and re-

sponsiveness among SMEs [11,25]. In Vietnamese SMEs, AI has enabled adaptive responses to unexpected disruptions [26], and generative AI contributes by enabling predictive decision support [43].

The relevance of AI for resilience is particularly evident during crises. AI-driven strategies improve transparency, last-mile delivery, and agile procurement, while AI-integrated analytics enhance alliance management and operational performance [27,28]. ML models such as CGANs help optimize member selection in supply chain alliances [44]. AI-based sourcing strategies enable proactive operational adjustments in response to emerging threats [27].

Post-pandemic research confirms AI's critical role in fostering resilience. Studies emphasize predictive modeling and intelligent automation as key to recovery and continuity [29,66]. AI-powered analytics and demand forecasting tools help maintain balance and increase resilience, especially in fast-evolving environments [3,23,30,42].

3.3. Optimizing Supply Chain Processes

AI significantly improves supply chain performance across key processes such as demand forecasting, inventory management, logistics planning, and automation [5,10,12,20,22,23,28,33–36,41,42,44–53,57,58,67–69].

The critical role of artificial intelligence—particularly through big data analytics capabilities—in enhancing supply chain agility by improving information alignment and collaboration has been highlighted, emphasizing its importance in achieving responsiveness and adaptability in dynamic and uncertain environments [33].

AI-driven predictive analytics and real-time data processing reduce lead times, improve accuracy, and lower operational costs. Case study analyses using the SCOR model show how AI strengthens service levels, product quality, and safety, while also addressing sustainability [45]. AI-enhanced decision support systems (DSSs), particularly those incorporating explainable AI (XAI), bring transparency and reliability to decision-making [57].

AI has been mapped across various digital transformation initiatives, emphasizing its role in improving logistics and inventory strategies [67]. Blockchain-integrated AI systems help overcome data inconsistency and latency in IoT-driven supply chains [46], while in finance, AI supports transaction optimization, credit risk assessment, and supplier financing [68].

Omnichannel models, such as in the blood supply chain, show how AI balances supply and demand using intelligent mechanisms [34]. AI tools like CNNs and BiLSTM enhance pattern recognition, resource allocation, and predictive analysis [47]. Reinforcement learning adds adaptivity, particularly in dynamic inventory systems [12]. AI also contributes to risk mitigation in project management and enhances coordination in complex supply networks [69].

AI supports logistics automation, improving vehicle routing and distribution efficiency [44]. It enhances e-commerce through intelligent product recommendations and product information management [48]. Agent-based systems boost interoperability through IoT and smart contracts [49].

Emerging technologies such as federated learning allow privacy-preserving collaborative models for shared risk prediction [35]. Research on autonomous robots identifies key adoption factors, including efficiency gains and cost barriers [36], while AR-based tools support organizational performance in planning and operations [5].

3.4. Applications in Sustainability

AI enables sustainability in supply chains by reducing waste, controlling emissions, and supporting ethical sourcing across environmental, social, and governance (ESG) dimensions [14,26,32–34,37,38,47,54,55,58–65,70,71].

Environmental sustainability benefits from AI's ability to optimize operations, reduce greenhouse gas emissions, and manage resources efficiently [14]. AI ensures product security, supports responsible sourcing, and enhances supply chain transparency. In healthcare, AI improves supply chain traceability and responsiveness, especially post-pandemic [59].

Neurosymbolic ML approaches support sustainability by identifying non-compliant suppliers and enabling ethical audits [32]. Intelligent Teledermatology Systems (ITDS) exemplify AI's role in optimizing healthcare logistics and service delivery [70].

In closed-loop supply chains (CLSCs), AI aids in waste reduction and resource recovery [58]. Green supply chain management (GSCM) uses tools like AIoE to embed sustainable decision-making into operations [60]. AI also supports humanitarian supply chains by improving coordination and resource use in disaster response [33].

AI-driven analytics align supply with market needs, enhance resource efficiency, and support green supplier selection [61]. Predictive tools estimate carbon neutrality indices, helping firms comply with environmental regulations [62]. In construction supply chains, AI identifies risks and supports sustainable practices [71].

In the post-COVID financial landscape, AI optimizes supply chain finance (SCF), supporting sustainability by reducing waste and inefficiencies [54]. AI-powered routing tools, using CNNs and BiLSTM, help reduce environmental impact, while AI supports circular economy (CE) strategies through better resource recovery [26,47].

Medical drones enhance healthcare supply chains by reducing emissions and supporting SDG targets [37]. AI-based collaboration improves eco-efficiency and emissions control through big data analytics [63,64]. In Industry 4.0, AI enhances energy efficiency via predictive maintenance and quality control [65], and supports transparency through visibility systems and ethical compliance tools such as AI-based judicial reasoning models [38,55].

3.5. Challenges and Barriers

Several studies have explored the challenges and barriers to AI adoption in supply chain management, highlighting issues such as data quality, interoperability, ethical concerns, and scalability [12,14,19,20,30,32,35,36,39,40,42,43,45,49–51,56,57,68,71–77]. These challenges impact the effective integration of AI-driven solutions across various supply chain functions.

Despite its transformative potential, AI adoption in supply chain management faces several challenges. Key barriers include data quality issues, lack of skilled personnel, high implementation costs, and concerns regarding the economic benefits of AI investments [45]. Organizations often struggle to integrate AI with existing systems due to interoperability challenges and the complexity of legacy infrastructures. Additionally, regulatory uncertainties and ethical considerations, such as data privacy and algorithmic biases, pose significant hurdles to AI adoption in supply chains [14].

One major limitation is the reluctance of suppliers to share data [32], which restricts the effectiveness of AI-driven risk management systems. Additionally, the integration of AI in supply chains requires continuous adaptation and training of personnel to keep up with technological advancements [50]. Ethical considerations, including the need for responsible AI usage and mitigation of biases in decision-making, also pose significant challenges. Furthermore, variations in AI performance across different models highlight the necessity for continuous model adaptation and validation to ensure reliability in real-

world applications, comparing the performance of ChatGPT and Bard in supply chain contexts, demonstrating how different AI models yield varying levels of accuracy, relevance, and readability [72].

The lack of explainability in AI models exacerbates adoption challenges, as practitioners often find black-box models difficult to trust. Efforts to develop explainable AI frameworks, such as the SHapley Additive exPlanations (SHAP) technique, have been explored to enhance transparency and interpretability in AI-driven decision support systems [57]. Furthermore, AI apprehensions among managerial personnel can hinder the effectiveness of risk alert tools, emphasizing the need for a balanced approach between technological and human elements in supply chain management [39].

Scalability and integration with existing infrastructures pose additional barriers to AI implementation. Many AI-driven solutions remain at a theoretical or experimental stage, with limited deployment in real-world industry settings [12]. AI implementation in supply chain finance faces challenges related to fraud detection, supplier onboarding, and administrative efficiency [68]. Moreover, the lack of digital readiness and slow adoption of AI-driven technologies, particularly in the FMCG industry, pose further constraints [20].

Ethical and legal implications, including AI-driven surveillance technologies leading to biased decision-making and privacy infringements, remain significant concerns [40]. Additionally, research highlights issues such as lack of trust in AI outcomes, cybersecurity risks, and uncertainties regarding the cost–benefit trade-off in AI adoption [71]. Addressing these barriers requires organizations to develop strategies that align AI adoption with long-term business objectives [51].

Organizational and cultural factors also play a critical role in AI adoption. A structured review identified issues such as resistance to AI-driven automation, integration difficulties with legacy systems, and the lack of comprehensive AI governance frameworks [73]. Furthermore, the cultural and managerial enablers of AI adoption remain underexplored, necessitating further research on behavioral factors influencing successful AI integration [74].

Additional challenges include multi-actor collaboration complexities and disparities in data accessibility, which hinder the seamless implementation of AI-driven solutions [74]. Overcoming these barriers requires targeted policy interventions and organizational change management strategies to enhance AI readiness in supply chain contexts.

Agent-based AI systems, while promising, face adoption challenges due to the need for standardized protocols and interoperability with enterprise resource planning (ERP) systems [49]. Furthermore, selecting appropriate AI models for specific supply chain tasks remains a challenge. For instance, demand forecasting models require careful selection of inputs and parameters to ensure reliability and accuracy [42]. Organizations must invest in research and development to optimize AI-driven forecasting techniques for their unique supply chain needs.

Scalability, ethical considerations, and integration complexities continue to impede widespread AI adoption. Resistance to AI implementation arises due to concerns over data privacy, algorithmic biases, and interoperability with legacy systems. For instance, the adoption of federated machine learning for supply chain risk prediction is constrained by disparities in data access, algorithmic selection, and data-sharing reluctance [35].

Another critical challenge lies in the cost and perceived value of AI technologies. Research on autonomous robot adoption suggests that while cost is a major determinant, firms may struggle to recognize the full potential benefits of automation, thereby limiting adoption rates [36]. Furthermore, concerns surrounding explainability and transparency in AI-driven decision-making persist, as stakeholders demand greater interpretability in AI-generated insights. Addressing these challenges requires strategic invest-

ments in AI governance frameworks and interdisciplinary collaboration to enhance trust and adoption [30].

3.6. Managing Supply Chain Dynamics and Disruptions

In the initial analysis of the 66 selected articles, no substantial focus was identified on the application of AI in managing dynamic and disrupted production-distribution systems. Despite the relevance of this topic to modern supply chain challenges, this gap suggests that current literature reviews may overlook this crucial dimension. To ensure a more comprehensive understanding of the field, additional pivotal studies—Priore et al. (2019) [80], Badakhshan and Ball (2023) [81], Ivanov (2020) [82], Modgil et al. (2022) [27], and Yashan et al. (2024) [83]—were incorporated into the discussion. These works provide critical insights into how AI can be leveraged to mitigate both operational volatility and systemic disruptions in supply chain networks.

Modern supply chains are increasingly exposed to volatility, uncertainty, and sudden disruptions in both supply and demand. As such, AI has emerged as a strategic enabler, enhancing decision-making, adaptability, and resilience. For instance, Ivanov (2020) [82] investigates the distinctive features of epidemic outbreaks—characterized by long-term disruptions, ripple effects, and simultaneous supply-demand shocks—and demonstrates, via simulation-based modeling, how AI-enhanced digital twins can predict and mitigate the impacts of pandemics on global supply chains. Notably, the study underscores that factors such as the timing of facility closures and the speed of epidemic propagation are pivotal in determining performance outcomes.

Priore et al. (2019) [80] contribute a machine learning-based framework designed to dynamically select optimal replenishment policies in rapidly evolving supply chain environments. Their inductive learning approach, utilizing C4.5 decision trees, facilitates managers' understanding of the interplay between controllable and uncontrollable variables, resulting in significant cost savings and reduced bullwhip effects. Complementarily, Badakhshan and Ball (2023) [81] extend this approach by developing a digital twin framework that integrates machine learning with discrete-event simulation, aiming to balance inventory and cash management during both physical and financial disruptions. Their inclusion of financial metrics, such as the Cash Conversion Cycle (CCC), offers a nuanced understanding of liquidity interdependencies across the supply network.

Further deepening the discourse, Modgil et al. (2022) [27] highlight five critical areas where AI fortifies supply chain resilience: transparency, last-mile delivery, personalized stakeholder solutions, disruption impact minimization, and agile procurement strategies. Their empirical findings emphasize AI's role in enhancing dynamic capabilities, thus enabling firms to better anticipate, respond to, and recover from disruptions.

Yashan et al. (2024) [83] propose a synergistic integration of blockchain and AI to address transparency and trust issues that often exacerbate disruption impacts. Their study illustrates how AI-driven predictive analytics, combined with blockchain's immutable ledger, can prevent fraud, optimize traceability, and enhance real-time visibility across complex global networks, offering a robust framework for disruption management.

Taken together, these studies underscore the transformative potential of AI in fortifying supply chain resilience and responsiveness. While Priore et al. (2019) [80] and Badakhshan and Ball (2023) [81] emphasize operational and financial decision support, Ivanov (2020) [82] and Modgil et al. (2022) [27] broaden the perspective by incorporating digital twins and dynamic capabilities into disruption response strategies. Yashan et al. (2024) [83] further extend the conversation by advocating for integrated technology frameworks that fuse AI with blockchain to achieve unparalleled transparency and robustness.

AI integration transcends mere technological advancement; it signifies a structural reconfiguration toward intelligent, adaptive, and resilient supply networks. Future research may benefit from synthesizing these approaches—combining adaptive replenishment strategies, financial sensitivity, dynamic capability development, and blockchain-enabled transparency—to build holistic, disruption-resilient models that reflect the intricacies of global supply chains.

3.7. Geographical and Industry-Specific Differences in AI Adoption

An analysis of the selected studies reveals considerable geographical and industry-specific heterogeneity in the adoption of artificial intelligence (AI) within supply chain management (SCM). These differences are shaped by contextual factors such as digital maturity, regulatory environment, sectoral requirements, and cultural readiness, all of which influence the implementation pathways and performance outcomes of AI-driven supply chains.

Several studies highlight a strong regional focus, which introduces potential biases but also uncovers context-specific dynamics. For example, research conducted in India emphasizes AI's role in alliance management during the COVID-19 crisis and the need for adaptive strategies in auto component industries [28,66]. Similarly, studies in Jordan and the broader MENA region explore digital transformation through AI, particularly in e-commerce and industrial sectors [50,51]. These contexts often rely on perception-based surveys, revealing both enthusiasm for AI and concerns regarding implementation capacity.

In contrast, studies based in developed economies, such as the United States and the United Kingdom, tend to focus on more advanced applications, including generative AI for education and risk surveillance, and emphasize explainability, transparency, and regulatory alignment [40,43,54]. In particular, research from the UK highlights the strategic integration of neurosymbolic AI and graph neural networks to support digital supply chain surveillance [19].

Other notable geographical examples include the following:

- Southeast Asia: Vietnamese SMEs adopting AI for agility and circular economy integration [26].
- Africa: Case studies from Ghana and South Africa showing AI's role in last-mile healthcare delivery and FMCG supply chain resilience [20,37].
- Pakistan and Indonesia: AI in humanitarian and healthcare logistics, focusing on operational efficiency under constrained resources [34,70].

These findings suggest that while AI adoption is a global phenomenon, its drivers and barriers vary considerably. Developing regions often emphasize practical outcomes (e.g., cost savings, efficiency), whereas developed regions explore advanced AI concepts (e.g., XAI, federated learning) with more focus on governance and data ethics [35,57].

The reviewed literature also indicates distinct patterns of AI adoption across industries. Manufacturing remains the most represented sector, particularly in studies addressing predictive maintenance, quality control, and sustainability in smart factories [45,65]. Here, AI contributes to performance optimization through deep learning, computer vision, and digital twin technologies.

Healthcare and humanitarian logistics form another cluster of interest. Studies in these domains highlight AI's value in improving traceability, responsiveness, and decision support under crisis conditions [24,33,59]. These sectors show a higher adoption of AI for agility and resilience rather than cost-based efficiency alone.

Retail and e-commerce applications focus on customer experience, demand stimulation, and inventory optimization. AI tools such as recommender systems and sentiment analysis are used to drive performance via customer engagement and operational adapta-

tion [48,50]. Meanwhile, finance-oriented supply chains leverage AI for fraud detection, credit assessment, and smart contracting, indicating an emerging frontier of AI-SCM integration in financial services [57,68].

The construction and fashion industries, though less frequently represented, are emerging as testbeds for AI applications in sustainability, reverse logistics, and risk mapping [58,71].

Finally, the energy, water, and food sectors are gaining visibility, particularly in multi-industry forecasting applications, underscoring AI's growing versatility in critical infrastructure contexts [42].

Table 2 indicates that sector-specific AI implementations are often closely tied to regional characteristics. For instance, sustainable supply chain models in India's clothing and healthcare sectors reflect national policy trends and resource constraints [59,62], while advanced AI applications in European and North American studies mirror higher digital maturity and regulatory readiness [40,74]. These variations reinforce the need for localized AI strategies and context-sensitive policy frameworks.

In sum, AI adoption in SCM is not uniform; it is shaped by the interplay between geography, industry, and institutional readiness. Future research should further explore these dimensions, particularly in underrepresented regions and sectors, to support equitable and effective diffusion of AI technologies across global supply chains.

These geographical and industry-specific differences are not merely descriptive but have profound implications for the nature, pace, and success of AI integration in supply chain management. Contextual factors such as digital infrastructure maturity, regulatory frameworks, workforce skills, and sector-specific operational complexities fundamentally shape the pathways through which AI is adopted and scaled. For instance, regions with advanced digital ecosystems and supportive policy environments tend to experience more seamless and accelerated AI integration, while industries characterized by high complexity or stringent compliance requirements may face distinct barriers despite high potential benefits.

Moreover, cultural attitudes toward technology adoption and the availability of local expertise also influence managerial perceptions and investment decisions, thereby affecting AI implementation outcomes. These variations highlight the need for nuanced, context-aware strategies that align AI adoption with local capabilities and constraints.

Future research could benefit from cross-country and cross-sector comparative analyses to identify best practices and adaptive models that account for these contextual contingencies. Additionally, longitudinal studies examining how evolving economic, technological, and regulatory environments impact AI integration trajectories across different settings would further enrich the understanding of global AI adoption dynamics in supply chains.

3.8. Emerging Techniques and Future Directions

Recent advances in artificial intelligence (AI) are reshaping supply chain management through enhanced decision-making, real-time optimization, and predictive capabilities. The most promising developments include explainable AI, reinforcement learning, digital twins, generative AI, and AI-human intelligence collaboration [10–12,19,21,29,31,32,34,35,38,43,46,52,54,55,63,64,67,68,75,76]. These innovations are increasingly integrated with disruptive technologies such as blockchain, IoT, and knowledge graph reasoning.

Neurosymbolic AI—combining machine learning with symbolic reasoning—has gained relevance for enhancing transparency and trust in supply chain applications [19]. Similarly, knowledge graph reasoning powered by graph neural networks (GNNs) has

shown potential in risk detection, especially in revealing hidden dependencies across supply networks [32].

In complex environments like humanitarian logistics, AI–human intelligence (AI–HI) collaboration is proving essential. Hybrid decision support frameworks have been developed to combine the computational power of AI with human judgment, particularly in high-stakes decision-making under uncertainty [31].

AI-driven platforms that integrate big data analytics, machine learning, and digital twins are redefining SCM practices [21]. These tools enable enhanced simulation and operational planning capabilities. In addition, applications in supply chain finance and omnichannel logistics are contributing to the automation of decision support systems [34,68]. The role of AI in SCM thus calls for new interdisciplinary frameworks capable of capturing its disruptive influence [75].

The combination of AI with technologies such as blockchain and IoT is advancing supply chain resilience, transparency, and security [11,46]. GNNs and other predictive models improve supply chain visibility and support proactive procurement strategies [38]. Furthermore, digital twins are expected to play a central role in simulating and optimizing supply chain operations under different conditions [29].

Generative AI (GAI), including large language models such as ChatGPT, is being explored for applications in scenario modeling, communication, and decision automation [43,52]. Coupled with reinforcement learning, GAI has the potential to support autonomous supply chain optimization [12]. Meanwhile, explainable AI continues to address transparency and regulatory concerns, particularly in cybersecurity and risk management contexts [30,76].

Emerging research also highlights the potential of AI in enhancing sustainability. Digital learning platforms, predictive analytics, and green supply chain analytics are being used to reduce waste, monitor carbon emissions, and support environmental goals [64]. AI-enabled frameworks for traceability and supplier selection are increasingly relevant in aligning supply chains with ESG criteria [55,63].

Lastly, ethical and governance frameworks must accompany technological advancements. As AI adoption scales, there is a growing need for responsible deployment, explainability, and human oversight [10,31]. Research should further explore scalable and ethical AI solutions that ensure long-term resilience and sustainability.

To further explore the role of artificial intelligence in supporting sustainable supply chains, future research must address specific gaps that go beyond general optimization. As AI adoption grows, there is a growing need to understand how these technologies can directly contribute to environmental, social, and governance (ESG) goals across supply chain operations. Table 3 presents structured directions for future investigations, focusing on key sustainability-related applications of AI.

Table 3. Future research directions for AI in sustainable supply chain management.

Research Direction	Description
Life-Cycle Sustainability Assessment (LCSA)	Explore the use of AI, particularly machine learning and generative models, to automate and enhance life-cycle assessments (LCAs), allowing for continuous evaluation of environmental, social, and economic impacts across supply chain stages.
AI and Circular Economy	Investigate the integration of AI with circular economy principles, including intelligent disassembly planning, remanufacturing optimization, and reverse logistics through reinforcement learning and digital twins.

Table 3. *Cont.*

Research Direction	Description
Green Supplier Selection	Develop explainable AI models for sustainable supplier evaluation based on ESG performance, compliance, and environmental risk profiling to enable more informed and ethical sourcing decisions.
Energy and Emission Optimization	Leverage AI-driven digital twins and optimization algorithms to simulate energy use and emissions in logistics and operations, supporting the planning of low-carbon supply chain scenarios.
AI for ESG Reporting and Traceability	Examine how AI can support automated and accurate sustainability reporting, ensuring traceability of environmental performance indicators and alignment with regulatory requirements.
Ethical and Governance Frameworks	Propose governance models that guide the ethical implementation of AI for sustainability, addressing transparency, accountability, fairness, and long-term environmental justice in supply chain practices.

4. Discussion

This systematic literature review was conducted to address significant research gaps identified in earlier studies on the application of AI in SCM. Previous reviews either focused narrowly on specific techniques—such as reinforcement learning [12] or explainability [76]—or lacked comprehensive analyses across supply chain phases, particularly overlooking recent developments such as generative AI, neurosymbolic reasoning, and sustainability-focused applications. For example, Toorajipour et al. (2021) [10] provided an early but largely descriptive review, without exploring emerging AI paradigms or sector-specific implementations. Similarly, Smyth et al. (2024) [11] focused on prescriptive analytics for resilience but did not integrate sustainability or cross-phase AI adoption. In contrast, this review offers a more holistic and updated synthesis of AI applications in SCM between 2021 and 2024, combining bibliometric and content analysis methods to classify studies across phases, techniques, and functions.

The study had five primary objectives: (1) to examine the role of AI in enhancing supply chain resilience, (2) to identify AI-driven solutions for process optimization, (3) to assess AI's contributions to sustainability in supply chains, (4) to investigate challenges and barriers to implementation, and (5) to outline future research directions.

Through a PRISMA-guided methodology, 66 peer-reviewed articles were selected using defined inclusion and exclusion criteria. A combination of bibliometric tools (VOSviewer 1.6.20, RStudio 4.4.2) and qualitative analysis enabled the categorization of findings across four thematic axes: resilience, optimization, sustainability, and implementation challenges. Studies were also classified by AI technique, supply chain phase, and functional application.

Key findings from this review highlight the growing sophistication and diversification of AI techniques used in SCM. Methods such as machine learning, predictive analytics, and reinforcement learning are widely applied to enhance demand forecasting, logistics coordination, and inventory management, leading to streamlined operations, cost reductions, and improved service delivery [11,18,19,21,24,32,45]. Emerging technologies—including generative AI and digital twins—offer promising capabilities for simulation, scenario modeling, and real-time decision-making. Explainable AI and neurosymbolic approaches are addressing concerns about algorithmic transparency, while AI–human intelligence collaboration is gaining relevance in complex decision-making environments, such as humanitarian and disaster relief logistics.

This broader scope contrasts with prior literature such as Jahin et al. (2025) [13], which focused only on AI in risk assessment, and Hao and Demir (2024) [14], who analyzed adoption factors using an ESG framework but did not explore AI functionalities or phase-specific applications. Our review complements and expands these contributions by connecting AI technologies directly to their supply chain roles and implications, including for governance and long-term sustainability.

In terms of resilience, AI supports proactive risk identification and facilitates faster recovery from disruptions. The use of predictive models and adaptive learning enhances the ability of supply chains to anticipate and mitigate cascading risks across multiple phases. Regarding sustainability, AI contributes to emissions monitoring, waste reduction, and green supplier selection. It supports not only environmental objectives but also generates economic and social benefits, fostering a holistic approach to sustainability [14,34,47,59,60].

However, despite these advantages, significant challenges to widespread AI adoption remain. Many organizations struggle with integrating AI into legacy systems due to technical complexity, high implementation costs, and limited access to clean and representative data. Additional concerns involve algorithmic opacity, data privacy, and ethical implications, which are particularly relevant in global or vulnerable supply chains [14,20,45,71,75]. These issues can delay the transition from experimental applications to large-scale deployment and must be addressed through robust governance frameworks, ethical standards, and scalable solutions [12,39,57,73].

Moreover, the literature reveals a notable gap in research focusing explicitly on the use of AI in managing supply chain dynamics under conditions of high uncertainty, such as multi-phase disruptions, systemic risks, or cross-sectoral crises. This represents a critical area for future inquiry, especially as supply chains become increasingly complex and interdependent.

To address these gaps, this study provides two structured research agendas. Table 3 presents future directions specifically focused on the role of AI in supporting sustainable supply chains, while Table 4 outlines broader research opportunities across technological and managerial dimensions. Together, these agendas highlight the need for hybrid AI models, advanced simulation tools, ethical governance frameworks, and scalable, context-specific solutions that bridge technical innovation and real-world adoption.

Table 4. Future research directions.

Research Area	Description	Recommended Methodological Approaches
Hybrid AI Models	Development of AI frameworks that integrate machine learning, graph neural networks (GNNs), and neurosymbolic AI to ensure transparency, reasoning capability, and interpretability in decision-making.	Design science research; development and testing of prototype systems; experimental validation using real-world datasets.
Explainable AI (XAI)	Integration of interpretable AI methods (e.g., Integrated Gradients, symbolic reasoning) to enhance trust, accountability, and regulatory compliance.	Multi-case study research; human-in-the-loop evaluations; usability and trustworthiness assessments; structured surveys of end-users.
Reinforcement Learning (RL)	Application of RL in real-time supply chain optimization and autonomous decision-making under uncertainty.	Simulation-based research; reinforcement learning model deployment in pilot environments; performance benchmarking under dynamic conditions.

Table 4. *Cont.*

Research Area	Description	Recommended Methodological Approaches
Generative AI (GAI)	Exploration of GAI for predictive analytics, scenario modeling, simulation, and autonomous communication within supply chains.	Scenario-driven simulation studies; participatory action research; design and validation of proof-of-concept applications.
AI–Human Intelligence Collaboration (AI–HI)	Development of hybrid frameworks that combine AI and human expertise for complex decision-making in uncertain environments (e.g., humanitarian logistics).	Mixed-methods research; controlled experiments comparing AI-only versus hybrid AI–human systems; focus groups with practitioners.
AI-Enabled Digital Twins	Simulation and optimization of supply chain operations using digital twins enhanced with real-time AI-based learning.	Advanced simulation modeling; iterative development of digital twin prototypes; longitudinal industrial case studies.
Knowledge Graph Reasoning	Use of GNNs and symbolic reasoning to infer hidden links, supplier dependencies, and potential risks in complex networks.	Ontology and knowledge graph construction; experimental validation of GNN reasoning capabilities; explainability and robustness testing.
AI for Governance and Compliance	Development of AI models for supporting contract enforcement, ethical compliance, and legal reasoning in SCM.	Legal-technical case studies; design science methodologies; expert workshops with compliance and legal specialists; regulatory sandbox testing.
AI and Emerging Technologies	Convergence of AI with blockchain, IoT, and big data analytics to improve visibility, traceability, and cybersecurity.	Pilot deployment studies; system architecture evaluations; cross-industry comparative case analyses; cybersecurity stress testing.
Green and Sustainable SCM with AI	Design of AI-based frameworks that promote environmentally sustainable practices (e.g., carbon tracking, eco-routing).	Field experiments in sustainable supply chain contexts; environmental performance monitoring; longitudinal assessments of carbon reduction initiatives.
Ethical and Responsible AI Adoption	Creation of governance models that ensure fair, explainable, and human-centered AI deployment in supply chains.	Delphi panels with multidisciplinary experts; policy analysis; structured interviews with stakeholders; comparative assessments of governance frameworks.
Data Privacy and Federated Learning	Research on decentralized AI models that ensure data confidentiality while enabling collaboration across supply networks.	Simulation of federated environments; empirical validation of privacy-preserving algorithms; inter-organizational pilot implementations.

5. Limitations

While this review provides a comprehensive and up-to-date analysis of AI applications in supply chain management, several limitations must be acknowledged. First, the review focused on studies published between 2021 and 2024. Although this timeframe was selected to capture the most recent developments—particularly emerging technologies such as generative AI and neurosymbolic reasoning—it may have excluded earlier foundational contributions as well as very recent preprints not yet indexed.

Second, the search was limited to peer-reviewed, English-language publications available in the Scopus and ScienceDirect databases. Although both databases are widely

recognized and cover a broad range of relevant literature, this scope may have excluded regional studies, gray literature, or relevant publications indexed in alternative repositories such as Web of Science, IEEE Xplore, or SpringerLink.

Third, the eligibility criteria emphasized studies that explicitly addressed both AI and supply chain applications. As a result, interdisciplinary research employing adjacent terms—such as decision-support systems, intelligent automation, or digital transformation—may have been inadvertently excluded, even when highly relevant.

Fourth, the processes of content interpretation and thematic classification were conducted manually, following a structured protocol using the StArt 2.3.4.2 tool and PRISMA guidelines. Despite efforts to ensure consistency and validation through repeated review cycles, subjective bias in the interpretation and categorization of studies cannot be entirely eliminated.

Fifth, one methodological limitation concerns the application of the threshold score (≥ 40) used during the article selection process to filter studies for thematic relevance. While this quantitative filter ensured that only articles with a significant focus on artificial intelligence and supply chain management were retained, it may have inadvertently excluded recent publications or studies with novel perspectives that, despite their relevance, did not yet accumulate sufficient keyword density or citation weight. This introduces a potential citation and keyword-based bias, which may affect the comprehensiveness of the review. Although a manual validation step was employed to confirm the relevance of the included articles, the risk of overlooking valuable emerging research remains an inherent constraint. Future reviews may consider complementary qualitative screening strategies to mitigate this limitation and ensure broader thematic inclusivity.

Finally, although the review offers a thorough bibliometric and qualitative synthesis, it does not include empirical validation of the AI tools or sector-specific evaluations of implementation outcomes. The insights provided are thus based on published findings rather than first-hand experimentation or industrial assessment. Future research could expand this work through meta-analyses, longitudinal case studies, or real-world implementation frameworks.

6. Conclusions

This review contributes to both academic understanding and practical discourse by offering a structured and forward-looking overview of AI applications in supply chain management (SCM). The findings confirm that AI is not merely enhancing individual supply chain functions but is catalyzing a systemic transformation toward intelligent, adaptive, and sustainable supply networks. Nevertheless, the realization of AI's full potential depends on overcoming implementation challenges and aligning technological progress with ethical, regulatory, and organizational frameworks.

In terms of theoretical contributions, this study advances the field in several significant ways. First, unlike prior literature reviews [10,11], which often addressed specific AI techniques or narrowly focused on isolated SCM functions, this review employs a multidimensional thematic framework that systematically integrates resilience, process optimization, sustainability, and adoption challenges. Second, it delivers an updated bibliometric synthesis spanning 2021–2024, capturing the fast-evolving landscape of AI applications post-pandemic and bridging temporal gaps left by earlier reviews. Third, by explicitly aligning bibliometric clusters with thematic axes, it introduces a novel analytical approach that strengthens the link between the structural and substantive evolution of the literature. Furthermore, the identification and incorporation of underexplored areas—most notably AI's role in managing dynamic and disrupted supply chains—expand the theoretical and practical scope of AI in SCM research.

Notably, the COVID-19 pandemic has acted as a significant accelerant for AI adoption in SCM, as evidenced by several of the reviewed studies [27,82,83]. The crisis exposed critical vulnerabilities in global supply chains, driving a surge in AI-driven initiatives aimed at enhancing real-time visibility, predictive risk assessment, and autonomous decision-making. Applications such as digital twins, AI-enabled forecasting, and dynamic resource allocation gained prominence as companies sought to navigate unprecedented levels of disruption. This surge not only reinforced the strategic value of AI in crisis management but also catalyzed broader digital transformation agendas that are likely to shape SCM well beyond the pandemic. Synthesizing these insights underscores AI's role as both a tactical response tool and a long-term enabler of supply chain resilience and adaptability.

Future research should prioritize the empirical validation of emerging AI techniques, the development of interoperable platforms tailored for SMEs, and in-depth exploration of AI's potential to support long-term environmental and social sustainability in global supply chains. As supply chains continue to face mounting pressures to become more resilient, sustainable, and ethically governed, AI stands out as a pivotal enabler—provided its deployment is guided by inclusive, transparent, and context-sensitive governance frameworks.

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

Appendix A

Table A1. PRISMA 2020 checklist.

Section and Topic	Item #	Checklist Item	Location Where Item is Reported
TITLE			
Title	1	Identify the report as a systematic review.	Title
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Abstract
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Section 1.1
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Section 1.3

Table A1. *Cont.*

Section and Topic	Item #	Checklist Item	Location Where Item is Reported
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Section 2.3
Information sources	6	Specify all databases, registers, websites, organizations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Section 2.2
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Section 2.2
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Section 2.3
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Section 2.3
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g., for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Section 3.1
	10b	List and define all other variables for which data were sought (e.g., participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Section 3.1
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Section 2.3
Effect measures	12	Specify for each outcome the effect measure(s) (e.g., risk ratio, mean difference) used in the synthesis or presentation of results.	Section 3
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g., tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Section 2.3
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Section 2.3
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Tables and Figures throughout the article

Table A1. Cont.

Section and Topic	Item #	Checklist Item	Location Where Item is Reported
Synthesis methods	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	Section 3
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g., subgroup analysis, meta-regression).	Section 3
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	Section 3
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Section 2.3
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Section 4
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	PRISMA Flowchart (Figure 3)
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Section 2.3
Study characteristics	17	Cite each included study and present its characteristics.	Section 3.1
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Section 2.3
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g., confidence/credible interval), ideally using structured tables or plots.	Section 3
Results of syntheses	20a	For each synthesis, briefly summarize the characteristics and risk of bias among contributing studies.	Section 3
	20b	Present results of all statistical syntheses conducted. If meta-analysis was performed, present for each the summary estimate and its precision (e.g., confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Section 3
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Section 3
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	Section 3
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Section 2.3
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Section 4
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Section 4
	23b	Discuss any limitations of the evidence included in the review.	Section 4

Table A1. Cont.

Section and Topic	Item #	Checklist Item	Location Where Item is Reported
Discussion	23c	Discuss any limitations of the review processes used.	Section 4
	23d	Discuss implications of the results for practice, policy, and future research.	Section 4
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Section 2
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Section 2
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Section 2
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	“Acknowledgments” section
Competing interests	26	Declare any competing interests of review authors.	“Conflicts of Interest” section
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	“Data Availability Statement” section

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