INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES
Vol 15, Issue 11, (2025) E-ISSN: 2222-6990

Exploring Artificial Intelligence in Resilient Supply Chain and Reverse Logistics: A Scoping Review

Taher Ben Yahya[1]*, Noriza Mohd Jamal[1], Mohammed Alawi Al-Sakkaf[2] and Rim Chakraoui[3]
[1]Faculty of Management, Universiti Teknologi Malaysia (UTM), Skudai Johor 81310, Malaysia, [2]College of Administrative Science, Hadhramout University, Yemen, [3]Lusail University, Doha, Qatar
***Corresponding Author Email:** taher.binyahya@gmail.com

DOI Link: http://dx.doi.org/10.6007/IJARBSS/v15-i11/26841
Published Date: 03 November 2025

Abstract
This study investigates the role of Artificial Intelligence (AI) in bolstering resilience in supply chain management (SCM) and reverse supply chain management (RSCM). A scoping review of 44 peer-reviewed articles (2020–2024) is carried out to explore key themes: AI definitions, its influence on supply chain resilience (SCR) and reverse logistics (RL), prevailing methodologies, and barriers to deployment. The analysis suggests that AI tools, such as machine learning (ML), predictive analytics, and optimization algorithms, are crucial in improving demand forecasting, real-time tracking, risk mitigation, and RL operations, thereby enhancing effectiveness, backing circular economy principles, and aligning with the sustainable development goals (SDGs) adopted by the United Nations. However, challenges persist, including organizational obstacles like conflicting objectives and limited awareness, technological challenges such as subpar data quality and high costs, and ethical concerns related to responsibility and AI decision-making. The study underscores AI's transformative potential in SCM and RSCM, demonstrating its ability to revolutionize logistics while tackling sustainability issues. It advocates for strategic coherence, robust data management, and enhanced AI expertise among stakeholders to overcome implementation challenges. These findings provide valuable insights for scholars and industry professionals, facilitating the progress of adaptive, resilient, and sustainable supply chain systems capable of navigating upcoming trials in a dynamic global context.
Keywords: Supply Chain Management, Reverse Supply Chain Management, Artificial Intelligence, Scoping Review, Supply Chain Resilience, Reverse Logistics

Introduction
The rapid growth of digital technologies and recent advances in artificial intelligence (AI) have significantly enhanced the AI tools used by manufacturing firms to manage supply chains (SC) and logistics operations (Yamin et al., 2024). Literature on logistics defines AI as advanced

technologies capable of performing cognitive functions and operations similar to human intelligence, such as learning, real-time interaction, and problem-solving in logistics operations. AI also boosts the ability to communicate with machines or devices that support logistics operations and generate innovative ideas that benefit entire SC networks (Dubey et al., 2021; Olan et al., 2024a; Yamin et al., 2024). Pichai Sundararajan, the CEO of Google, stated, "Artificial Intelligence is probably the most vital thing humanity has ever worked on. It is more profound than electricity or fire" (Alfawaz & Alshehri, 2022, p. 1).

In SC and reverse logistics (RL), AI technologies such as machine learning (ML), natural language processing (NLP), and predictive analytics offer unparalleled opportunities for optimization and sustainability. Integrating AI capabilities to manage SC systems within organizations has the potential to boost efficiency, mitigate risks linked to SC disruptions, and improve delivery accuracy and time to market. Moreover, implementing ML in supply chain management (SCM) will refine data classification and pattern detection, offering more insights and reducing errors for future improvements.

AI has a broad and escalating impact on achieving the Sustainable Development Goals (SDGs) (Leal Filho et al., 2024), According to Vinuesa et al. (2020), AI can aid in accomplishing 79% of SDGs (Kar et al., 2022). Alhasawi et al. (2023) noted that the application of AI in the SC and the logistics sector is forecasted to grow by 42.9% annually in the upcoming years. A McKinsey survey revealed that 93% of SC managers plan to redesign their SC for improved resilience (Alhasawi et al., 2023). For instance, Olan et al. (2024a) highlighted that by integrating AI technologies into their SC process, Tesla achieved 75% automation of the entire production process, leading to enhanced performance and reduced waste.

Regarding reverse supply chains (RSC), unlike traditional supply chains, RSC encounter unique challenges such as intricate return processes, unpredictable product conditions, and the need for efficient resource recovery. In this context, AI applications play a crucial role in supporting closed-loop systems by enhancing resource recovery, recycling, and waste reduction efforts. Harnessing AI in RL addresses these obstacles by optimizing returns, automating sorting, and predicting future return trends, ultimately establishing a more efficient and sustainable closed-loop system. Through these advancements, AI not only fortifies operational resilience but also aids industries in adopting a more sustainable and responsible approach to logistics. This paper provides a comprehensive scoping review of AI's role in fostering sustainability and resilience within SCM, with a focus on RL. By scrutinizing recent papers in this field, this study aims to elucidate both the potential and the challenges linked to integrating AI into adaptive, sustainable, and resilient logistics systems. This exploration underscores AI's transformative impact on attaining sustainability goals and strengthening robust supply chain strategies. To deepen this comprehension, the study addresses the following key questions:

1. What are the various definitions of AI provided in the existing literature?
2. How does AI contribute to strengthening supply chain resilience (SCR) and RL?
3. What are the most prevalent AI techniques employed for resilient supply chain and RL?
4. What challenges and limitations currently hinder the integration of AI in supply chain and RL?

Background Literature

This section analyzes the background knowledge relevant to the AI application in supply chain management (SCM) or reverse supply chain management (RSCM). The literature is divided into four main themes: 1) AI: Definition and classification, 2) Overview of AI in SCM and RSCM, 3) Techniques and applications in SC and RSC, and 4) AI challenges and barriers in SC and RSC. This classification aids in synthesizing essential insights, enhancing the understanding of AI's role in boosting supply chain processes and addressing associated challenges.

Artificial Intelligence: Definitions and Taxonomy

Artificial intelligence (AI) is a branch of computer science dedicated to creating systems that can perform tasks typically requiring human intelligence (Pournader et al., 2021). Such tasks include speech recognition, experiential learning, problem-solving, and decision-making. To achieve this, AI systems often rely on machine learning (ML), deep learning (DL), and neural networks, which enable them to detect patterns, generate insights, and adapt to new data. ML represents a subset of AI, much like electromagnetics which is a field within physics. Within ML, DL serves as a further subset, encompassing both discriminative and generative models. DL also underpins large language models (LLMs), with tools such as ChatGPT and Google Gemini integrating generative techniques and LLM architectures (Sharma et al., 2022).

The literature does not yet offer a definitive or universally accepted definition of AI. AI applications and technologies have been extensively discussed in recent works and studies. The term "artificial intelligence" was introduced by John McCarthy in 1955 to explore machines' ability to utilize language and solve problems for humans (McCarthy et al., 2006; Pournader et al., 2021; Bhattacharya et al., 2024). The Oxford Dictionary defines AI as "the theory and development of computer systems capable of performing tasks typically necessitating human intelligence, such as visual perception, speech recognition, decision-making, and language translation" (Richter et al., 2022). The Association for the Advancement of Artificial Intelligence (AAAI's) definition of AI is "advancing the scientific understanding of the mechanisms underlying thought and intelligent behavior and their manifestation in machines" (Helo & Hao, 2022, p. 2). Nevertheless, the literature offers various definitions of AI, each representing different perspectives and emphases within the domain. Table 1 outlines these definitions as identified in the reviewed literature, along with their respective sources.

Table 1
AI definition mentioned in previous literature

No	Article Title	Domain	Authors	Definition
1	Artificial intelligence and machine learning applications in agricultural supply chain: a critical commentary	ML	(Aylak, 2021)	(Machine Learning) ML methodologies provide a learning mechanism that seeks to learn from experience, from training results to executing a task. Various statistical measures, evolving over time with practice, assessingthe model's efficiency.
2	The aspects of artificial intelligence in different phases of the food value and supply chain	AI	(Baciuliene et al., 2023)	AI is defined as a technical advantage that cannot be replicated by other technologies.
3	Building supply-chain resilience: an artificial intelligence-based techniques and decision-making framework	AI	(Belhadi et al., 2022)	AI is based on a set of tools, techniques and algorithms. It is used to enable a system (machine and equipment) to acquire knowledge from information and data collected from its external environment and to administer the resulting cognitive utilities to support the potential entities.
4	Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation	AI	(Belhadi et al., 2024)	AI is the ability of a system to acquire learnings by analyzing the external environment's data and using acquired learnings to adjust or make new plans against environmental changes.
5	What drives the corporate payoffs of using generative artificial intelligence?	AI	(Bughin, 2024)	The range of computer systems and techniques which are now able to replicate some of the human cognitive abilities. Based on data and new discriminative techniques.
6	Production-level artificial intelligence applications in semiconductor supply chains	AI	(Chien et al., 2023)	AI is a subfield of computer science that is concerned with intelligent behavior in artifacts. It includes disciplines natural language processing, knowledge representation, automated reasoning, ML, computer vision, and robotics.

No	Article Title	Domain	Authors	Definition
7	Production-level artificial intelligence applications in semiconductor supply chains	ML	(Chien et al., 2023)	ML is a discipline of AI that deals with the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy.
8	Production-level artificial intelligence applications insemiconductor supply chains	DL	(Chien et al., 2023)	DL can ingest unstructured data in its raw form, for instance, text, images, or sensor data. It can automatically determine the set of features that distinguish different categories of data from one another.
9	Role of artificial intelligence in operations environment: a review and bibliometric analysis	AI	(Dhamija & Bag, 2020)	AI is the process of manufacturing enabled by machines which can imitate human activities in their original form.
10	Artificial intelligence in operations management and supply chain management: an exploratory case study	AI	(Helo & Hao, 2022)	AI refers to the ability of machines to learn from experience and make decisions on a series of performances as a human with intelligence.
11	Generative artificial intelligence in supply chain and operations management: A capability-based framework for analysis and implementation	Gen-AI	(Jackson et al., 2024)	Generative AI (GAI), a branch of ML that can create new content, including text, images, music, or video, by learning patterns from existing data.
12	How can artificial intelligence impact sustainability: A systematic literature review	AI	(Kar et al., 2022)	Intelligence in AI is an ability to do reasoning, problem solving, learning, and integrate various human functions like perception, attention, memory, language, or planning.
13	Using emerging technologies to improve the sustainability and resilience of supply chains in a fuzzy environment in the context of COVID-19	AI	(Kazancoglu et al., 2023)	AI is a branch of computer science with the main goal of developing computer technology that can act and think like a human being.

No	Article Title	Domain	Authors	Definition
14	Sustainable supply chain finance and supply networks: The role of artificial intelligence	AI	(Olan et al., 2024a)	AI systems are technologically driven systems with the ability to simulate human cognitive skills such as analyzing complex problems, visual analytics, optimum performance, and providing solutions.
15	Artificial intelligence applications in supply chain management	AI	(Pournader et al., 2021)	AI is a domain in computer science focused on developing systems that can do activities typically requiring human intelligence.
16	Artificial intelligence in logistics and supply chain management: A primer and roadmap for research	Gen-AI	(Richey et al., 2023)	Generative AI refers to integrating ML models to fabricate novel content. This encompasses text, audio, video, imagery, software code, and simulations based on large datasets that train the generative model.
17	Artificial intelligence for electricity supply chain automation	AI	(Richter et al., 2022)	AI is a collective term, which combines tools to substitute the need for human cognitive ability including machine perception and ML procedures.
18	Barriers related to AI implementation in supply chain management	AI	(Shrivastav, 2022)	AI is a multi-disciplinary field of science that aims to build “intelligent” systems.
19	RFID supply chain data deconstruction method based on artificial intelligence technology	AI	(Zhang & Li, 2023)	AI is the science of developing intelligent machines or machines to simulate, refine, and supplement human intelligence.

Based on the above definitions, it has been observed that there is no clear evidence defining AI in the context of SCM or RSCM. Articles revised as part of this paper generally defined AI as a field focused on creating systems that imitate human intelligence or behaviors. This includes using tools, techniques, and algorithms to enable machines to learn from and respond to their environment. Common themes include the capability to perform tasks requiring cognitive functions like perception, learning, and problem-solving.

Overview of AI in supply chain resilience (SCR) and reverse logistics (RL)

Supply chain resilience (SCR) refers to the ability of a supply chain system to effectively handle disruptions and quickly recover to its previous operational capacity or a better one after interruption ensuring steady-state performance (Modgil et al., 2021). General supply chains encounter challenges in achieving stability due to uncertainties and vast data volumes. Consequently, companies often resort to short-term forecasting and concentrate on improving their supply chain operations (Ivanov, 2022; Mukherjee et al., 2023). Many researchers argue that artificial intelligence (AI) can enhance SCR by accelerating recovery capabilities; its adoption can assist in predicting demand and optimizing supply chain strategies for inventory and resource allocation (Ismagiloiva et al., 2020). Furthermore, AI can assess how specific events may impact the entire supply chain over time, ensuring smoother operations and sustained efficiency (Dwivedi et al., 2021; Mukherjee et al., 2023; Zhang & Li, 2023).

SCM is a sophisticated and complex system, not only due to its dependencies on numerous chains but also because of the dynamic nature of customer preferences, suppliers, and manufacturing changes (Shrivastav, 2022). Therefore, integrating AI into SCM requires a highly collaborative ecosystem that encourages seamless data exchange, real-time decision-making, and adaptive responses to emerging challenges.

Yamin et al. (2024) emphasize that the rapid adoption of digital technologies in managing logistics operations has facilitated the acceptance of AI tools, enhancing the agility of logistics operations. In recent years, the use of AI for modeling and simulating complex systems has become more widespread. Implementing AI in SC and RSC modeling and simulations allows for sophisticated scenario-based analysis, ultimately improving decision-making by gaining a better understanding of system and consumer behavior (Pournader et al., 2021). Yamin et al. (2024) also suggest that AI has the potential to lower transaction costs through rigorous monitoring and big data analytics.

AI plays a vital role in transforming SC or RSC throughout the production process. Therefore, SCM's objective is to digitalize the production process, connect stakeholders and assets, align products with client specifications, and achieve a competitive advantage (Alfawaz & Alshehri, 2022). Alhasawi et al. (2023) argue that integrating AI and Machine Learning (ML) helps reduce the impact of disruptions, ensuring corporate stability through precise forecasting and demand management. For instance, AI and ML are increasingly employed in agricultural supply chains for their advanced computational capabilities and real-time monitoring abilities (Aylak, 2021).

Walmart, leveraging AI to manage and analyze substantial data to enhance customer service, utilizes its Social Genome tool, based on Big Data analytics, to comprehend customer preferences and behaviors by analyzing social media activities (Helo & Hao, 2022). DHL, a logistics giant, uses ChatGPT to automate operations, enhance efficiency in warehouse management, and provide driver support. Similarly, Instacart, a prominent US grocery delivery service, collaborates with OpenAI to incorporate ChatGPT for quicker and more user-friendly shopping experiences (Jackson et al., 2024).

When consumers return products, AI assists in automatic categorization through image processing and computer vision capabilities. The algorithm identifies defects, directs products accordingly, improves the efficiency of return processes, identifies cost-saving opportunities, and monitors frequently returned items within the Reverse Logistics (RL) process (S. Mukherjee et al., 2024).

In conclusion, AI significantly enhances contractor-supplier collaboration during supply chain disruptions, optimizes warehouse performance, demand management, and product shelf life monitoring. These capabilities enable companies to effectively navigate diverse market segments and make informed business decisions. The use of AI technologies is essential for employees to efficiently manage supply chain operations.

AI Techniques and Applications Used in SC and RSC

Techniques and applications used in SC and RSC leverage various technologies to boost efficiency and sustainability. In SC, AI-powered predictive analytics and ML models help forecast demand, optimize inventory levels, and enhance route planning (Alfawaz & Alshehri, 2022). The use of Internet of Things (IoT) devices enables real-time tracking of goods, improving visibility throughout the SC (Toorajipour et al., 2021). Blockchain has also enhanced SCM, improving operational efficiency, and promoting the circular economy (Leal Filho et al., 2024). In RSC, advanced sorting and recycling technologies, including robotics and AI-assisted material classification, facilitate the efficient processing of returned products. Data analytics tools help identify patterns in returns and design effective recovery strategies, while cloud-based platforms streamline collaboration between stakeholders. Table 2 summarizes the techniques and applications used in SC or RSC in the literature.

Over the years, the world has been progressing towards a digital future, particularly in industry 4.0 technologies (Toorajipour et al., 2021). AI technologies such as ML, DL, Robotics, Big Data, Blockchain, Cloud Computing, and IoT are prominent examples of these technologies. In general, the methods most used in SCM offer the opportunity to acquire human capabilities, such as thinking and acting like humans, reasoning and acting rationally, and thinking like humans. According to Ferreira and Reis (2023), AI approaches can be classified into four distinct groups. These categories include human thinking (HTT), human acting (HAT), rational thinking (RTT), and rational acting (RAT) techniques. These techniques offer the opportunity to improve forecasting in SCM.

Oluleye et al. (2023) argue that the approach currently used in RSC is not efficient in achieving systemic circularity of materials. Moreover, to support this argument, a study conducted by (Rakhshan et al., 2021) found that a design-related factor often influences the circularity of materials. Therefore, the implementation of AI algorithms may make it easier to select circular materials with a longer lifespan and reusability. Given constraints on selecting materials with circularity features from various options, an optimization strategy employing an Artificial Neural Networks (ANN) algorithm could be an effective technique for making judgments or choices that yield optimal outcomes (Oluleye et al., 2023). The ANN is a new type of AI created using modern methods to mimic human brain cells, structuring how the brain functions. Neural networks are now the most popular approach in SCM for solving demand planning issues (Kazancoglu et al., 2023).

Table 2
AI technologies and applications area mentioned in previous literature.

No	Author	AI Technology Used	Applications Area	Sector	SC/ RSC
1	(Aylak, 2021)	Machine learning, optimization Algorithms	Yield prediction, logistics optimization, demand forecasting	Agricultural Supply Chain	SC
2	(Baciuliene et al., 2023)	Machine learning, neural networks, robotics	Food production, distribution, quality control	Food Supply Chain	SC
3	(Belhadi et al., 2022)	fuzzy logic, Wavelet neural networks, Multi-criteria Decision-making (MCDM)	Supply chain resilience, decision support	Manufacturing Supply Chain	SC
4	(Belhadi et al., 2024)	Predictive Analytics, Machine Learning, Data Analytics	Resilience uilding, performance optimization	Various Sectors	SC
5	(Benzidia et al., 2021)	Big Data Analytics, AI-based supply chain integration	Green logistics, hospital management	Healthcare, Sustainability	SC
6	(Bhattacharya et al., 2024)	Deep Neural Networks, Genetic Algorithms, Swarm Intelligence, artificial neural networks	Reverse logistics, recycling optimization	Closed-loop Supply Chains	RSC
7	(Bu, 2021)	Machine Learning, Multi-objective Optimization	Logistics efficiency, optimization	Logistics Engineering	SC
8	(Cannas et al., 2024)	Machine Learning, Expert Systems, Predictive Analytics	Inventory ,management, risk management	Operations and Supply Chain Management	SC
9	(Chen, 2022)	Machine learning, automatic ML frameworks, image processing	Waste management and recycling	Environment, Urban management	RSC
10	(Chien et al., 2023)	Machine learning, deep learning	roduction Efeficiency, supply chain optimization	Semiconductor Manufacturing	SC
11	(Dhamija & Bag, 2020)	Genetic Algorithms, expert systems, Big Data	Operations management, logistics	General Operations and Supply Chains	SC/ RCM

No	Author	AI Technology Used	Applications Area	Sector	SC/ RSC
12	(Dubey et al., 2021)	Supply Chain Analytics, Cognitive Technologies	Operational performance, financial performance	B2B Supply Chains	SC
13	(Garrido-Hidalgo et al., 2019)	Internet of Things (IoT), Cloud Computing	Reverse supply chain, real-time monitoring	Industry 4.0	RSC
14	(Gupta et al., 2021)	AI-based risk prediction, self-training systems	Supply chain disruption management	Supply Chain Disruption Management	SC
15	(Helo & Hao, 2022)	Deep neural networks, machine learning, natural language processing, artificial neural networks	Operations management, supply chain lanning	Operations and Supply Chain Management	SC
16	(Hendriksen , 2023)	Large language models, predictive analytics	Risk Mmitigation, operational optimization	Supply Chain Management	SC
17	(Jackson et al., 2024)	Generative AI, machine learning, decision support systems	Demand forecasting, inventory optimization	Operations and Supply Chain	SC
18	(Kar et al., 2022)	Reinforcement learning, regression models	Sustainability practices, environmental management	Various Industries	SC/ RCM
19	(Kazancoglu et al., 2023)	Blockchain, Industry 4.0, AI	Sustainability, resilience	Automotive	SC
20	(Kosasih et al., 2024)	Neurosymbolic AI, hybrid models	Demand forecasting, risk management	Supply Chain Management	SC
21	(Long et al., 2023)	Deep reinforcement learning	Healthcare supply chain mode optimization	Healthcare	SC
22	(Modgil et al., 2021)	Simulation, real-time pracking, predictive analytics	Resilience building, supply chain risk management	General Supply Chains	SC
23	(Mosallanezhad et al., 2023)	Metaheuristic algorithms, IoT optimization modeling	Pandemic waste management, sustainable supply chain	Supply Chain, Healthcare	RSC
24	(Mukherjee et al., 2023)	Machine learning, predictive analytics	Supply chain resilience, firm performance	Emerging Markets	SC
25	(Neto et al., 2023)	Genetic algorithms, simulation	Waste management, economic and	Circular Economy and	RSC

No	Author	AI Technology Used	Applications Area	Sector	SC/ RSC
			environmental optimization	Waste Management	
26	(Nikseresht et al., 2022)	Optimization-driven methods, intuitionistic fuzzy solutions	Sustainable development ecision-making, volatile, uncertain, complex, and ambiguous (VUCA) environment	Sustainability and Environment al Management	SC
27	(Olan et al., 2024a)	Fuzzy set theory, data analytics	Supply chain finance, network optimization	Finance and Supply Networks	SC
28	(Oluleye et al., 2023)	Machine learning, deep learning, artificial neural networks	Circular materials selection, pre-demolition auditing, reverse logistics	Building Construction Industry	SC/ RC M
29	(Pawlicka & Bal, 2022)	Machine learning, predictive analytics	Omnichannel logistics, financial sustainability	Clothing Industry Logistics	SC
30	(Pereira & Shafique, 2024)	Big Data Analytics, Machine Learning	Supply chain agility, disaster relief operations	Humanitarian Supply Chain	SC
31	(Pournader et al., 2021)	Machine Learning, Deep Learning, Natural Language Processing	Demand forecasting, inventory management, supply chain optimization	General Supply Chain	SC
32	(Rajesh, 2020)	GreyTheory , layered analytic network process (ANP)	Risk mitigation, decision support	Electronic Manufacturin g Supply chains	SC
33	(Richey et al., 2023)	Generative AI, robotic process automation, machine learning	Logistics, operational efficiency	Logistics and Supply Chain Management	SC
34	(Richter et al., 2022)	Forecasting, optimization, deep reinforcement learning, neural networks	Energy management, predictive maintenance, autonomous trading	Electricity Supply Chain	SC
35	(S. Mukherjee et al., 2024)	Machine learning, image processing	Reverse logistics, circular economy	Circular Economy Developing Countries	RSC
36	(Samadhiya et al., 2023)	Machine learning, predictive analytics	Disruption management, supply chain resilience	Healthcare	SC

No	Author	AI Technology Used	Applications Area	Sector	SC/ RSC
37	(Sharma et al., 2021)	Big ata Analytics, Machine Learning	Food logistics, supply chain optimization	Food Industry	SC
38	(Sharma et al., 2022)	Artificial Neural Networks, Genetic Algorithms, Fuzzy Logic	Demand planning, green supply chain management	General Supply Chain	SC
39	(Shrivastav, 2022)	machine learning, simulation, Optimization	Implementation arriers, risk mitigation	General Supply Chain	SC
40	(Wang et al., 2021)	IoT analytics, IoTtechnology	Smart healthcare, agriculture and manufacturing	Technology	SC
41	(Wilson et al., 2022)	Mechanical AI, analytical AI, intuitive AI	Reverse logistics functions, circular economy	Circular Economy and Reverse Logistics	RSC
42	(Yamin et al., 2024)	Predictive analytics, machine learning	Supply Chain Agility, Resilience Building	Logistics and Manufacturing	SC
43	(Yang et al., 2024)	Optimization algorithms, data analytics	sustainability performance, reverse logistics	Manufacturing Supply Chain	SC/ RCM
44	(Zhang & Li, 2023)	Machine learning, RFID data analysis	Supply chain efficiency, real-time tracking, inventory management	General Supply Chain with RFID	SC

The incorporation of AI technologies into supply chain management (SCM) showcases a diverse range of applications across various sectors, as delineated in Table 2. For instance, Nikseresht et al. (2022) utilized optimization techniques and intuitionistic fuzzy logic in sustainability and environmental management, concentrating on decision-making in volatile, uncertain, complex, and ambiguous (VUCA) environments. Similarly, Wang et al. (2021) investigated IoT analytics to transform smart healthcare, agriculture, and manufacturing processes. Advanced approaches such as Grey Theory and layered analytic network processes were employed by Rajesh (2020) to improve risk mitigation and decision support in electronic manufacturing supply chains. Oluleye et al. (2023) applied machine learning (ML) and artificial neural networks for circular material selection and pre-demolition assessment in the construction industry.

Furthermore, Modgil et al. (2021) demonstrated predictive analytics and real-time tracking to enhance resilience and risk management across general supply chains. These research works collectively underscore the transformative capacity of AI in tackling diverse challenges and optimizing SCM procedures. Nonetheless, it is noteworthy that despite the increasing adoption of AI in numerous SCM functions, organizations face significant challenges and obstacles during its integration (Shrivastav, 2022), which will be elaborated on in the subsequent section.

AI Challenges and Barriers in SC and RSC

The integration of AI in SC and RSC offers substantial opportunities for enhanced efficiency and resilience. However, numerous obstacles and challenges impede their widespread adoption. A fundamental assumption for any weak AI system used in the industry is the constancy of the underlying data distribution, enabling the system to generalize when faced with new, previously unknown data (Shrivastav, 2022). Cannas et al. (2024) argue that a significant amount of clean data is crucial for training and testing models, along with the necessity to implement sophisticated hybrid approaches to address the uncertainties and ambiguities inherent in actual data. Rajesh (2020) notes the integration of AI with decision-support models, providing predictive insights, although decision-making complexity remains a barrier.

Modgil et al. (2021) emphasize AI's role in fostering resilience in SC through predictive analytics, hindered by challenges such as data availability and trust in AI technologies. These studies collectively highlight AI's multifaceted role in strengthening SCM and RSCM practices while addressing specific challenges across various sectors. Shrivastav (2022) outlined ten barriers to AI implementation in SCM, encompassing organizational challenges like misaligned goals, limited AI understanding among stakeholders, lack of top management support, and technological obstacles such as insufficient data quality, limited infrastructure, and the opaque nature of AI models. (Majumdar et al., 2021) examined barriers to AI implementation in SCM within the context of Industry 4.0, mainly focusing on the textile and clothing industry. It highlights organizational hindrances like inadequate top management commitment and understanding, technological challenges such as poor IT infrastructure and cybersecurity issues, and operational hurdles like high implementation costs and skill shortages. Moreover, external factors like insufficient government support and unclear legal frameworks compound these challenges (Subhodeep Mukherjee et al., 2024). Table 3 summarizes and highlights AI's role in enhancing sustainability, resilience, and efficiency under volatile and uncertain conditions. Applications span sectors like construction, agriculture, healthcare, and energy, improving decision-making, forecasting, and operational agility. AI facilitates circular economy adoption, optimizes closed-loop processes, and boosts resilience through dynamic reconfiguration and risk sensing. Moreover, AI-integrated tools, such as IoT and big data analytics, drive real-time monitoring and sustainability innovations, addressing barriers like governance and change management.

Table 3
Key insights and barriers to AI adoption in SC and RSC: A review of existing literature

No	Study	Key Findings	AI Challenges/Barriers Adoption in SC/RSC
1	(Aylak, 2021)	AI/ML enhances monitoring, forecasting, and decision-making in agricultural SCs.	Data quality issues, high implementation cost in agricultural SCM.
2	(Baciuliene et al., 2023)	AI improves efficiency across various phases of the food SC using advanced technologies.	Social and economic barriers, including resistance to technology adoption.
3	(Belhadi et al., 2022)	AI enhances resilience by predicting and managing disruptions in SCs.	Difficulty in standardizing AI frameworks and high data quality requirements.
4	(Belhadi et al., 2024)	AI boosts SC resilience and long-term performance in dynamic environments.	Operationalization challenges under dynamic SC conditions.
5	(Benzidia et al., 2021)	Enhanced environmental performance via big data analytics and artificial intelligence (BDA-AI) technologies	Data confidentiality, Lack of standardization.
6	(Bhattacharya et al., 2024)	AI optimizes closed-loop SC processes, enhancing sustainability and efficiency.	Uncertainty in RL and complexity in managing returned goods.
7	(Bu, 2021)	ML and AI optimize logistics operations, improving efficiency and reducing costs.	High-dimensional data handling and lack of tailored optimization models.
8	(Cannas et al., 2024)	AI methods enhance competitiveness by improving process efficiency and reducing costs.	Data quality, investment costs, and skill deficiencies.
9	(Chen, 2022)	Improved garbage classification with ML-based frameworks	High costs, Poor effectiveness of systems
10	(Chien et al., 2023)	AI enhances production and SC efficiency in semiconductor manufacturing.	Scalability and interpretability issues of AI models.
11	(Dhamija & Bag, 2020)	AI is pivotal in optimizing operations and enhancing SC performance.	Limited adoption due to high costs and lack of skilled workforce.
12	(Dubey et al., 2021)	AI-driven analytics improves decision-making and performance during crises.	Data sharing challenges and dynamic market conditions during crises.
13	(Garrido-Hidalgo et al., 2019)	IoT enhances reverse SCM through real-time tracking and cloud-based monitoring.	Communication bottlenecks and reliability issues in large-scale IoT networks.
14	(Gupta et al., 2021)	AI improves resilience by enabling dynamic response to disruptions in SC.	Limited analytical power of traditional systems and integration complexities.
15	(Helo & Hao, 2022)	Explores the implementation of AI in SCM and its value in business through case studies, showing AI improves decision-making, process optimization, and operational efficiency.	High costs of implementation, lack of skilled personnel, and integration challenges with existing systems.

No	Study	Key Findings	AI Challenges/Barriers Adoption in SC/RSC
16	(Hendriksen, 2023)	AI revolutionizes SCM by enhancing efficiency and mitigating disruption impacts.	Dependence on human sensemaking and interpretive processes for AI integration.
17	(Jackson et al., 2024)	GAI enhances decision-making, process optimization, and risk management in SCM.	High computational costs and complexity in operationalizing GAI capabilities.
18	(Kar et al., 2022)	AI supports sustainable practices across various industries, improving resource efficiency.	Trade-offs in cost, time, and quality in sustainable operations.
19	(Kazancoglu et al., 2023)	Emerging technologies, including AI, enhance SC sustainability and resilience under uncertain conditions like COVID-19.	Lack of top management support and challenges in demand planning and logistics optimization.
20	(Kosasih et al., 2024)	Neurosymbolic AI enhances explainability in SCM, improving trust and adoption.	Limited application in critical SCM functions and explainability-performance trade-offs.
21	(Long et al., 2023)	AI-driven optimization improves mode selection in healthcare SCs.	High initial investment and adaptation challenges in healthcare contexts.
22	(Modgil et al., 2021)	AI enhances SC resilience by enabling risk sensing and dynamic reconfiguration.	Dependence on data availability and trust in AI predictions.
23	(Mosallanezhad et al., 2023)	Effective RSC network using IoT for pandemic waste	High-risk handling of COVID-19 Pandemic Wastes (CPWs), Sustainability constraints
24	(Mukherjee et al., 2023)	AI enhances resilience and performance of MSMEs by improving SCM agility.	Limited application scope and cross-sectional data limitations.
25	(Neto et al., 2023)	AI-based simulation optimizes economic and environmental aspects of WEEE reverse chains.	High cost of implementation and regulatory compliance issues.
26	(Nikseresht et al., 2022)	AI tools help in sustainable decision-making under VUCA, analyzing influential research trends.	VUCA complexity, lack of integrated frameworks for decision-making.
27	(Olan et al., 2024a)	AI optimizes SC finance, improving financial and operational efficiencies.	Regulatory challenges and high initial investment costs.
28	(Oluleye et al., 2023)	AI facilitates circular economy adoption in construction through systemic circularity.	Data integration issues, limited AI adoption in construction SCM.
29	(Pawlicka & Bal, 2022)	AI supports sustainable finance and omnichannel logistics, driving operational innovation.	Financial risk and lack of integrated data systems.
30	(Pereira & Shafique, 2024)	AI enhances SC agility and collaboration in dynamic environments like disaster management.	Coordination and data sharing issues among stakeholders.
31	(Pournader et al., 2021)	AI applications improve decision-making and efficiency in SC operations.	Data fragmentation and integration challenges.

No	Study	Key Findings	AI Challenges/Barriers Adoption in SC/RSC
32	(Rajesh, 2020)	AI integrates with decision-support models for enhancing SC resilience strategies.	Complex decision-making due to interconnected SC risks.
33	(Richey et al., 2023)	Proposes a roadmap for research on integrating AI in logistics and SCM to enhance decision-making and operational efficiency.	Data privacy concerns, lack of transparency in AI models, and workforce adaptability.
34	(Richter et al., 2022)	AI optimizes electricity SC automation, improving forecasting and grid reliability.	Integration challenges with legacy systems, high data heterogeneity.
35	(S. Mukherjee et al., 2024)	AI optimizes RL, enhancing circular economy performance in MSMEs.	Dependence on government support and technological readiness.
36	(Samadhiya et al., 2023)	Examines AI's role in improving healthcare SC resilience through adaptability and collaboration.	Complexity in collaboration and limitations in dynamic capability realization.
37	(Sharma et al., 2021)	AI and big data drive sustainable innovations in the food SC.	Data management complexities and technological literacy gaps.
38	(Sharma et al., 2022)	Highlights AI's transformative impact on SCM through trend and gap analysis.	Lack of standardized frameworks and the need for industry-specific AI solutions.
39	(Shrivastav, 2022)	Identifies major AI implementation barriers, including change management and governance issues.	Resistance to change, lack of AI governance, and multi-actor coordination challenges.
40	(Wang et al., 2021)	Evolution of IoT with focus on security and thematic trends	IoT security, algorithm issues, privacy concerns.
41	(Wilson et al., 2022)	AI enhances RL within circular economy through better decision-making and efficiency.	Integration complexities and data quality issues in RL.
42	(Yamin et al., 2024)	AI and HR strategies improve agility and resilience in logistics SCs.	Need for human capital development and overcoming cultural resistance.
43	(Yang et al., 2024)	RL and SSCI positively influence sustainability, moderated by organizational learning.	Limited empirical data on sustainability impacts in developing nations.
44	(Zhang & Li, 2023)	AI-enhanced RFID improves data analysis efficiency in SC operations.	High initial investment, resistance to technological change.

Methodology

A scoping review was conducted to assess the current state of research on AI technologies or systems utilized in the field of SCM or RSCM. This methodology was selected due to the abundance of papers focusing on AI in SC and RSC, signifying a vast area of investigation. A scoping review does not require well-defined inquiries or a testable hypothesis, which is why it was favored over a systematic literature review (Panagou et al., 2024). Additionally, conducting scoping reviews aims to pinpoint and outline the existing evidence present in the literature (Munn et al., 2018).

To meet the scoping review standards, we have followed the Arksey and O'Malley (2005) framework scoping review stages:
Stage 1: Identifying the research question/s
Stage 2: Identifying relevant studies
Stage 3: Studying and analyzing the selected studies.
Stage 4: Charting the data
Stage 5: Collating, summarizing, and reporting the results

Identifying the research question/s

The research questions guiding this scoping review, which have been outlined in the introduction, focus on exploring core aspects of AI in SC and RL, including its definitions, contributions to resilience, prevalent techniques, and associated challenges. This section discusses the next stage of the scoping review process.

Identifying the relevant studies.

In order to gather the relevant studies, the keywords were searched in the Google Scholar search engine (www.scholar.google.com), Web of Science (WoS) (www.webofscience.com) and Scopus (www.scopus.com). All databases are major search engines for searching scholarly sources. The Scopus database was adopted for this study for the following reasons:

1- Scopus offers a wide range of literature coverage, with the capability for citation analysis (Pournader et al., 2021).
2- One of the world's largest abstract and citation databases for peer-reviewed papers (Ferreira & Reis, 2023).
3- The Scopus database provides comprehensive coverage of journal articles indexed in other databases such as WoS, ScienceDirect, Emerald Insight, and Taylor & Francis (Oluleye et al., 2023).
4- All papers selected for the scoping review are indexed in the WoS database, ensuring their scholarly credibility. Among these, 31 papers are ranked as Q1, reflecting their position in top-tier journals with the highest impact. Additionally, ten papers are classified as Q2, indicating strong academic quality, while two papers fall under Q3, and one paper is categorized as Q4.
5- Generates fewer and more targeted results when compared to Google Scholar engine.

The assembled list of keywords is applied to the title, abstract, and keywords using the query syntax supported by Scopus (designated as TITLE-ABS-KEY). Keywords related to AI, separated by Boolean logic "OR," are combined using Boolean logic "AND" with keywords related to SC and RSC, also separated by Boolean logic "OR." The final syntax used to search for the relevant articles is provided below:

Keywords query: (“AI" OR "ant colony optimization" OR "artificial neural network*" OR "artificial intelligence" OR "bayesian" OR "bees algorithm" OR "cluster analysis" OR "deep learning" OR "decision tree" OR "intelligent automation" OR "support vector machine" OR "machine learning" OR "intelligent agents" OR "fuzzy set" OR "unsupervised learning" OR "supervised learning" OR "reinforcement learning" OR "computational intelligence" OR "predictive model*" OR "neural networks" OR "regression analysis" OR "regression methods"

OR "digital technology" OR "computer vision" OR "image processing" OR "self-learning" OR "self learning" OR "transfer learning" OR "cognitive computing" OR "logic programming")

AND ("closed-loop supply chain" OR "closed-loop supply chain networks" OR "closed-loop supply chain network design" OR "closed-loop supply chain management" OR "reverse supply chains" OR "product recovery" OR "circular economy" OR "reverse supply chain management" OR "sustainable supply chain*" OR "green supply chain*" OR "reverse supply chain" OR “reverse logistics").

Selection Process and Analyze the Selected Studies

As of November 2024, the search resulted in 3,563 records in Scopus. In addition to the specified criteria, the inclusion of this review paper involved: 1) Selection of articles closely related to the research questions targeting AI's impact, challenges, and strategic implications in SC or RSC; with a focus on understanding AI's impact in this domain, 2) articles published between 2020 and 2024, 3) peer-reviewed articles in scientific journals, and 4) articles addressing the research questions, yielding 2,741 documents. The exclusion criteria included: 1) book chapters, 2) working papers, 3) articles in languages other than English, and 4) articles lacking full text, resulting in 1,637 documents. Finally, given the large number of results, we refined the search to articles containing the keywords "Supply Chain," "Artificial Intelligence," and "Reverse Logistics," resulting in 372 articles.

Considering the significant number of eligible articles, a final selection of 56 papers was reviewed and summarized. Conference articles were excluded, leaving 44 papers for further analysis based on the following reasons:

1- A scoping review's purpose is to map existing literature and identify themes and gaps. Analyzing 44 articles allows for a comprehensive approach, highlighting major themes and discussing critical insights in detail.
2- The final 44 publications were chosen based on their relevancy to the research questions and contributions to the field, focusing on important and highly cited studies.
3- The selected 44 articles provide in-depth insights into crucial topics and advancements in SCM or RL using AI.
4- Evaluating 372 articles might be excessively time-consuming and resource-intensive for this study. Focusing on 44 articles allows for a more detailed and manageable examination of the period.

In conclusion this paper scoping review method focused on papers published between 2020 and 2024 to ensure relevance to current AI advancements in SCM and RSCM. We selected 44 out of 372 articles based on strict relevance to our research questions and their significant contributions to the field. This targeted approach allowed us to manageably explore major themes and identify knowledge gaps, fitting the scoping review’s aim to map and detail the latest developments in a rapidly evolving area.

Charting the Data

As part of the scoping review process, data from the articles were charted to identify key themes and trends. The outcomes of this thematic grouping are presented in the literature review section, where the studies are discussed based on their contributions to the field.

Results

Analysis of the full text disclosed 44 articles (Table 4) that explore the use of AI in SC and RSC. Before diving into the analysis specifics, it is vital to analyze the data pertaining to the final selection outcomes for the 372 papers. Figure 2 illustrates the distribution of total articles across the reviewed period from 2019 to 2024. Figure 3 demonstrates the frequency of the selected papers reviewed by this study.

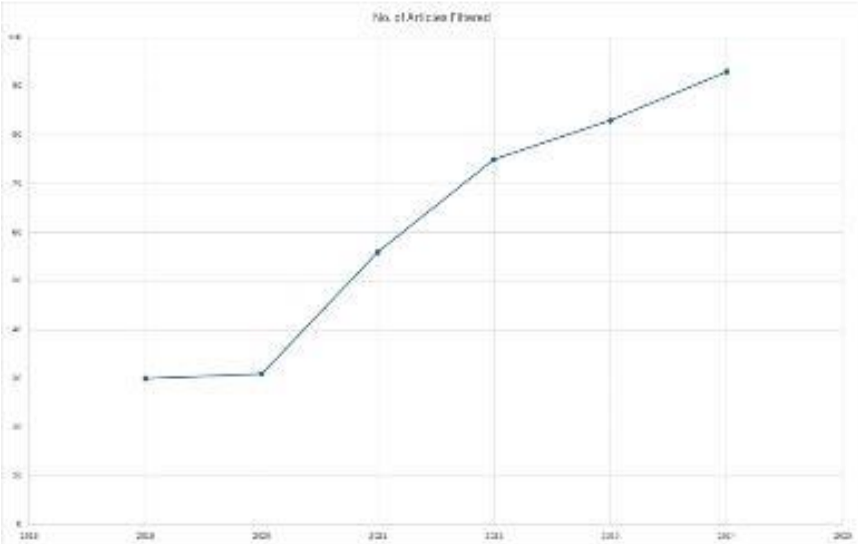

Figure 2. AI and SC/RSC filtered publications from 2019–2024 (Source: Scopus)

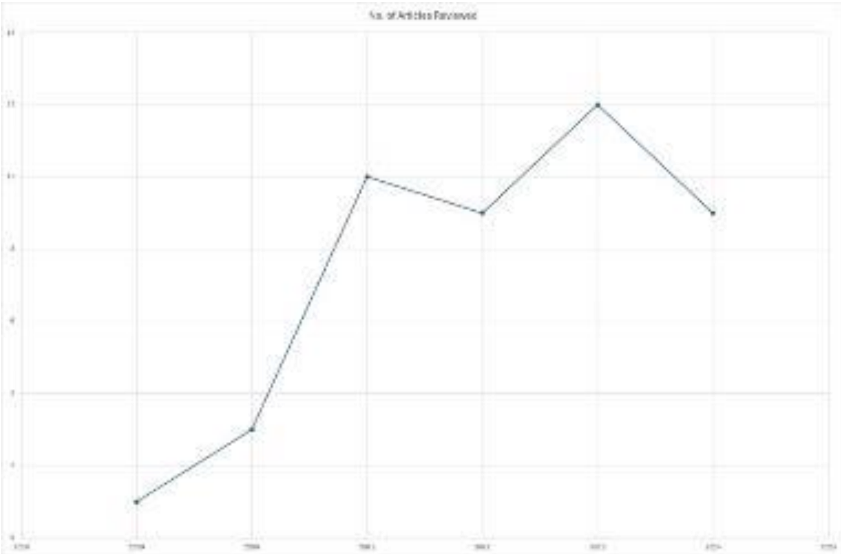

Figure 3. AI and SC/RSC for the reviewed publications from 2019–2024

We conducted an exhaustive review of one article published in 2019 and three articles from 2020. Our emphasis has been on examining more recent articles, especially from the past four years. Specifically, we analyzed ten articles in 2021, nine articles in 2022, 12 articles in 2023, and nine articles in 2024. The country analysis was carried out using the Scopus website. However, the Scopus database provides information on the country of publication but does not specify the country where the study was conducted. This differentiation is particularly critical for academics and researchers. Figure 4 showcases the top 10 countries where the filtered papers were published. In contrast, Figure 5 portrays the 44 countries of publication, and Figure 6 indicates where the studies from these 44 reviewed papers were primarily focused or conducted.

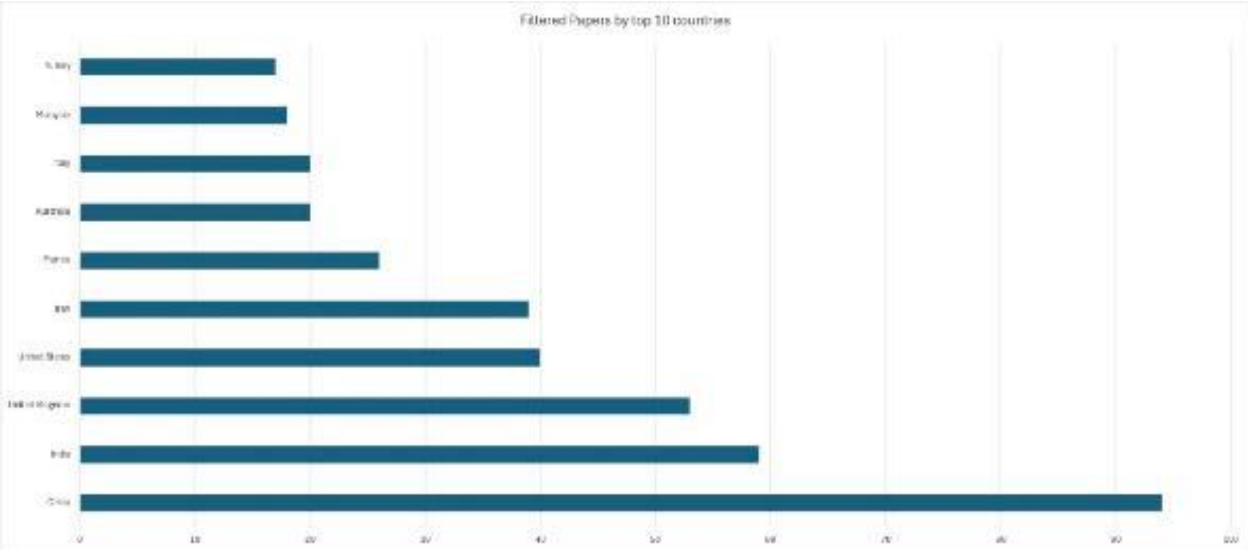

Figure 4. Filtered papers by top 10 countries(Source: Scopus)

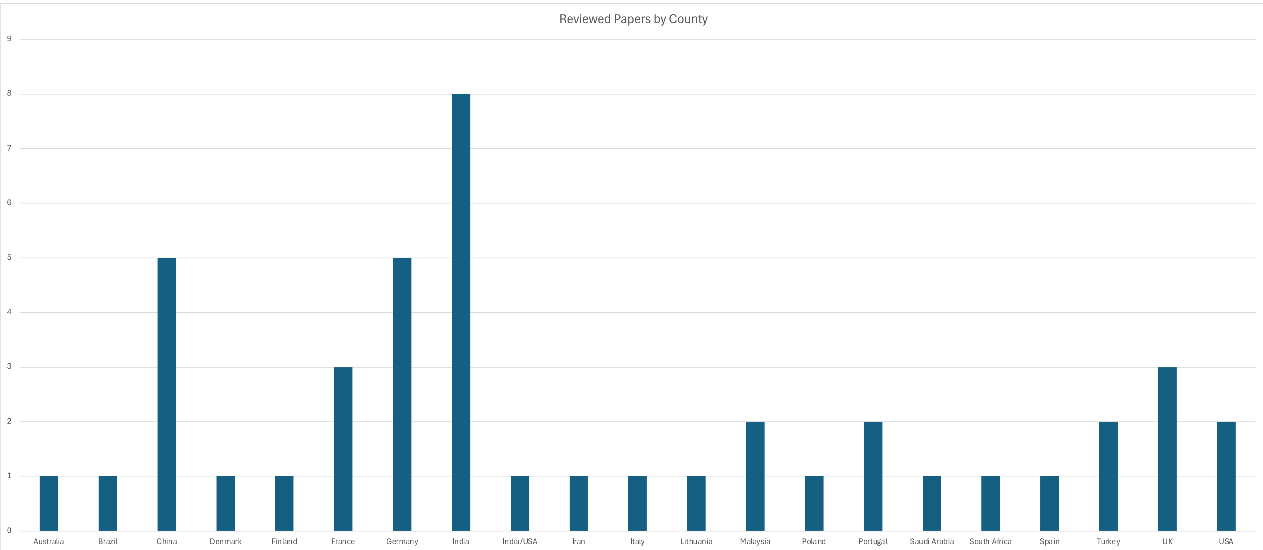

Figure 5. Reviewed papers by country

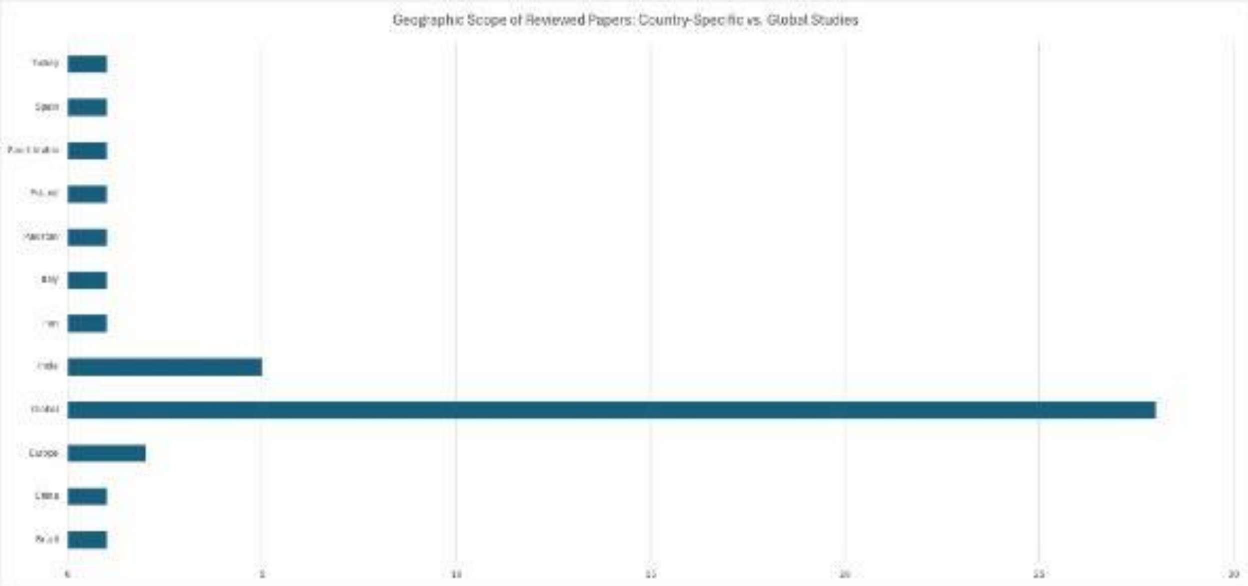

Figure 6. Geographic scope of reviewed papers: country-specific vs. global studies

Based on the Scopus analytical tool, the refined set of 372 papers indicated that the top 11 subject areas prominently showcased the field of Engineering in 21% of the publications focusing on the application of AI in SC and RSC contexts. Environmental Science and Computer Science followed, each contributing 15% of the total publications, while Management represented 14% and Energy 10%. These findings underscore the interdisciplinary aspect of research on AI in SC and RSC, highlighting its significance across technical and managerial domains. Figure 7 depicts the analysis summary.

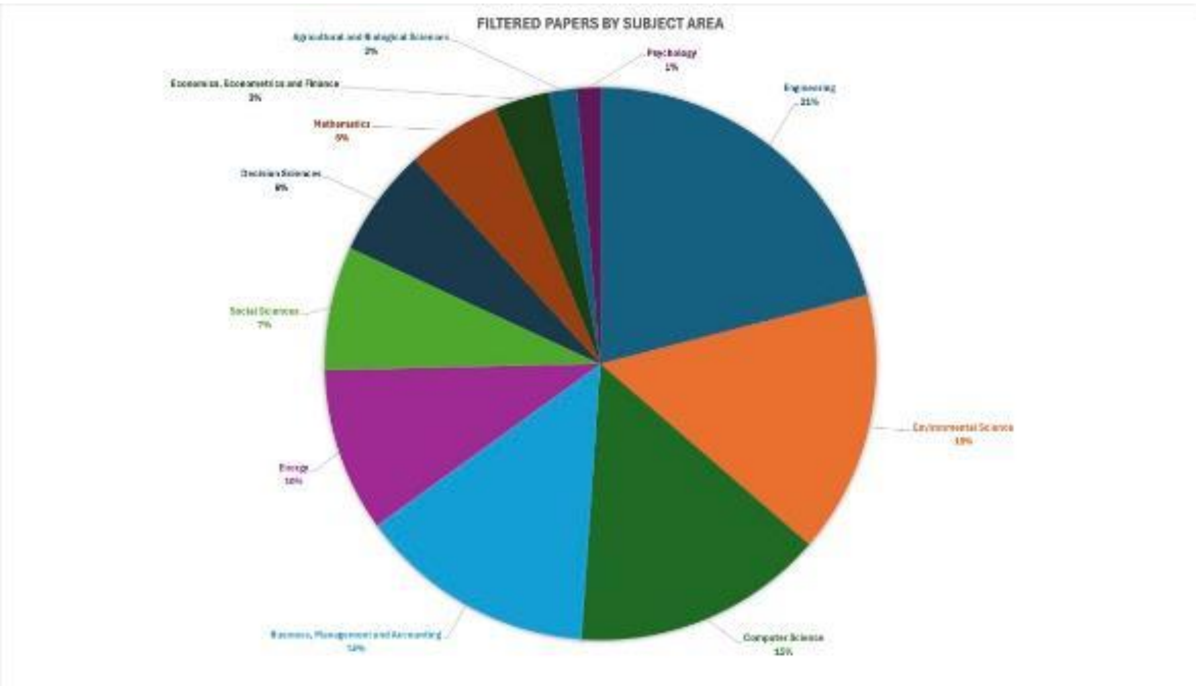

Figure 7. Filtered papers by subject area (Source: Scopus)

The scoping review of the 44 publications covered 37 different journals, illustrating the comprehensive range that showcases the multidisciplinary nature of artificial intelligence (AI) in supply chain (SC) or retail supply chain (RSC). The "International Journal of Production Research" has the highest number of articles published on the interface of AI and SC, followed by "Annals of Operations Research," "IEEE Transactions on Engineering Management," and Procedia CIRP.

The scoping review includes a diverse selection of articles, all indexed in the WoS database, ensuring their academic credibility and relevance. Most articles are published in high-impact journals, with 31 classified as Q1 and ten as Q2, indicating the robust academic quality of the sources. Remarkably, five of the reviewed papers were published in the International Journal of Production Research, a leading journal in the field. Other prominent journals include Annals of Operations Research, from which two papers were selected, along with Computers & Industrial Engineering, Computers in Industry, Energy Reports, and Engineering Applications of Artificial Intelligence, with one paper chosen from each. Figure 8 presents a summary of the chosen journals.

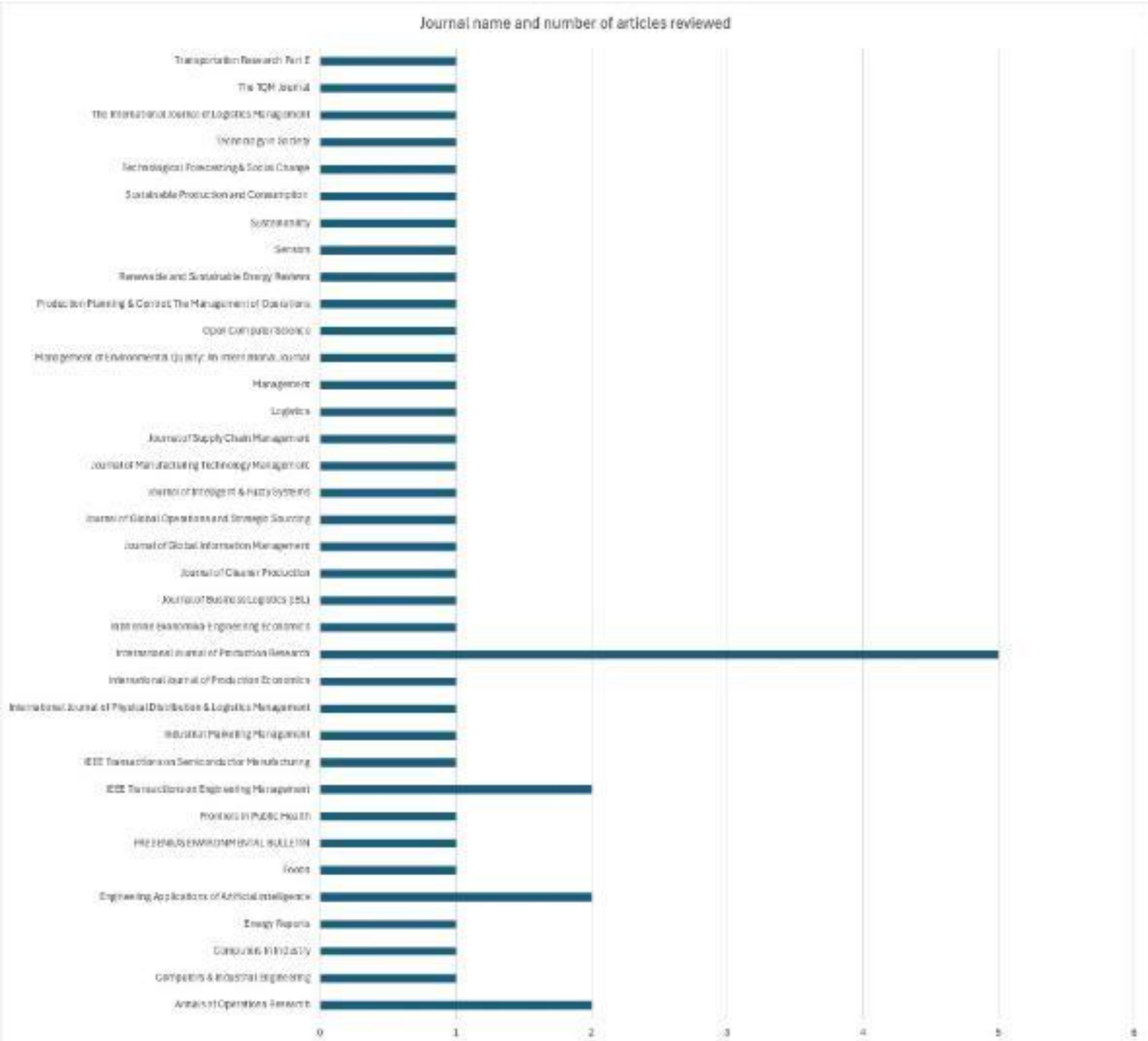

Figure 8. Journal name and number of papers reviewed

This diverse range emphasizes the interdisciplinary nature of the research, covering operations research, industrial engineering, and the applications of AI in SCM. The inclusion of such journals highlights the robustness and comprehensiveness of the scoping review. The provided keywords cover various interconnected domains, emphasizing the significance of emerging technologies, sustainability, and SCM. "Artificial Intelligence (AI)" and "Machine Learning (ML)" are the most frequently mentioned keywords, emphasizing their crucial role in fostering innovation and improving decision-making across industries. Other commonly cited keywords include "Sustainability," "Circular Economy," "Supply Chain Resilience," and "Supply Chain Management," highlighting the increasing emphasis on developing flexible, efficient, and environmentally sustainable systems. Moreover, terms like "Energy Management," "Healthcare Supply Chains," and "Agri-Food Systems" illustrate the sector-specific applications of these technologies. Figure 9 illustrates a word cloud generated from the keywords extracted from all 44 papers reviewed in this study, providing a visual representation of the principal themes and concepts addressed in the literature.

Figure 9. Word cloud of keywords mentioned in the reviewed papers.

Discussion

The swiftly evolving landscape of SCM provides significant opportunities for harnessing AI systems and tools to address complex challenges. However, current research often neglects crucial aspects that could enhance the integration of AI technologies in SCM. By examining the first question in this paper, the limited emphasis on adaptability in dynamic or rapidly changing environments within SCM is underscored. Consequently, the literature discussions mainly revolve around imitating human behavior (Dhamija & Bag, 2020; Pournader et al., 2021; Helo & Hao, 2022; Bughin, 2024; Olan et al., 2024b) or functional capabilities that involve problem-solving, decision-making, and autonomous learning (Helo & Hao, 2022). Nonetheless, these definitions do not delve into ethical considerations or social impacts. Future research could define AI, ML, and Gen-AI in a manner that encompasses ethical guidelines, responsible use, and societal effects. Definitions, especially concerning complex models like DL and Gen-AI, lack coverage of explainability, which is an increasingly critical issue.

Moving on to the second research question in this paper, the authors argue that AI empowers SCM by automating routine tasks, analyzing large volumes of structured and unstructured data for real-time insights, and enabling adaptive responses to dynamic market conditions. This integration improves efficiency, enhances demand forecasting, reduces risks, and supports sustainable practices by utilizing predictive analytics, autonomous systems, and data-driven strategies. It is crucial to note that as AI technologies evolve, the provided definitions may become outdated, requiring continuous updates to align with emerging innovations.

AI plays a pivotal role in strengthening SCR and RL; however, its integration is not without challenges. While AI offers significant opportunities to boost productivity and quality, it also brings risks such as overreliance on AI systems, inappropriate delegation of authority, misplaced trust in AI evaluations, and potential unethical usage affecting employees or customers (Hendriksen, 2023). To effectively leverage AI's potential, organizations must move beyond technical implementation and address the human and ethical dimensions of AI adoption. This includes managing human perceptions, nurturing an AI-aware culture, and providing training to enable effective AI-human collaboration. Moreover, ethical and accountability concerns related to delegating decision-making authority to AI systems must be proactively addressed. Organizations should establish control mechanisms to prevent misuse, monitor AI behavior, and mitigate potential social issues like job displacement arising from AI integration (Hendriksen, 2023). By balancing technical, human, and ethical considerations, AI can significantly enhance the development of more resilient and adaptive supply chains and RL systems.

The findings of this scoping review underscore the application of SCM and its associated technologies across various sectors, aptly addressing the third research question posed in this paper. This highlights the interdisciplinary nature and broad relevance of SCM, demonstrating its adaptability and significance across diverse domains. General supply chains, manufacturing, and healthcare emerge as the most frequently studied sectors in the literature due to their pervasive impact and practical importance, particularly post the COVID-19 pandemic. Additionally, sectors like sustainability and environmental management, circular economy, and RL were mentioned in the reviewed papers, with RL having considerably fewer papers compared to SCM, as evidenced in Table 2, where only 11 out of the 44 reviewed papers focused on RSC.

Based on the studies reviewed in Table 2, AI technologies reveal that ML is the most prevalent, appearing in multiple studies alongside other methods such as DL, predictive analytics, and optimization algorithms. This highlights ML's essential role in addressing various challenges within SCM. Additionally, technologies like genetic algorithms, fuzzy logic, and big data analytics frequently complement ML to enhance decision-making and problem-solving. Advanced methodologies such as deep reinforcement learning, natural language processing (NLP), artificial neural networks (ANN), and cognitive technologies are increasingly integrated, indicating a shift towards more sophisticated, hybrid AI systems. These commonalities underscore the broad applicability of AI in optimizing operations, improving predictive accuracy, and supporting decision-making processes in complex SC environments.

Table 3 addresses the fourth research question by summarizing the barriers to implementing AI technology in SC and RSC operations. These barriers can be classified into four key areas, offering a structured understanding of the challenges hindering AI adoption: 1) Organizational barriers, such as the lack of top management support and misaligned strategic objectives, often impede AI adoption. 2) Technological challenges, including poor data quality, fragmented IT systems, and inadequate infrastructure, lack of standardized frameworks, and hinder integration. 3) Operational issues, such as high implementation costs, human acceptance and skill gaps, and difficulties in integrating AI with legacy systems pose significant hurdles. Lastly, 4) External factors like regulatory uncertainties and limited government support exacerbate these challenges. Collectively, these barriers emphasize the need for strategic alignment, robust data governance, and enhanced AI literacy across organizations to maximize the benefits of AI in SCM and RSC.

During sizable data transfers, companies must consider upgrading outdated systems and ensuring cross-functional coherence; neglecting this could lead to significant hurdles during the transfer or adoption of AI (Venâncio et al., 2022). These challenges highlight the crucial need for strategic alignment, robust data governance, and a cooperative strategy to fully exploit AI's capabilities in supply chain management. Furthermore, the lack of standardized protocols and frameworks for AI integration in SCM results in compatibility issues and inefficiencies. Establishing industry-wide standards can ease the transition to AI and enhance interoperability among diverse systems (Hangl et al., 2022).

The findings in the results section underscore the interdisciplinary nature of AI in SCM, showcasing its ability to drive innovation and efficiency across industries. However, they also highlight the need for further research to tackle implementation challenges, such as data availability and sector-specific customization, to maximize the benefits of AI integration. While AI offers transformative opportunities for SCM and RSC, its successful implementation necessitates overcoming significant barriers. Addressing these challenges through collaborative efforts, strategic planning, and technological investments is crucial to fully harness AI's potential and drive SC innovation.

Conclusion

AI plays a crucial role in advancing SCM and RSCM, enhancing resilience, efficiency, and sustainability. This analysis highlights AI's potential in optimizing SCs through predictive analytics, real-time monitoring, and resource retrieval, effectively tackling operational challenges and encouraging circular economy practices. However, AI integration encounters obstacles like organizational, technological, and ethical barriers, including issues related to data quality, high implementation costs, and the lack of standardized frameworks. Overcoming these challenges requires strategic alignment, robust governance, and a deeper understanding of the ethical implications of AI. Future research should focus on enhancing AI frameworks, improving data integration, and addressing the ethical dimensions of AI adoption in SCM and RSCM. In the context of RL, AI technologies address challenges such as complex return processes, resource recovery, and waste reduction by optimizing operations and enabling more efficient closed-loop systems. These advancements not only strengthen operational resilience but also support industries in achieving sustainability goals through innovative solutions.

Delving into aspects such as algorithmic accountability, bias mitigation, and data privacy is essential for ensuring responsible and equitable AI deployment. By addressing these constraints and ethical considerations, researchers and practitioners can effectively harness AI's transformative potential in establishing sustainable and resilient supply chain systems. One notable limitation of this study is the rapidly changing landscape of AI technologies, which may render some findings obsolete quickly, necessitating continual updates to ensure relevance. Moreover, contextual factors such as regional economic conditions, industry-specific regulations, and organizational culture are not fully examined in the review, despite significantly impacting the adoption and outcomes of AI. Resolving these limitations could significantly enhance the rigor and practical relevance of future research in this domain.

Disclosure Statement

No potential conflict of interest was reported by the author(s) and this research received no external funding.

References

Alfawaz, K. M., & Alshehri, A. A. (2022). Applying Artificial Intelligence in Supply Chain Management. *Communications in Mathematics and Applications*, *13*(1), 367-377. https://doi.org/10.26713/cma.v13i1.1976

Alhasawi, E., Hajli, N., & Dennehy, D. (2023, 13-15 Sept. 2023). A Review of Artificial Intelligence (AI) and Machine Learning (ML) for Supply Chain Resilience: Preliminary Findings. 2023 IEEE International Symposium on Technology and Society (ISTAS),

Arksey, H., & O'Malley, L. (2005). Scoping studies: towards a methodological framework. *International journal of social research methodology*, *8*(1), 19-32.

Aylak, B. L. (2021). ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS IN AGRICULTURAL SUPPLY CHAIN: A CRITICAL COMMENTARY. *Fresenius Environmental Bulletin*, *30*(7A), 8905-8916. <Go to ISI>://WOS:000678352300010

Baciuliene, V., Bilan, Y., Navickas, V., & Civin, L. (2023). The Aspects of Artificial Intelligence in Different Phases of the Food Value and Supply Chain. *Foods*, *12*(8), Article 1654. https://doi.org/10.3390/foods12081654

Belhadi, A., Kamble, S., Fosso Wamba, S., & Queiroz, M. M. (2022). Building supply-chain resilience: an artificial intelligence-based technique and decision-making framework. *International Journal of Production Research*, *60*(14), 4487-4507. https://doi.org/10.1080/00207543.2021.1950935

Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2024). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*, *333*(2), 627-652. https://doi.org/10.1007/s10479-021-03956-x

Benzidia, S., Makaoui, N., & Bentahar, O. (2021). The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. *Technological Forecasting and Social Change*, *165*, Article 120557. https://doi.org/10.1016/j.techfore.2020.120557

Bhattacharya, S., Govindan, K., Dastidar, S. G., & Sharma, P. (2024). Applications of artificial intelligence in closed-loop supply chains: Systematic literature review and future research agenda. *Transportation Research Part E: Logistics and Transportation Review*, *184*, 103455. https://doi.org/10.1016/j.tre.2024.103455

Bu, S. H. (2021). Logistics engineering optimization based on machine learning and artificial intelligence technology. *Journal of Intelligent & Fuzzy Systems*, *40*(2), 2505-2516. https://doi.org/10.3233/jifs-189244

Bughin, J. (2024). What drives the corporate payoffs of using generative artificial intelligence? *Structural Change and Economic Dynamics*, *71*, 658-668. https://doi.org/https://doi.org/10.1016/j.strueco.2024.09.011

Cannas, V. G., Ciano, M. P., Saltalamacchia, M., & Secchi, R. (2024). Artificial intelligence in supply chain and operations management: a multiple case study research. *International Journal of Production Research*, *62*(9), 3333-3360. https://doi.org/10.1080/00207543.2023.2232050

Chen, X. R. (2022). Machine learning approach for a circular economy with waste recycling in smart cities. *Energy Reports*, *8*, 3127-3140. https://doi.org/10.1016/j.egyr.2022.01.193

Chien, C. F., Ehm, H., Fowler, J. W., Kempf, K. G., Monch, L., & Wu, C. H. (2023). Production-Level Artificial Intelligence Applications in Semiconductor Supply Chains. *Ieee Transactions on Semiconductor Manufacturing*, *36*(4), 560-569. https://doi.org/10.1109/tsm.2023.3322142

Dhamija, P., & Bag, S. (2020). Role of artificial intelligence in operations environment: a review and bibliometric analysis. *Tqm Journal*, *32*(4), 869-896. https://doi.org/10.1108/tqm-10-2019-0243

Dubey, R., Bryde, D. J., Blome, C., Roubaud, D., & Giannakis, M. (2021). Facilitating artificial intelligence powered supply chain analytics through alliance management during the pandemic crises in the B2B context. *Industrial Marketing Management*, *96*, 135-146. https://doi.org/10.1016/j.indmarman.2021.05.003

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., & Eirug, A. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994.

Ferreira, B., & Reis, J. (2023). Artificial Intelligence in Supply Chain Management: A Systematic Literature Review and Guidelines for Future Research. International Joint conference on Industrial Engineering and Operations Management,

Garrido-Hidalgo, C., Olivares, T., Ramirez, F. J., & Roda-Sanchez, L. (2019). An end-to-end Internet of Things solution for Reverse Supply Chain Management in Industry 4.0. *Computers in Industry*, *112*, 103127. https://doi.org/https://doi.org/10.1016/j.compind.2019.103127

Gupta, S., Modgil, S., Meissonier, R., & Dwivedi, Y. K. (2021). Artificial Intelligence and Information System Resilience to Cope With Supply Chain Disruption. *IEEE transactions on engineering management*. https://doi.org/10.1109/tem.2021.3116770

Hangl, J., Behrens, V. J., & Krause, S. (2022). Barriers, drivers, and social considerations for AI adoption in supply chain management: a tertiary study. *Logistics*, *6*(3), 63.

Helo, P., & Hao, Y. Q. G. (2022). Artificial intelligence in operations management and supply chain management: an exploratory case study. *Production Planning & Control*, *33*(16), 1573-1590. https://doi.org/10.1080/09537287.2021.1882690

Hendriksen, C. (2023). Artificial intelligence for supply chain management: Disruptive innovation or innovative disruption? *Journal of Supply Chain Management*, *59*(3), 65-76. https://doi.org/10.1111/jscm.12304

Ismagiloiva, E., Dwivedi, Y., & Rana, N. (2020). Visualising the knowledge domain of artificial intelligence in marketing: A bibliometric analysis. Re-imagining Diffusion and Adoption of Information Technology and Systems: A Continuing Conversation: IFIP WG 8.6 International Conference on Transfer and Diffusion of IT, TDIT 2020, Tiruchirappalli, India, December 18–19, 2020, Proceedings, Part I,

Ivanov, D. (2022). Viable supply chain model: integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic. *Annals of Operations Research*, *319*(1), 1411-1431. https://doi.org/10.1007/s10479-020-03640-6

Jackson, I., Ivanov, D., Dolgui, A., & Namdar, J. (2024). Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2024.2309309

Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review. *Journal of Cleaner Production*, *376*, 134120. https://doi.org/https://doi.org/10.1016/j.jclepro.2022.134120

Kazancoglu, I., Ozbiltekin-Pala, M., Mangla, S. K., Kumar, A., & Kazancoglu, Y. (2023). Using emerging technologies to improve the sustainability and resilience of supply chains in a fuzzy environment in the context of COVID-19. *Annals of Operations Research*, *322*(1), 217-240. https://doi.org/10.1007/s10479-022-04775-4

Kosasih, E. E., Papadakis, E., Baryannis, G., & Brintrup, A. (2024). A review of explainable artificial intelligence in supply chain management using neurosymbolic approaches. *International Journal of Production Research*, *62*(4), 1510-1540. https://doi.org/10.1080/00207543.2023.2281663

Leal Filho, W., Ribeiro, P. C. C., Mazutti, J., Lange Salvia, A., Bonato Marcolin, C., Lima Silva Borsatto, J. M., Sharifi, A., Sierra, J., Luetz, J., Pretorius, R., & Viera Trevisan, L. (2024). Using artificial intelligence to implement the UN sustainable development goals at higher education institutions. *International Journal of Sustainable Development & World Ecology*, 1-20. https://doi.org/10.1080/13504509.2024.2327584

Long, P., Lu, L., Chen, Q. L., Chen, Y. F., Li, C. L., & Luo, X. C. (2023). Intelligent selection of healthcare supply chain mode - an applied research based on artificial intelligence. *Frontiers in Public Health*, *11*, Article 1310016. https://doi.org/10.3389/fpubh.2023.1310016

Majumdar, A., Garg, H., & Jain, R. (2021). Managing the barriers of Industry 4.0 adoption and implementation in textile and clothing industry: Interpretive structural model and triple helix framework. *Computers in Industry*, *125*, 103372. https://doi.org/https://doi.org/10.1016/j.compind.2020.103372

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. *AI magazine*, *27*(4), 12-12.

Modgil, S., Gupta, S., Stekelorum, R., & Laguir, I. (2021). AI technologies and their impact on supply chain resilience during COVID-19. *International Journal of Physical Distribution & Logistics Management*, *52*(2), 130-149.

Mosallanezhad, B., Gholian-Jouybari, F., Cárdenas-Barrón, L. E., & Hajiaghaei-Keshteli, M. (2023). The IoT-enabled sustainable reverse supply chain for COVID-19 Pandemic Wastes (CPW). *Engineering Applications of Artificial Intelligence*, *120*, Article 105903. https://doi.org/10.1016/j.engappai.2023.105903

Mukherjee, S., Baral, M. M., Nagariya, R., Chittipaka, V., & Pal, S. K. (2023). Artificial intelligence-based supply chain resilience for improving firm performance in emerging markets. *Journal of Global Operations and Strategic Sourcing*. https://doi.org/10.1108/jgoss-06-2022-0049

Mukherjee, S., Nagariya, R., Mathiyazhagan, K., Baral, M. M., Pavithra, M. R., & Appolloni, A. (2024). Artificial intelligence-based reverse logistics for improving circular economy performance: a developing country perspective. *International Journal of Logistics Management*. https://doi.org/10.1108/ijlm-03-2023-0102

Mukherjee, S., Nagariya, R., Mathiyazhagan, K., Baral, M. M., Pavithra, M. R., & Appolloni, A. (2024). Artificial intelligence-based reverse logistics for improving circular economy performance: a developing country perspective. *The international journal of logistics management*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/IJLM-03-2023-0102

Munn, Z., Peters, M. D., Stern, C., Tufanaru, C., McArthur, A., & Aromataris, E. (2018). Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC medical research methodology*, *18*, 1-7.

Neto, G., de Araujo, S. A., Gomes, R. A., Alliprandini, D. H., Flausino, F. R., Amorim, M., & Zhao, J. (2023). Simulation of Electronic Waste Reverse Chains for the Sao Paulo Circular Economy: An Artificial Intelligence-Based Approach for Economic and Environmental Optimizations. *Sensors*, *23*(22), Article 9046. https://doi.org/10.3390/s23229046

Nikseresht, A., Hajipour, B., Pishva, N., & Mohammadi, H. A. (2022). Using artificial intelligence to make sustainable development decisions considering VUCA: a systematic literature review and bibliometric analysis. *Environmental Science and Pollution Research*, *29*(28), 42509-42538. https://doi.org/10.1007/s11356-022-19863-y

Olan, F., Arakpogun, E. O., Jayawickrama, U., Suklan, J., & Liu, S. F. (2024a). Sustainable Supply Chain Finance and Supply Networks: The Role of Artificial Intelligence. *IEEE transactions on engineering management*. https://doi.org/10.1109/tem.2021.3133104

Olan, F., Arakpogun, E. O., Jayawickrama, U., Suklan, J., & Liu, S. F. (2024b). Sustainable Supply Chain Finance and Supply Networks: The Role of Artificial Intelligence. *IEEE transactions on engineering management*, *71*, 13296-13311. https://doi.org/10.1109/tem.2021.3133104

Oluleye, B. I., Chan, D. W. M., & Antwi-Afari, P. (2023). Adopting Artificial Intelligence for enhancing the implementation of systemic circularity in the construction industry: A critical review. *Sustainable Production and Consumption*, *35*, 509-524. https://doi.org/10.1016/j.spc.2022.12.002

Panagou, S., Neumann, W. P., & Fruggiero, F. (2024). A scoping review of human robot interaction research towards Industry 5.0 human-centric workplaces. *International Journal of Production Research*, *62*(3), 974-990. https://doi.org/10.1080/00207543.2023.2172473

Pawlicka, K., & Bal, M. (2022). Sustainable Supply Chain Finances implementation model and Artificial Intelligence for innovative omnichannel logistics. *Management-Poland*, *26*(1), 19-35. https://doi.org/10.2478/manment-2019-0082

Pereira, E. T., & Shafique, M. N. (2024). The Role of Artificial Intelligence in Supply Chain Agility: A Perspective of Humanitarian Supply Chain. *Inzinerine Ekonomika-Engineering Economics*, *35*(1), 77-89. https://doi.org/10.5755/j01.ee.35.1.32928

Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. *International Journal of Production Economics*, *241*, 108250. https://doi.org/https://doi.org/10.1016/j.ijpe.2021.108250

Rajesh, R. (2020). A grey-layered ANP based decision support model for analyzing strategies of resilience in electronic supply chains. *Engineering Applications of Artificial Intelligence*, *87*, 103338. https://doi.org/https://doi.org/10.1016/j.engappai.2019.103338

Rakhshan, K., Morel, J. C., & Daneshkhah, A. (2021). Predicting the technical reusability of load-bearing building components: A probabilistic approach towards developing a Circular Economy framework. *Journal of Building Engineering*, *42*, Article 102791. https://doi.org/10.1016/j.jobe.2021.102791

Richey, R. G., Jr., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of business logistics*, *44*(4), 532-549. https://doi.org/10.1111/jbl.12364

Richter, L., Lehna, M., Marchand, S., Scholz, C., Dreher, A., Klaiber, S., & Lenk, S. (2022). Artificial Intelligence for Electricity Supply Chain automation. *Renewable & Sustainable Energy Reviews*, *163*, Article 112459. https://doi.org/10.1016/j.rser.2022.112459

Samadhiya, A., Yadav, S., Kumar, A., Majumdar, A., Luthra, S., Garza-Reyes, J. A., & Upadhyay, A. (2023). The influence of artificial intelligence techniques on disruption management: Does supply chain dynamism matter? *Technology in Society*, *75*, Article 102394. https://doi.org/10.1016/j.techsoc.2023.102394

Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., & Munim, Z. H. (2022). The role of artificial intelligence in supply chain management: mapping the territory. *International Journal of Production Research*, *60*(24), 7527-7550. https://doi.org/10.1080/00207543.2022.2029611

Sharma, S., Gahlawat, V. K., Rahul, K., Mor, R. S., & Malik, M. (2021). Sustainable Innovations in the Food Industry through Artificial Intelligence and Big Data Analytics. *Logistics*, *5*(4), 66. https://www.mdpi.com/2305-6290/5/4/66

Shrivastav, M. (2022). Barriers Related to AI Implementation in Supply Chain Management. *Journal of Global Information Management*, *30*(8). https://doi.org/10.4018/jgim.296725

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, *122*, 502-517. https://doi.org/https://doi.org/10.1016/j.jbusres.2020.09.009

Venâncio, A. L. A. C., Loures, E. d. F. R., Deschamps, F., Justus, A. d. S., Lumikoski, A. F., & Brezinski, G. L. (2022). Technology prioritization framework to adapt maintenance legacy systems for Industry 4.0 requirement: an interoperability approach. *Production*, *32*, e20210035.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications*, *11*(1), 233. https://doi.org/10.1038/s41467-019-14108-y

Wang, J. X., Lim, M. K., Wang, C., & Tseng, M. L. (2021). The evolution of the Internet of Things (IoT) over the past 20 years. *Computers & Industrial Engineering*, *155*, Article 107174. https://doi.org/10.1016/j.cie.2021.107174

Wilson, M., Paschen, J., & Pitt, L. (2022). The circular economy meets artificial intelligence (AI): understanding the opportunities of AI for reverse logistics. *Management of*

Environmental Quality: An International Journal, *33*(1), 9-25. https://doi.org/10.1108/MEQ-10-2020-0222

Yamin, M. A., Almuteri, S. D., Bogari, K. J., & Ashi, A. K. (2024). The Influence of Strategic Human Resource Management and Artificial Intelligence in Determining Supply Chain Agility and Supply Chain Resilience. *Sustainability*, *16*(7), Article 2688. https://doi.org/10.3390/su16072688

Yang, K., Thoo, A. C., Ab Talib, M. S., & Huam, H. T. (2024). How reverse logistics and sustainable supply chain initiatives influence sustainability performance: the moderating role of organisational learning capability. *Journal of Manufacturing Technology Management*, *35*(1), 141-163. https://doi.org/10.1108/JMTM-04-2023-0143

Zhang, H. Y., & Li, Z. (2023). RFID supply chain data deconstruction method based on artificial intelligence technology. *Open Computer Science*, *13*(1), Article 20220265. https://doi.org/10.1515/comp-2022-0265