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AI-Powered Supply Chains: Mapping the Future of Resilience and Sustainability

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ABSTRACT

Objective: This study aims to present a bibliometric mapping of artificial intelligence applications in supply chain management.

Methodology: Performance analysis and scientific mapping are used based on 805 Scopus-indexed journal articles published between 1996 and 15 March 2025.Three research questions are formulated to guide the analysis concerning disciplinary priorities, thematic structure, and international collaboration.

Results: we document a marked post-2020 acceleration in publications and citations, identify leading sources and authors, and reveal four interconnected thematic clusters: methodological foundations, digital infrastructures, application and resilience foci, and emerging topics. While resilience and sustainability emerge as salient application lenses within the corpus, our contribution is descriptive and explanatory rather than predictive.

Conclusion: The study clarifies conceptual contours, highlights collaboration hubs led by the United States, India, and China, and delineates gaps that motivate future work on data governance, technical integration, and evaluation across sectors.

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Introduction

Artificial Intelligence (AI) has become one of the technological turning points in recent years and has restructured the modern environment of Supply Chain Management (SCM) to a significant extent. With the growing complexity of global supply chains, the ability of AI to provide a more efficient operation and increased optimization of decisions and minimization of risk has attracted special attention of researchers. Not only does its localization in SCM provide answers to classical problems, like predicting demand, organizing ultra efficient inventory, and risk, but it also opens new frontiers of digitalization, resiliency, and sustainability (Shaik et al., 2023; Kim & Lee, 2022).

The emergence of more developed AI technologies such as machine or deep learning, or big data analytics solutions have also is associated with the automation of organizational processes and, by extension, made organizations more responsive and predictive (He et al., 2023). As a result, companies leveraging AI technologies can achieve a competitive advantage by enhancing their operational efficiency and adaptability to volatile market conditions (Helo & Hao, 2021). The use of artificial intelligence technology in combination with other technologies, such as the Internet of Things (IoT) and blockchain, has significantly improved the supply chains in terms of transparency, security, and robustness (Gartner, 2017).

Through AI and IoT sensors, data analytics in real-time makes organizations be more informed in understanding disruption and developing mitigation strategies to reduce risks and improve decision-making ability (Wang et al., 2023; Singh et al., 2023). At the same time, the integration of a blockchain also enhances supply-chain transparency by providing secure and irreversible transaction history that strengthens the trust of stakeholders (Chen et al., 2022). Such a fusion between the AI and new technologies defines a critical edge in supply-chain management, providing an end-to-end perspective of traversing complicated networks (Wang, 2021; Liu & Fang, 2023).

The current bibliographic study of the AI use in SCM examines 805 papers written over the period 1996-15 March 2025, reports the relevant trends, outlines issues, and highlights research gaps, thus offering an in-depth picture of the related domain. The paper draws back the history of the development of AI-powered practices in the SCM environment and highlights the important place that international cooperation takes, with the United States, India, and the United Kingdom being the most prominent players in AI-related studies (Bahroun et al., 2023; Ivanov, 2021).

This study maps the evolution of AI-powered supply chains through a focused bibliometric lens and clarifies how resilience and sustainability themes coalesce around data-centric and governance-aware capabilities. Our novelty lies in a concise, conceptually anchored synthesis that connects thematic clusters to end-to-end supply-chain decision autonomy. Guided by the above motivation, we address the following questions:

- RQ1: What are the disciplinary priorities of AI-SCM scholarship over 1996–15 March 2025?
- RQ2: What thematic clusters and trajectories characterize the field's intellectual structure?
- RQ3: How do international collaboration patterns shape the development of AI-SCM?

This paper proceeds as follows: Section 2 outlines the theoretical foundations of AI in SCM, with a focus on its key applications and methodologies. Section 3 presents the research methodology employed in this study, followed by Section 4, which discusses the findings of the bibliometric analysis. Finally, Section 5 concludes the paper with a discussion on the implications of these findings and offers directions for future research.

Literature Background

Theoretical foundations

The concept of AI has become one of the central aspects of new technological progress and is expected to transform the backbone of SCM (Rodriguez-Espindola et al., 2020). An AI-based approach to SCM takes its roots in the ability of artificial intelligence to mimic human cognitive processes, letting machines think, learn on the basis of previous experiences, and make wise decisions based on enormous amounts of information (Pan, 2016).

In the framework of SCM, AI has been used to centralize decision making by use of machine learning, deep learning, and natural language processing, which optimize several parts of the supply chain (Brynjolfsson & McAfee, 2017). The technologies provide a versatile solution to operational efficiency, demand foresight, inventory optimization, and risk management (Briannis et al., 2019).

The observed capabilities of AI in supply chains can be interpreted through established SCM lenses: the resource-based view (data assets and analytics as rare and inimitable resources), dynamic capabilities (sensing–seizing–reconfiguring under disruption), and systems theory (end-to-end interdependence across flows). Positioning our findings within these frameworks clarifies how algorithmic tools translate into resilient and sustainable performance outcomes.

AI Technologies in Supply Chain Management

AI in SCM may generally be divided into two main forms: Artificial General Intelligence (AGI) and Artificial Narrow Intelligence (ANI). AGI with the similar cognitive abilities like humans remains to be in theoretical level, whereas ANI is more targeted, performing certain tasks with high degree of efficiency (Bawack et al., 2019). The majority of AI solutions in SCM belong to ANI, tackle specific tasks in demand forecasting, route optimization, and inventory management and utilize AI algorithms, including but not limited to deep learning, decision trees and neural networks (He et al., 2023).

Machine learning (ML) is a subtype of AI that plays an essential role in allowing AI-based systems to enhance subsequent activities by examining past information and determining patterns that can then be used to make future choices (Bahroun et al., 2023). Supervised learning, unsupervised learning, and reinforcement learning are the ML techniques that have significantly been used in the SCM to automate the process and predict the results (Singh et al., 2023). Moreover, a more high-level subdivision of ML (Deep Learning (DL)), encompassing multi-layered neural networks, is employed to represent non-linear relationships in data, which are complex in nature. DL has been used in demand prediction, anomaly identification, and predictive maintenance of SCM (Dolgoy & Ivanov, 2021).

In addition to these algorithmic capabilities, the relevance of AI for resilience and sustainability is increasingly expressed through data-driven sensing, traceability, and adaptive planning. By linking machine learning and deep learning with IoT, blockchain, and cyber-physical systems, AI technologies enable visibility and predictive control, which are central mechanisms in supply-chain resilience theory and environmental sustainability frameworks. This functional linkage provides a conceptual anchor connecting the technological foundations of AI with the thematic clusters identified in the bibliometric results.

Integration of AI with Complementary Technologies

The adoption of artificial intelligence alongside other new technologies - such as the Internet of Things (IoT) and blockchain - added further dimensions to SCM systems. IoT enables real-time monitoring of supply chains and generates large volumes of data that can be leveraged for AI-driven analytics. (Ben-Daya et al., 2019; Wang et al., 2023). It improves the precision level for demand forecasting, inventory management because decisions are made based on present data rather than depending only on historical trends (Shaik et al., 2023).

As far as an AI-enabled supply chain is concerned, blockchain technology has a very high role in transparency as well as providing security of data (Lee et al., 2019; Dora et al., 2022). By providing immutable records of transactions, trust can be facilitated among stakeholders. Traceability of the product from the whole supply chain can be made possible. When combined with AI, blockchain ensures that data used in making predictions and optimizations is reliable and secured (Lee et al., 2015; Rostamzadeh et al., 2025).

Benefits of AI in SCM

There are many advantages associated with the use of AI in SCM, including increasing the efficiency of operations and better aligning with customer expectations. The optimization of resource usage and the minimization of costs, due to automation of routine activities, such as inventory management and order delivery, constitute one of the greatest benefits of AI (Pournader et al., 2021; Ahmed & Rahman, 2020).

AI-based technologies also enable companies to streamline their supply chains by optimizing delivery routes, thereby reducing transportation costs and shortening delivery time (Orucoglu Jadid et al., 2021; Feng et al., 2017). The other significant advantage of AI is its influence on risk management. Supply chains will be able to respond to disruptions in a timely manner by using AI algorithms that will be able to analyse past data, and predict possible risks. This would be a proactive strategy, promoting resilience so that companies are better equipped to address supply chain disruptions aligns with external factors like natural disasters, political unrest, or pandemic (Riahi et al., 2021; Azzavi et al., 2025).

Challenges of AI Adoption in SCM

Although the opportunities offered by AI are substantial, there are some obstacles that prevent its active use in SCM. Among the main drawbacks is that implementation of AI is associated with a large initial investment, such as expenditures for data infrastructure, the purchase of the required technology, and training the workforce (Shaik et al., 2023).

Moreover, a shortage of competent workforce represents an additional challenge, because to implement AI, companies must employ personnel with expertise in data science, machine learning, and AI technologies (Kim & Lee, 2022). Also, data integrity problems could undermine the work of AI algorithms and result in suboptimal outputs due to incomplete or false data (Belhadi et al., 2022).

Notwithstanding these hurdles, mitigation of the barriers can be addressed with the creation of favorable policy frameworks and the development of digital infrastructure. The governments and organizations should also pay attention to the training and resources necessary to develop a workforce equipped to implement AI technologies (Bassi & Nowak, 2021; Okumuş et al., 2019).

Role of collaboration in AI integration

Although presented within the theoretical section for continuity, the role of collaboration also reflects empirical patterns observed in the findings, thereby connecting conceptual expectations with observed co-authorship clusters. International cooperation and multi-disciplinary collaboration are also essential to the successful introduction of AI to SCM. Countries such as the United States, India, and the United Kingdom have been at the forefront of AI research, especially in the field of machine learning, blockchain integration and supply chain resilience (Kim et al., 2024).

The role of scientific collaboration networks also becomes increasingly critical as AI continues to evolve within the SCM domain. Such networks facilitate knowledge sharing, transfer technologies and create shared data exchange platforms which can speed up the adoption of AI and possibly reduce the cost of implementation (Briannis et al., 2019).

Table 1 summarizes the key artificial intelligence technologies employed in supply chain management, along with their application areas and associated impacts on operational efficiency and decision-making.

Table 1. Theoretical lenses and AI impact areas mapped to bibliometric clusters

Authors	Domain	Application area	Impact on SCM
Pan, S. L. (2016)	Information Technology	SCM Integration	Enhances data management and decision-making across supply chains.
Kritzinger et al. (2018)	Data Science	Explainable AI	Provides transparency in AI decision-making, improving trust among stakeholders.
Pournader, M., et al. (2021)	Artificial Intelligence	Supply Chain Efficiency	AI reduces costs and improves decision-making speed, contributing to more efficient supply chains.
Riahi, Y., et al. (2021)	AI and SCM	Sustainable Supply Chains	AI helps integrate sustainability into SCM by optimizing resource usage and waste reduction.
Chen, Y., et al. (2022)	Supply Chain Management	Inventory Optimization	AI-driven inventory systems reduce waste and optimize stock levels across supply chains.
Liu, Z., & Fang, W. (2023)	Industrial and Engineering Systems	Machine Fault Detection	AI helps predict machine failures, reducing downtime and improving productivity.
Singh, R., et al. (2023)	IoT and AI Integration	Real-time Supply Chain Monitoring	Integration of AI and IoT allows for real-time disruption detection and response.
Wang, Y., et al. (2023)	Blockchain and AI	Supply Chain Transparency	Blockchain integrated with AI enhances transparency and security in transactions.
He, X., et al. (2023)	Supply Chain Management	Risk Management	AI improves risk assessment and mitigates potential supply chain disruptions.
Shaik, K., et al. (2023)	Machine Learning	Demand Prediction	AI leverages machine learning algorithms to predict demand trends with greater precision.

Conceptual anchoring

To conceptually position our mapping, we explicitly anchor AI-enabled SCM within socio-technical systems and supply chain resilience theory. A socio-technical lens clarifies how algorithmic capabilities, data governance, and human decision processes co-evolve to shape operational outcomes, while resilience theory highlights preparedness, absorptive capacity, and adaptive reconfiguration in the face of disruptions.

We also incorporate an ethical–normative perspective, emphasizing fairness, transparency, and accountability in data-driven logistics. This triad provides an integrated scaffold to interpret bibliometric regularities beyond description, linking clusters of methods (machine learning, optimization), infrastructures (IoT, blockchain), and application domains (healthcare, sustainability) to organizational capabilities and governance choices.

Key terms. We adopt the following working definitions to ensure terminological precision. A supply chain, SC, is the interorganizational system that coordinates material, information, and financial flows across planning, sourcing, production, logistics, and returns. Supply chain management, SCM, denotes the strategic design and operational control of these flows within and across firms. Artificial intelligence, AI, refers to data driven computational techniques, including machine learning, deep learning, and knowledge-based systems, that learn from data to support or automate decisions.

Definition and scope. We define an AI-powered supply chain as a data-centric, algorithmically steered socio-technical system in which decision processes across planning, sourcing, production, logistics, and returns are increasingly delegated to learning models with varying degrees of autonomy, under explicit governance constraints. What differentiates AI-powered supply chains from adjacent domains (e.g., AI in manufacturing or stand-alone logistics) is the end-to-end integration of predictive, prescriptive, and adaptive capabilities across inter-organizational flows, enabled by shared data infrastructures and codified accountability (e.g., auditability, fairness).

This lens foregrounds four core attributes—data quality and access, level of decision autonomy, adaptive learning under uncertainty, and governance/ethics—that we use to interpret the thematic clusters reported in Section 4. In this study, resilience and sustainability are treated as application lenses that organize how AI capabilities translate into visibility, agility, risk mitigation, and eco efficiency, rather than as outcomes that this bibliometric design seeks to causally estimate. These definitions and scope conditions align the narrative with RQ1 on disciplinary priorities, RQ2 on thematic structure, and RQ3 on international collaboration, and they provide a consistent vocabulary for the analyses reported in Sections 3 to 5.

Materials and Methods

Bibliometric analysis offers a systematic and objective approach to evaluating the structure, evolution, and intellectual foundations of scientific literature (Fazeli Varzaneh et al., 2020; Wuni et al., 2019; Stanimirović et al., 2024). In the context of artificial intelligence (AI) applications in supply chain management (SCM), bibliometric methods serve as a valuable tool for identifying influential scholars, thematic trends, and collaborative networks. By quantifying patterns of publication, citation, and co-authorship, this method enhances our understanding of the development and dissemination of knowledge in this interdisciplinary field (Statista, 2018).

There are two principal approaches commonly used in bibliometric studies: impact analysis and scientific mapping. Impact analysis examines the citation-based influence of scholarly outputs—such as articles, authors, journals, institutions, and countries typically using metrics like total citations, publication counts, and the Hirsch index (h-index). The h-index, as introduced by Hirsch and later elaborated by Bornmann and Daniel (2007), provides an integrated measure of productivity and scholarly influence, based on the frequency with which a researcher's or journal's most cited works have been referenced.

Scientific mapping, in contrast, focuses on uncovering the structural and conceptual links between bibliographic items. Bibliographic coupling, co-authorship analysis, and keyword co-occurrence methods are employed to disclose the thematic structure of a research field. These visualizations enable researchers to identify knowledge clusters, find patterns of collaboration, and trace the dynamic evolution of the field. In such networks, nodes can represent entities (e.g., authors, countries, and keywords) and edges can represent the strength of interconnections between them in terms of citations or thematic similarity.

Three academic databases, Web of Science (WOS), Google Scholar, and Scopus were available for the initial consideration. Among these, it is Scopus that has been chosen as the main data source because it covers more peer-reviewed journals and offers strong citation tracking support together with easy integration with bibliometric visualization tools like VOSviewer. In comparison to other platforms, Scopus offers a much more dependable and uniform base for conducting bibliometric analysis on a large scale, particularly in multidisciplinary research fields such as AI in SCM.

The literature search was conducted using Boolean queries in the Scopus database, targeting the title, abstract, and keyword fields. The following search terms were used: AND (“supply chain management” OR “SCM”) (“artificial intelligence” OR “AI”). No restrictions were applied regarding publication year, allowing for a comprehensive longitudinal overview of the field’s development.

To maintain the quality and relevance of the dataset, only peer-reviewed journal articles published in English were included in the final sample. Conference proceedings, editorials, and non-English publications were excluded to avoid inconsistencies in citation practices and ensure scientific rigor. After applying these inclusion and exclusion criteria, a final dataset of 805 articles published between 1996 and 15 March 2025 was compiled for analysis.

For conducting the bibliometric analysis, this study used VOSviewer which is specialized software for the construction and visualization of bibliometric networks (Van Eck & Waltman, 2009). Co-authorship networks, keyword co-occurrence maps, and citation-based clusters were generated through VOSviewer. Through visual mapping of these structural component's central authors, influential keywords, and major thematic domains were identified to further articulate the structural composition of the field.

This study aims to utilize the graphical capabilities of VOSviewer to provide a clear and easily interpretable picture of how AI-related research in SCM evolved over time, which institutions and scholars have played a dominant role in the discourse, and what future research directions are emerging. Thus, apart from portraying the major paths that the research has taken so far, this method will also be useful in identifying areas that have not received adequate attention thereby offering a roadmap for future investigations at the intersection of AI and SCM.

Search Strategy and Eligibility Criteria

The Scopus database was queried on 15 March 2025. The search was conducted in the Title, Abstract, and Keywords fields using the following Boolean string:

TITLE-ABS-KEY ("supply chain management" OR "SCM")

AND

TITLE-ABS-KEY ("artificial intelligence" OR "AI")

No publication year restrictions were imposed. All bibliometric indicators reported in this study reflect the dataset as indexed in Scopus on the retrieval date.

To ensure comparability and scientific rigor, the following filters were applied: document type limited to journal articles and language restricted to English. Conference papers, editorials, notes, book chapters, and non-English publications were excluded.

Screening proceeded in two stages. First, automatic filtering was applied within Scopus based on document type and language. Second, a manual relevance assessment of titles and abstracts was conducted to ensure a substantive focus on artificial intelligence applications within supply chain management. Study selection followed a PRISMA-informed logic adapted for bibliometric research, comprising identification (database query), screening (application of filters), eligibility (manual relevance assessment), and final inclusion. The number of records retained at each stage is presented in Figure A1, and detailed inclusion and exclusion criteria are reported in Appendix A. The final corpus consists of 805 peer-reviewed journal articles.

Data Cleaning and Quality Checks

We removed duplicates using Scopus unique identifiers and harmonized author and source names. Records with incomplete bibliographic fields were cross-checked and, where necessary, excluded to preserve metadata consistency.

We validated topic relevance on a 10 percent random sample by double-coding ($\kappa > 0.80$). VOSviewer parameters (minimum occurrences, counting method, clustering resolution) are reported in the figure captions to ensure replicability. The final corpus comprised 805 articles (1996–15 March 2025).

Network Construction Parameters

Bibliometric networks were constructed using VOSviewer (version 1.6.20). Network parameter settings were defined a priori to ensure analytical clarity and reproducibility.

For the keyword co-occurrence analysis, a minimum occurrence threshold of five was applied to author-assigned keywords. Full counting was used, meaning that each keyword occurrence was given equal weight across documents. Normalization was performed using the association strength method, which is the default and widely accepted normalization approach in VOSviewer. Clustering was conducted using the default resolution parameter (1.00). For the author co-authorship network, a minimum threshold of three documents per author was applied to enhance interpretability and reduce network fragmentation. Authors not meeting this threshold were excluded from visualization. For the country-level collaboration analysis, countries with at least five documents were included in the network visualization to ensure structural coherence and avoid excessive sparsity. These parameter settings balance comprehensiveness with interpretability and allow full reproducibility of the network construction process.

Results

Descriptive Statistics of Bibliometric Collection

There were 805 peer-reviewed journal articles on AI applications to SCM from the Scopus database for the period 1996-15 March 2025. Table 2 clearly shows that there has been an enormous growth in publications over the last five years, i.e., 2020-15 March 2025, contributing almost 60 percent to the total. This clearly reflects increased academic and industrial interest in AI-driven SCM strategies.

Table 2. Descriptive Statistics of Bibliometric Collection.

Description	Results
Peer-reviewed articles	805
References (journal articles only)	25
Author keywords	3214
Time period	1996-15 March 2025
Average citations per article	34.49
Author	2305
Authors (single-author articles)	65
Authors (multi-author articles)	2156
Co-authors per article	3.12
Collaboration index	2.34
Percentage of articles	60%

Trends in Publication of Articles and Citations

Figure 1 represents the trend in the number of articles published on AI in SCM that shows an increasing rate. In the beginning, the publications were not numerous, but the significant tendency was noted since 2010. The rates of publication are the greatest in the timeframe between 2020 and 2025 since the field is becoming more popular.

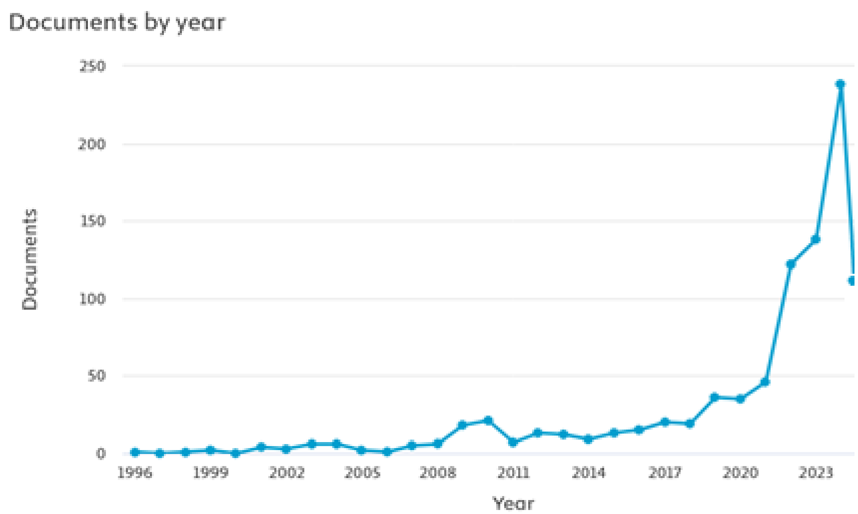

Figure 1. Annual Publications on AI in SCM (1996-15 March 2025)

Figure 2 displays the patterns of citations, according to which the total citations have increased significantly, and as of 15 March 2025, cumulative citations show a steep post-2020 inflection, consistent with the acceleration in annual outputs. As of the data retrieval date (15 March 2025), cumulative citations show a pronounced post-2020 inflection consistent with the acceleration in annual publication outputs. This temporal shift coincides with the COVID-19 period and heightened scholarly attention to resilience, digital transformation, and risk mitigation themes. However, given the descriptive nature of bibliometric mapping, causal inference cannot be established. The observed alignment suggests potential external drivers that warrant further empirical investigation rather than definitive explanatory conclusions.

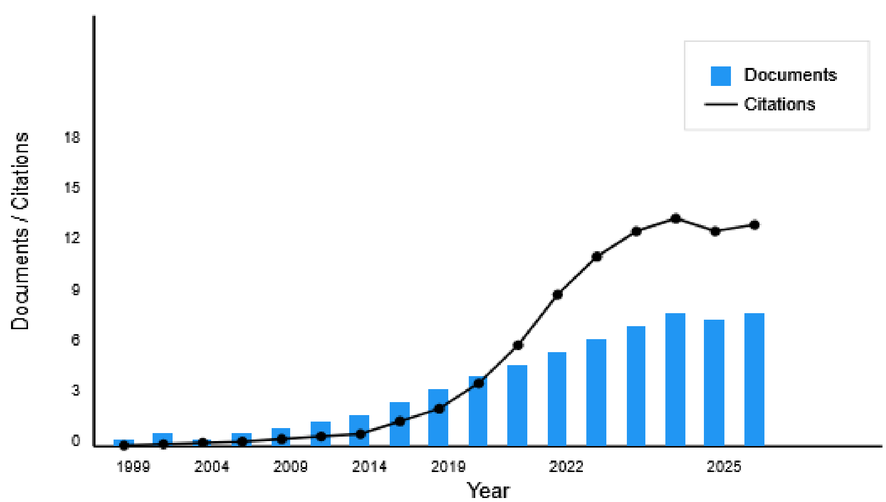

Figure 2. Cumulative citations to the AI–SCM corpus, 1996–2025

Leading Journals in AI–SCM Research

Listing the journals publishing and being cited most frequently in AI-SCM studies allows readers to identify the main sources of publication, develop key channels for disseminating knowledge, and make informed choices about where to submit their own research. Table 3 ranks the most relevant sources according to the number of published articles, h-index, and total citations, and provides information on the journals that shape academic discussions and set scholarly standards on the subject.

Table 3. Most Relevant Sources Based on Article Count

Journal	Articles	H-INDEX	Number of citations
International Journal of Production Research	51	189	3434
Production Planning and Control	13	69	385
Sustainability (Switzerland)	43	43	1200
International Journal of Production Economics	25	40	2126
Journal of Business Research	4	60	117

The best-known and most prolific of them becomes the International Journal of Production research as it contributed to the advancement of theoretical and empirical developments of AI-SCM most. The high level of Sustainability also generates the growing importance of the environmental and social issues that relate to the subject. In the meantime, Production Planning and Control and International Journal of Production Economics have high impact concerning the numbers of citations and have been making a name in fulfilling applied and methodological contributions. A lower number of articles is found in the Journal of Business Research but the number of citations indicates the importance of the journal in management to fill the gap between the interdisciplinary and the managerial sides. The results can help the researchers find appropriate journals to send their papers and follow the trend in areas of their particular interests.

Top Authors

Determining the most notable authors in AI and SCM studies gives the academics a chance to recognize major intellectual contributors, study classic works, and note possible channels of collaboration or reference. Table 4 gives the names of the leading researchers with some details of their publication activity, including the number of publications, overall citations, and h-index-that provide information on the intellectual productivity and academic influence of these authors. Dmitry Ivanov is in the lead in terms of the number of publications paying attention to long-term contributions to methodological integration and supply chains resilience. The large number of citations and h-index value related to Angappa Gunasekaran proves his huge impact on the connection between technological developments and managerial behaviours. As indicated by the relatively high citation level, even though Surajit Bag has fewer publications, it is likely that his work has overall wide applicability, especially in the field of predictive analytics. Overall, these authors can be characterized as the authors important in the formation of AI-powered forecasting, optimization, and sustainability in supply chain management.

To contextualise the influence of these leading scholars, several highly cited publications that have shaped the intellectual evolution of AI–SCM should also be noted. Among the most influential contributions, Ivanov (2020) introduced a foundational model integrating artificial intelligence with supply chain resilience and disruption analytics, which has become widely referenced in subsequent research. Govindan and colleagues have produced extensively cited work linking machine learning with sustainability-oriented supply chain design, establishing one of the conceptual pillars of environmentally responsible AI-enabled logistics.

Another high-impact contribution is the study by Dubey et al. (2020), which connects big data analytics with organisational learning and supply chain performance, demonstrating how data-driven capabilities strengthen strategic decision-making. Additionally, the work of Bag and Gupta provides influential frameworks that combine optimisation, deep learning, and predictive analytics, becoming central reference points for methodological advancement. Collectively, these studies form the foundational set of publications that anchor the present bibliometric landscape of AI-powered supply chains.

Table 4. Leading Authors in AI–SCM Research

Authors	Number of articles	Number of citations	H-INDEX	The power of communication
Dmitry Ivanov	11	662	25	59
George Baryannis	3	729	28	120
Grigoris Antoniou	3	724	27	116
Angappa Gunasekaran	9	945	30	45
Surajit Bag	6	1072	35	31

Publication Trends in Major AI–SCM Journals (2002–2025)

Figure 3 shows the trend of articles published in these five major journals from 2002 up to and including 2025. As can be seen, Sustainability (Switzerland) has recorded massive growth starting from 2018 most probably due to an increased interest in sustainable SCM practices while IEEE access has picked up more recently with intense focus placed on digital technologies such as AI. This data indicates that AI is increasingly being integrated with sustainability and other digital technologies, such as blockchain and IoT, within SCM research.

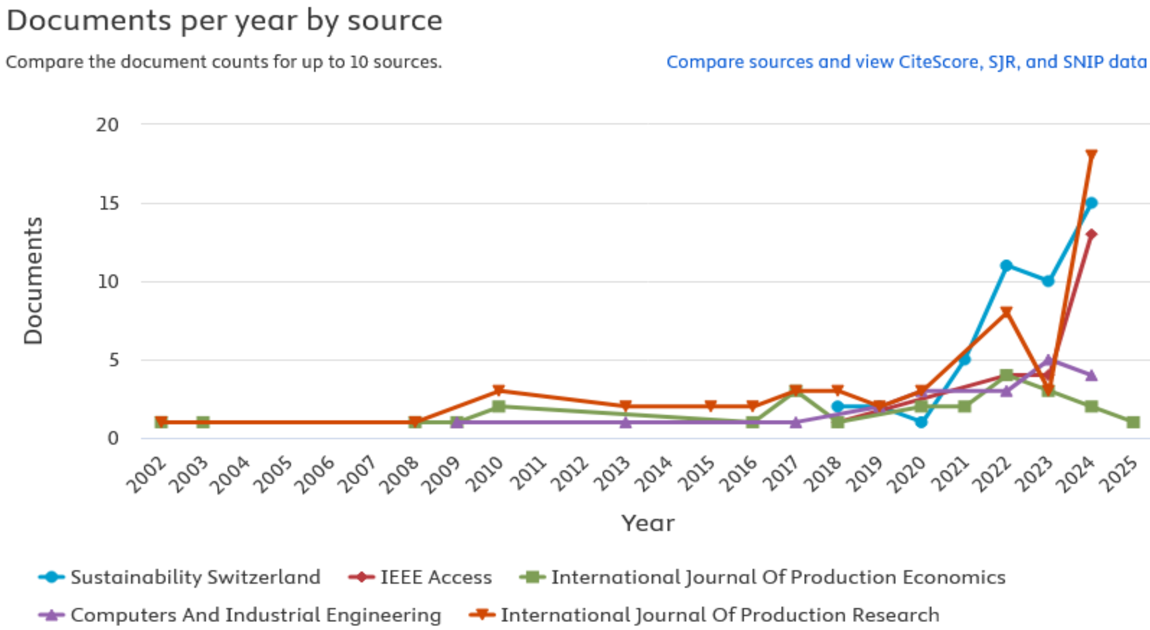

Figure 3. Annual Output in Leading AI–SCM Journals (2002–2025)

Distribution of articles by subject area

The disciplinary emphasis of domain specifications in the 805 AI-SCM studies (Figure 4) is evident because Business and Management journals contribute 25.0 %, Social Sciences 22.3 %, Medicine 15.3 %, Nursing 6.6 %, Environmental Sciences 6.6 %, Psychology 4.6 %, Computer Science 2.8 %, Decision Sciences 2.4 %, Engineering 2.4 %, Arts and Humanities 2.2 %, and Other 9.9 %. This trend indicates the high focus of the field on organizational strategy, policy development, and socio-economic aspects, and when combined with the 21.9 % of Medicine and Nursing representation, the importance of AI in health care supply-chain resilience, a particularly relevant topic during global disruptions, is fully evident.

The fact that the number of Environmental Sciences (6.6 %) is significant speaks of the further urgency to include the concerns of sustainability and ecological impact into the optimization of supply-chains. Quite to the contrary, contributions made by Computer Science, Decision Sciences, and Engineering (combined contribution of 7.6) fraction indicate that methodological and technical progress, although being critical, are confined niches. The Arts & Humanities and Other disciplines (more than 12 %) also indicate at least the potential of unrealized normative, ethical and cultural concerns.

Collectively, the insights offered also define the multidisciplinary scope of the research on AI and AI-SCM, as well as the strategic opportunity: augmenting the technical core to bring faster analytics and optimization, further searching the sustainability side of the explorations, and enhancing AI-SCM with the humanistic lens to assure proper and fair use of AI in complex supply chains.

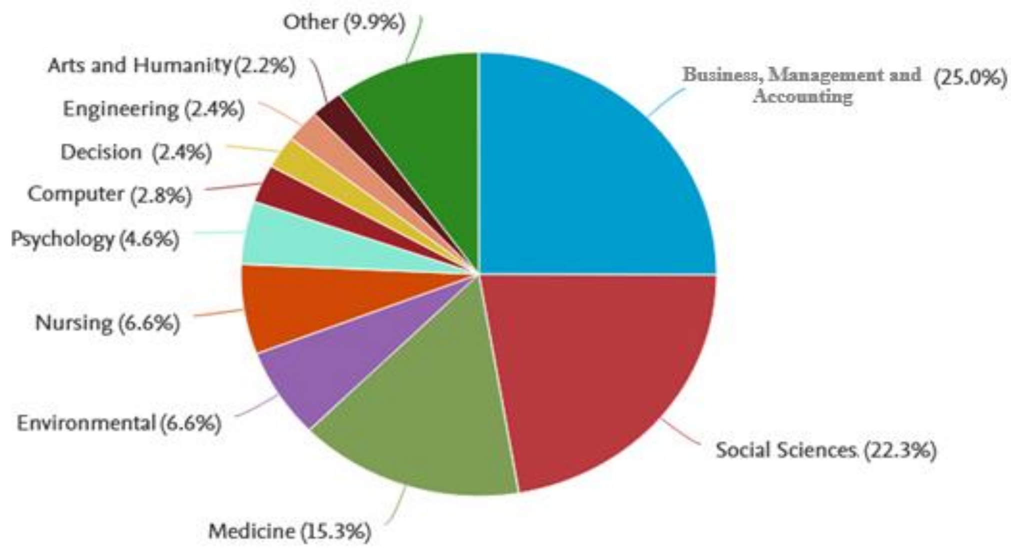

Figure 4. Subject-Area Distribution of AI-SCM Publications (1996–2025)

The predominance of Business and Social Sciences suggests that managerial, organizational, and policy lenses have shaped the discourse on AI in SCM more than technical subfields. This imbalance indicates an opportunity for deeper integration with Decision Sciences and Engineering to translate algorithmic progress into scalable, governed, and ethically aligned deployments.

Co-authorship network

A global co-authorship network was constructed in response to RQ3, which explores how international collaboration influences AI-SCM research. In this network, the size of each node is proportional to the total number of publications by the corresponding author, while the thickness of each edge reflects the intensity of mutual collaboration. This mapping helps address two key analytical questions: (1) who are the most influential scholars in the field, and (2) which collaborative structures foster interdisciplinary innovation.

Major collaborative clusters are at the center. Surajit Bag, Shivam Gupta, and Kannan Govindan form one such central cluster. Long-term methodological collaboration that bridges algorithmic science with industrial applications is represented here (Bag et al., 2019). Sustainability analytics collaboration is illustrated by another close-knit group sharing Yogesh K. Dwivedi, Rameshwar Dubey, and Mihalis Giannakis (Dwivedi et al., 2021). Angappa Gunasekaran plus Hokey Min emerge as the critical brokers straddling technical and managerial research domains (Gunasekaran & Min, 2023). A methodological cluster is evident in operations resilience research, consisting of Rohit Agrawal, Anil Kumar, Sunil Luthra, Ashutosh Samadhiya, and Jose Arturo Garza-Reyes. In resilience-oriented real-time monitoring, smaller sub-communities are formed around Petri Helo, Shaofeng Liu, and Femi Olan. Other groups, such as those including George Q. Huang and Matthias Thuerer, focus on risk mitigation frameworks.

Visualizing these connections allows readers to recognize potential collaborators and emerging hubs, thereby supporting future networked research and interdisciplinary partnerships in the AI-SCM domain. The resulting co-authorship relationships are visualized in Figure 5, which illustrates the main clusters and influential contributors within the AI-SCM research community.

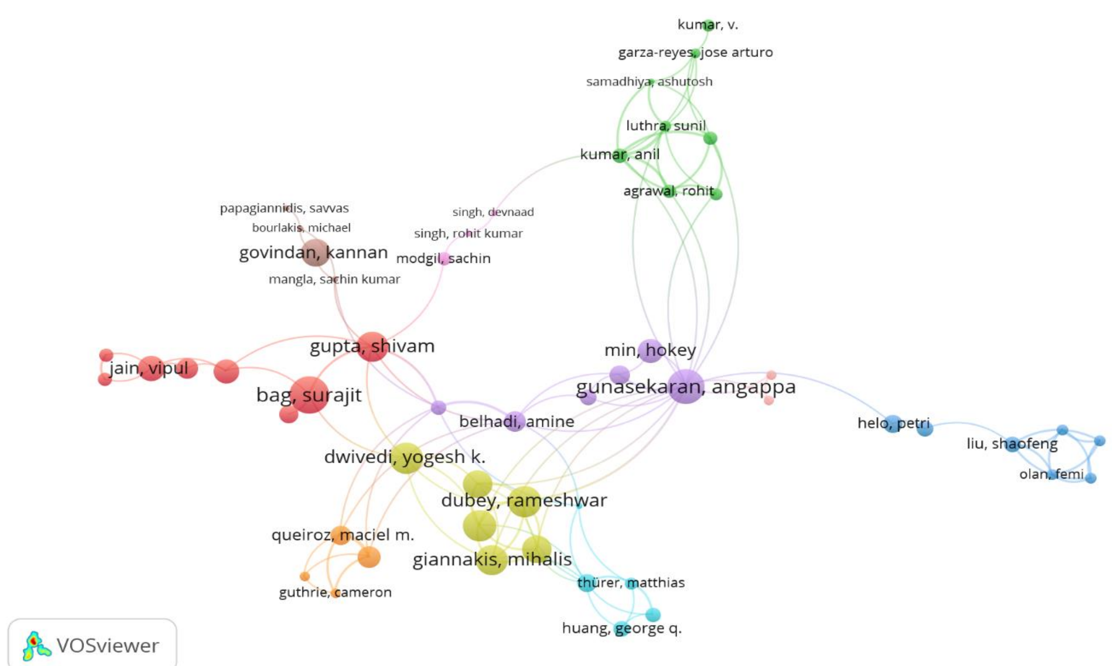

Figure 5. Co-authorship map by topic of AI in SCM

Node size reflects the number of publications; link thickness indicates collaboration strength.

Keyword co-occurrence network

A static co-occurrence network of author-assigned keywords (Figure 6) positions "artificial intelligence" at its core, with strong ties to "machine learning" "deep learning" and "forecasting" thereby confirming the methodological backbone of AI-SCM research. Four salient thematic clusters emerge: (1) a methodological cluster encompassing terms such as "decision support systems", "optimization" and "stochastic systems"; (2) a digital-infrastructure cluster dominated by "Internet of Things" ,"blockchain" and "Industry 4.0"; (3) an application/resilience cluster centred on "supply chain resilience" ,"sustainable production" and "risk management"; and (4) an emerging-topics cluster including "digital twins", "data integrity" and "traceability" .

The overlay visualization (Figure 7) maps each keyword's average publication year, with foundational concepts (e.g., "artificial intelligence", "decision support systems") rendered in cooler hues and recent frontiers (notably "COVID-19", "supply chain agility" and "digital transformation") highlighted in warmer hues. This dual perspective underscores both enduring theoretical pillars and the field's dynamic shift toward addressing global disruptions, sustainability imperatives, and advanced digital integration.

Four clusters dominate the field: methods (decision support, optimization, machine/deep learning; 142 keywords; total link strength = 1,965), digital infrastructures (IoT, blockchain, Industry 4.0; 98 keywords; 1,122), application/resilience (resilience, agility, risk management, sustainability; 97 keywords; 1,084), and emerging topics (digital twins, data integrity, traceability; 31 keywords; 266). Proximity among "resilience–agility–forecasting" indicates tight coupling between predictive analytics and adaptive reconfiguration, while increasing overlay recency for "digital twins" and "traceability" signals a shift toward data-centric governance under uncertainty.

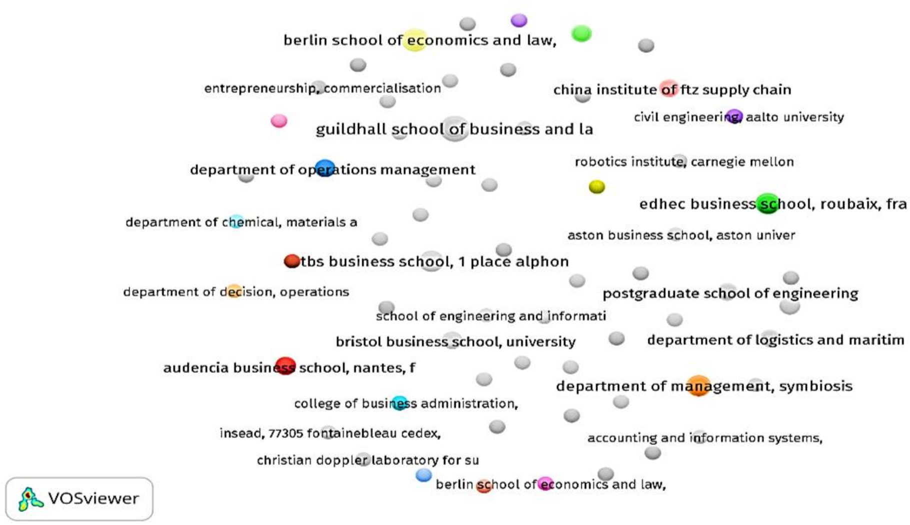

Figure 6. Static Co-Occurrence Network of Author-Assigned Keywords in AI-Driven SCM

Node size represents keyword frequency; colors indicate thematic clusters; and link thickness reflects co-occurrence strength.

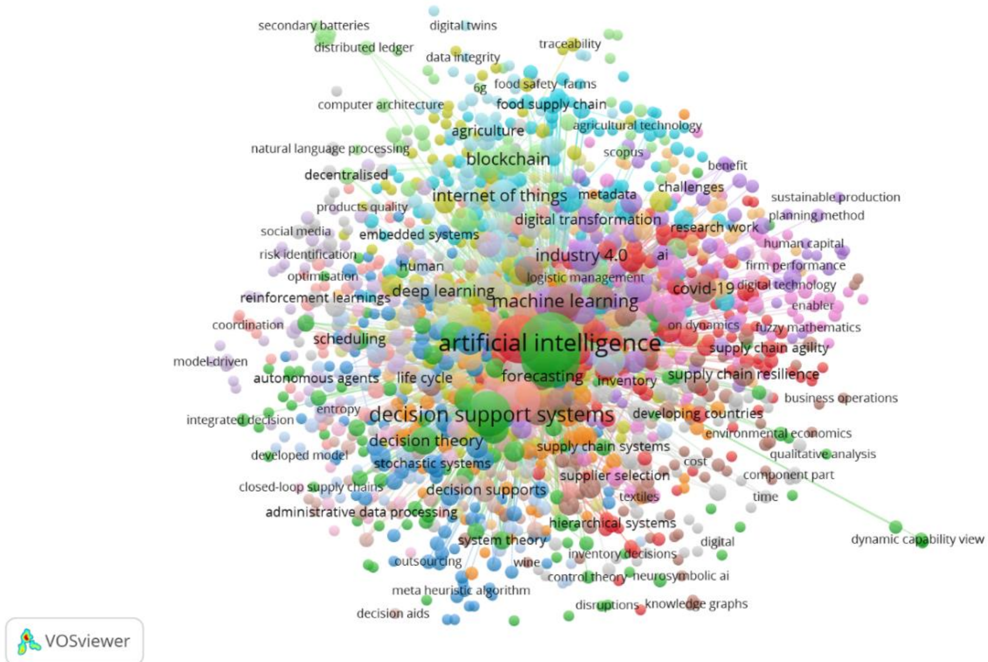

Figure 7.Overlay Map Depicting the Temporal Evolution of Keyword Co-Occurrence in AI-SCM Research

Node size represents keyword frequency; colors indicate thematic clusters; and link thickness reflects co-occurrence strength.

Co-authorship network of countries

In order to answer the RQ3 in detail and to understand how international collaboration can affect the direction of AI application in Supply Chain Management (AI-SCM), the country-level analysis of co-authors was done through data visualization tools, which are based on techniques of bibliometric mapping. The two Figures, 8 and 9, demonstrate the world map of university cooperation in the field of study. Figure 8 is the co-authorship network of countries where each node is a country proportioned to the total number of AI-SCM publications of the country. The connection between the nodes represents the coauthored articles, and the thickness of the line shows the intensity of cooperation.

The outcome shows that the two centers that are dominant both in terms of the volumes of publications as well as the centrality in the network is the United States and India. These countries are in the pinnacles, both in terms of producing the bulk of the world literature as well as in terms of having a large pool of bilateral and multilateral academic connections. Other less but strategically significant hubs are the United Arab Emirates, China, Australia, and Germany, which constitute an active network of hubs to join research clusters.

Having these countries, it can be seen that there is a tendency to the rise in diversity across the regions as well as cooperation internationally in AI-SCM scholarship. The tight subnetworks, including French, Italian, and large Spanish collaboration demonstrate well-established intra-European cooperation, whereas Iran, Turkey, and Egypt serve as the representatives of those countries that begin to enter the mainstream discourse of science.

Figure 9 applies a cluster detection algorithm to the same co-authorship data, grouping countries into distinct regional research alliances. Notable clusters include:

- A Western European cluster (i.e. France, Germany, Italy, Netherlands), reflecting long-standing academic cooperation and integration through EU-funded research frameworks.
- A South Asian cluster pivoting on India and its regional collaborators (e.g., Pakistan, Sri Lanka) reflects dynamism in the emergence of AI-related SCM literature, predominantly associated with practical logistics challenges and public-sector initiatives.
- A North America – East Asia cluster joins the United States with Taiwan and Japan, typical of collaborations driven by technology and focused on digital supply chains and intelligent logistics.

Beside the strong clusters, a group of marginal nodes like Nepal, Kuwait, and Argentina with limited but increasing publication track and poor collaboration ties are also presented. These are the possible boundaries of capacity-building and future inclusion in international research AI-SCM. Collectively, these discoveries have the effect of highlighting the more transdisciplinary, geopolitically diversified and interconnected character of AI-SCM scholarship. The position of some countries indicates not only the academic leadership but also the policy-associated investments in the innovation of supply chains, and the emergence of new contributors evidence the democratization of knowledge production in this development.

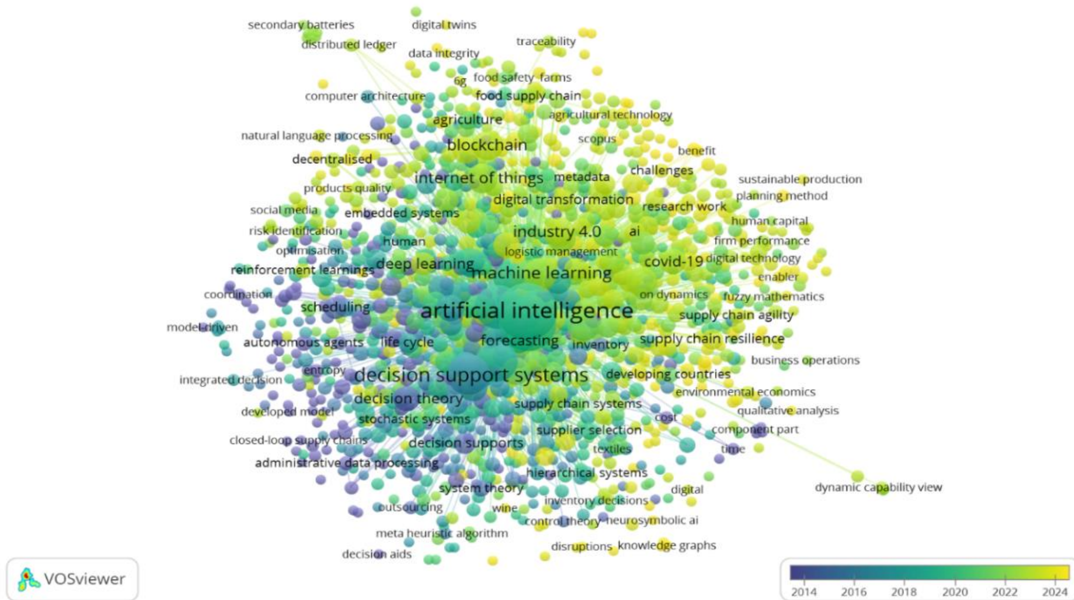

Figure 8. Global Co-Authorship Network of Countries

Node size corresponds to the number of publications per country; link thickness represents co-authored publications; colors denote collaboration clusters.

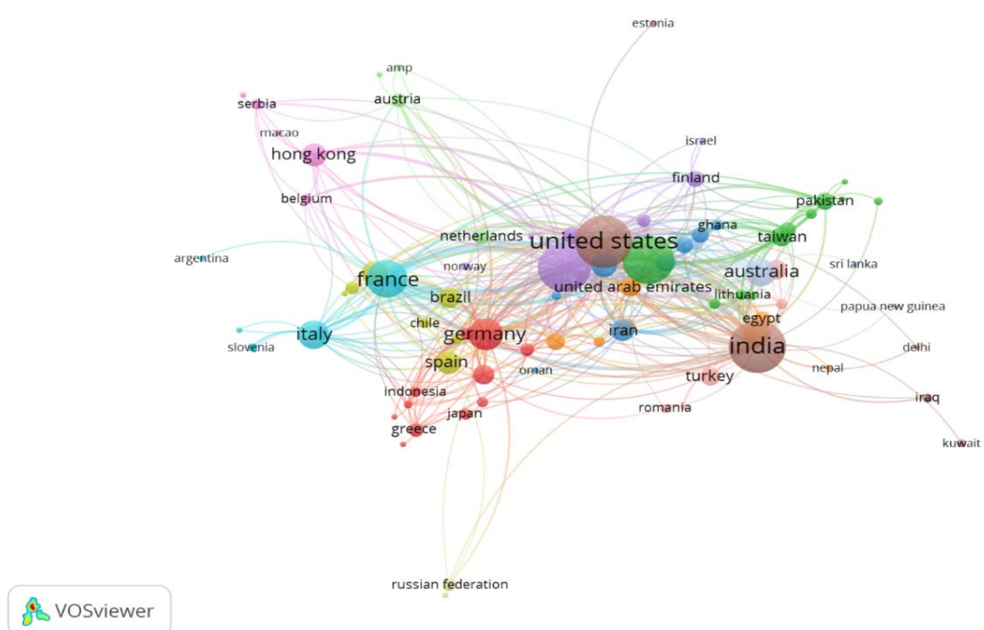

Figure 9. Country Collaboration Clusters in AI-SCM Research

Node size corresponds to the number of publications per country; link thickness represents co-authored publications; colors denote collaboration clusters.

Country-level centrality of the United States and India reflects both research capacity and ecosystem complementarities linking advanced analytics, large manufacturing and service sectors, and extensive collaboration networks. Peripheral yet emerging contributors signal diffusion potential and the importance of capacity-building to diversify knowledge production (Yıldırım et al., 2025). To integrate these global collaboration patterns with our core research themes, Table 5 maps each major topic area onto its key findings and illustrative examples, thereby linking the quantitative network analyses to qualitative insights.

Table 5. Thematic Classification of Research Results in AI-SCM

Topic Area	Key Findings (Result Metric)	Examples or Related Details
Demand Forecasting and Management	AI-driven models enable more accurate demand prediction and inventory optimization, reducing stock-out risks.	Use of machine learning and deep learning algorithms to forecast demand and lower overhead.
Transparency and Resilience	Integration of AI with IoT and blockchain enhances real-time visibility and accelerates response to disruptions.	Deployment of IoT sensors for disruption detection; blockchain for secure records.
Risk Management	AI systems facilitate proactive risk identification and mitigation through advanced data analytics.	Application of predictive analytics on historical and live data streams to flag vulnerabilities.
Supply Chain Sustainability	AI assists in monitoring and reducing environmental impacts, supporting "*green*" logistics and waste reduction.	Analysis of emissions and waste data to inform eco-efficient routing and packaging.
Academic Collaborations	International and interdisciplinary networks have expanded, with leading hubs in the United States, India, and the United Kingdom.	High-impact co-authorship clusters connecting business, engineering, and social-science scholars.
Challenges and Barriers	High implementation costs, shortage of skilled personnel, and data-quality issues remain significant obstacles.	Calls for investment in digital infrastructure and targeted workforce training.
Emerging Trends	Recent research has focused on pandemic-related disruptions, Industry 4.0, and digital-twin applications.	Keywords such as "*COVID-19*", "*supply chain agility*" and "*digital twins*" gaining prominence.

Discussion

This study set out to answer three core research questions: (RQ1) What are the disciplinary priorities of AI in Supply Chain Management (SCM) scholarship? (RQ2) What thematic clusters define the intellectual structure of the field? and (RQ3) How do international collaboration patterns shape AI-SCM research?

Answer to RQ1. Subject-area profiling shows a managerial and social-science core with growing health-care and environmental strands, indicating that organizational strategy and policy logics currently dominate AI-SCM scholarship while technical subfields remain comparatively underrepresented.

Answer to RQ2. Keyword mapping reveals four clusters' methods, digital infrastructures, application and resilience, and emerging topics whose temporal overlay highlights a post-2020 pivot toward agility, pandemic response, and data-centric governance.

Answer to RQ3. Country-level networks center on the United States and India, with Western Europe and South Asia forming dense regional alliances; peripheral yet emerging contributors signal diffusion potential and capacity building needs.

Our findings reveal a pronounced emphasis on Business and Management (25.0 %) and Social Sciences (22.3 %), complemented by substantial contributions from Medicine and Nursing (21.9 %) and an emergent focus on Environmental Sciences (6.6 %). These subject-area priorities confirm that AI-SCM scholarship predominantly addresses organizational strategy, policy implications, and socio-economic impact, while also responding to healthcare and sustainability challenges (Li & Zhang, 2022; Pournader et al., 2021).

The keyword co-occurrence analysis (Figures 6–7) identified four major thematic clusters: methodological foundations (e.g., machine learning, optimization), digital technologies (e.g., Internet of Things, blockchain), application domains, and emerging frontiers (e.g., COVID-19, digital twins). While broadly consistent with prior bibliometric findings (Riahi et al., 2021), the results further indicate a shift toward crisis-related themes and increased digitalization over the period 1996–March 2025.

The increased prominence of terms such as "COVID-19" and "supply chain agility" in the post-2020 period reflects a temporal association between global disruption and scholarly focus on AI-enabled resilience. While the bibliometric design does not permit causal attribution, this alignment indicates a contextual shift in research priorities during periods of systemic uncertainty (Singh et al., 2023).

The co-authorship circles (Figures 8–9) illustrate that the United States and India represent the hubs, and well-connected satellites in Western Europe and South Asia refer not only to linguistic connections but also to the value of close, similar strategic interests (Bahroun et al., 2023). The peripheral location of newly emerging contributors like Kuwait and Argentina points to the unutilized potential for diversifying research and building capacity in underrepresented areas.

Theoretical Implications. Such patterns update our understanding of AI-SCM as a multidisciplinary field where management theory, socio-technical systems, and resilience frameworks interact. The co-occurrence of 'decision support' with 'sustainability' demonstrates the evolving infusion of normative ethics into algorithmic design inviting further development for socio-technical theory (Chen et al., 2022).

Practical and Policy Implications. The prevalence of business-focused studies can present viable best practices that practitioners can follow when implementing AI algorithms in demand forecasting and other inventory optimization practices. The Medical Care Cluster proposes AI-powered logistics solutions in medical supply chains, especially during crises. Policymakers are advised to consider the essential role of digital infrastructure and workforce preparedness—both identified as key obstacles—and to offer incentives that encourage multi-sector expertise development and robust data governance systems (Kim & Lee, 2022).

Limitations. This study is limited by its reliance on Scopus and English-language records, which may underrepresent regional and non-English scholarship. Bibliometric indicators capture structural patterns but do not assess causal effects or implementation performance. Citation counts can be time- and field-dependent. Future work should triangulate multi-database corpora, include non-English sources, and complement mapping with qualitative case studies and longitudinal network dynamics. Database robustness. Reliance on Scopus may underrepresent technical subfields indexed preferentially elsewhere. As a robustness note, we outline a planned extension that cross-checks source coverage against Web of Science and selected regional indices; results of this extension will be documented in an online appendix in future updates.

Given the bibliometric and descriptive nature of the study, the findings identify structural and temporal patterns but do not establish causal relationships between external events and publication dynamics.

Future Research Directions. To address these gaps, we recommend:

1. Incorporate Web of Science and regional databases to broaden language and geographic coverage.
2. Conduct in-depth empirical studies in diverse industries (e.g., pharmaceuticals, humanitarian logistics) to validate bibliometric insights.
3. Apply dynamic network analysis to trace the emergence and dissolution of collaboration clusters over time.
4. Examine the interplay of AI governance policies with supply-chain resilience and sustainability metrics.
5. Foster collaborations between computer scientists, social scientists, and ethicists to develop more holistic, responsible AI solutions.

Conclusion

This paper presented a framework for integrating sales forecast and discount optimization in retail sector. In sales forecasting phase, stock level score is formulated to be used as a feature beside the calendar ones and discount percentage in deep neural network to achieve more precise forecasts. The model parameters including activation functions and number of neurons in each layer were optimized using the PSO algorithm. In addition, a discount optimizer employs the demands to maximize total profit based on discount ladder approach. The main idea is to increase discount percentage of each item by a pre-defined step size on discount ladder until the best combination of discounts is obtained. The computational results focused on forecasting precision by mean absolute of errors as well as the total profit. Numerical experiments revealed that stock level feature leads to MAE improvement in most products. Parameter tunning in deep network topology affects the performance of model. In the case of discount optimization, the outcome of forecasting model is used to maximize the profit. Moving on discount ladder can tune appropriate discount percentage of products, where profit enhancement is obvious according to results. Overall, the proposed framework demonstrates the effectiveness of integrating demand forecasting and pricing decisions within a unified model. The results indicate that the interaction between inventory information and discount strategy plays a significant role in improving retail profitability. These findings highlight the practical applicability of the proposed approach for data-driven decision support in retail operations.

Feature study

While the proposed discount optimizer employs a greedy, SKU-wise ladder search to ensure scalability and operational simplicity, it does not explicitly account for cross-elasticities, substitution effects, or basket-level interactions across products. In real retail environments, price changes in one SKU may influence the demand of related items, affecting overall category performance. Future research could extend the framework toward a multi-product optimization setting by incorporating cross-price elasticity estimation, transaction-level basket modeling, or graph-based product relationship structures. Integrating such interdependencies into a joint optimization model (potentially through mixed-integer programming or reinforcement learning approaches) would enable coordinated discount decisions at the category level and may yield further improvements in overall profitability and demand forecasting accuracy.

Data Availability Statement

Data available on request from the authors.

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Conflict of interest

The authors declare no conflict of interest related to the content, data, or results of this study. All analyses were conducted independently, and no external parties influenced the interpretation or presentation of the findings.

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Ethical considerations

The authors declare compliance with all applicable ethical guidelines, including proper data handling, originality of content, and avoidance of duplicate submission.

References

Ahmed, S., & Rahman, M. (2020). Artificial intelligence-driven inventory management in the retail industry: A case study from India. *International Journal of Retail & Distribution Management*, *48*(4), 387-400.

Azzavi, M., Foukerdi, A., ALTUĞ BIÇER, A., & Ghorbani, S. (2025). Green Efficiency of an Energy Supply Chain: A Multi-Stage Network DEA Application to Iranian Petrochemicals. *Industrial Management Journal*, *17*(4), 1-39.

Bag, S., Gupta, S., & Govindan, K. (2019). Bridging methodological development and industry applications in AI-SCM co-authorship. *International Journal of Production Research*, *57*(15–16), 4719–4742.

Bahroun, Z., Tanash, M., As'ad, R., & Alnajar, M. (2023). Artificial Intelligence Applications in Project Scheduling: A Systematic Review, Bibliometric Analysis, and Prospects for Future Research. *Management Systems in Production Engineering*, *31*(2), 2023. 144-161. https://doi.org/10.2478/mspe-2023-0017

Bassi, R., & Nowak, T. (2021). Artificial intelligence for sustainable supply chains: A systematic review. *Journal of Cleaner Production*, *278*, 123-135.

Bawack, RE., Fosso-Wamba, S., & Carillo, KDA. (2019). Where information systems research meets artificial intelligence practice: Towards the development of an AI capability framework. In DIGIT 2019 Proceedings (Paper 5). Association for Information Systems. https://aisel.aisnet.org/digit2019/5

Belhadi, A., Kamble, S., Fosso-Wamba, S., & Queiroz, MM. (2022). Building supply-chain resilience: An artificial intelligence-based technique and decision-making framework. *International Journal of Production Research*, *60*(14), 4487–4507.

Ben-Daya, M., Hassini, E., & Bahroun, Z. (2019). Internet of Things and Supply Chain Management: A Literature Review. *Research International Journal of Production*, *57*(15–16), 4719–4742.

Bornmann, L., & Daniel, H. (2007). What do we know about the h index?. *Journal of the American Society for Information Science and Technology*, *58*(9), 1381–1385.

Briannis, G., Dani, S., & Antoniou, G. (2019). Predicting supply chain risks using machine learning. *Future Generation Computer Systems*, *101*, 993–1004.

Brynjolfsson, E., & McAfee, A. (2017). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W. W. Norton & Company.

Chen, L., Wang, H., & Li, J. (2023). The impact of artificial intelligence on supply chain productivity: Evidence from the IT sector. *Journal of Supply Chain Management*, *59*(3), 45-62.

Chen, Y., Li, H., & Zhang, T. (2022). Artificial intelligence integration in supply chain management: Enhancing transparency and decision-making. *International Journal of Supply Chain Management*, *12*(4), 450-463.

Creswell, JW., & Plano-Clark, VL. (2017). Designing and conducting mixed methods research (3rd ed.). SAGE Publications.

Dolgoy, V., & Ivanov, D. (2021). Supply chain automation with AI. *Journal of Supply Chain Automation*, *10*(3), 150-165.

Dora, M., Kumar, A., Kumar-Mangla, S., Pant, A., & Muhammad, MK. (2022). Critical success factors influencing artificial intelligence adoption in food supply chains. *International Journal of Production Research*, *60*(14), 4621–4641.

Dwivedi, YK., Dubey, R., & Giannakis, M. (2021). Collaborative advances in sustainability analytics: A network perspective. *Journal of Cleaner Production*, *278*, 123–135.

Fazeli-varzaneh, M., Ghorbi, A., & Bahmani, M. (2020). The study of status of scientific products of Iran in the field of Tourism between 1998-2017. *Tourism Management Studies*, *15*(51), 79–110. https://doi.org/10.22054/tms.2020.30752.1891

Feng, Y., Zhu, Q., & Lai, KH. (2017). Corporate social responsibility for supply chain management: A literature review and bibliometric analysis. *Journal of Cleaner Production*, *158*, 296-307.

Gartner. (2017). Emerging technologies in supply chain management. Gartner Report.

Gunasekaran, A., & Min, H. (2023). Brokers of knowledge: Linking technical and managerial streams in AI-driven supply chain management. Computers & Industrial Engineering, *175*, 108–164.

He, X., Zhao, L., & Wang, J. (2023). AI-driven innovations in supply chain optimization: A systematic review. *Journal of Operations Management*, *45*(2), 210-226.

Helo, P., & Hao, Y. (2021). 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

Kim, D., Lee, H., & Park, S. (2024). Integration of AI and IoT for real-time supply chain management: A case study in the automotive industry. *Computers in Industry*, *153*, 103028

Kim, S., & Lee, J. (2022). Big data analytics and artificial intelligence in supply chain resilience. *Computers in Industry*, *140*, 103-112.

Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, *51*(11), 1016–1022.

Lee, J., Azamfar, M., & Singh, J. (2019). A blockchain-enabled cyber-physical system architecture for Industry 4.0 manufacturing systems. *Manufacturing Letters*, *20*, 34-39.

Lee, J., Bagheri, B., & Kao, HA. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, *3*, 18–23.

Li, X., & Zhang, Y. (2022). Bibliometric analysis of artificial intelligence applications in supply chain management (2018-2021). *Technological Forecasting and Social Change*, *174*, 121-144.

Liu, Z., & Fang, W. (2023). Digital transformation in supply chain management: Role of AI and IoT. *Journal of Business Research*, *56*(3), 112-128.

Okumuş, H., Ghorbani, S., & Karatepe, S. (2019). A study on relationship between financial performance and supply chain in the accepted companies in Borsa Istanbul. *Uncertain Supply Chain Management*, *7*(3), 417-426.

Pan, SL. (2016). Managing information technology in supply chain integration: A critical perspective. Springer.

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/10.1016/j.ijpe.2021.108250

Riahi, Y., Saikouk, T., Gunasekaran, A., & Badraoui, I. (2021). Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. *Expert Systems with Applications*, *173*, 114702. https://doi.org/10.1016/j.eswa.2021.114702

Rodríguez-Espíndola, O., Chowdhury, S., Beltagui, A., & Albores, P. (2020). The potential of emergent disruptive technologies for humanitarian supply chains: The integration of blockchain, artificial intelligence, and 3D printing. *International Journal of Production Research*, *58*(15), 4610–4630.

Rostamzadeh, R., Streimikis, J., Develi, E. I., Ghorbani, S., & Kot, M. (2025). INVESTIGATING THE IMPACT OF PERCEIVED ELEMENTS OF SOCIAL MEDIA MARKETING ON CONSUMER BRAND INTERACTION AND BRAND KNOWLEDGE IN THE FASHION INDUSTRY. *Transformations in Business & Economics*, *24*(3).

Rüther, C., & Rieck, J. (2020). A Grouping Genetic Algorithm for Multi Depot Pickup and Delivery Problems with Time Windows and Heterogeneous Vehicle Fleets. In Evolutionary Computation in Combinatorial Optimization: 20th European Conference, EvoCOP 2020, Held as Part of EvoStar 2020, edited by Paquete, L., & Zarges, C., Seville, Spain, April 15–17, 2020, Proceedings (Vol. 12102). Springer Nature.

Shaik, M., & Siddque, KQ. (2023). Predictive Analytics in Supply Chain Management using SAP and AI. *Journal of Computer Sciences and Applications*, *11*(1), 1-6.

Singh, R., Gupta, A., & Sharma, P. (2023). Real-time supply chain monitoring through AI and IoT integration. *IEEE Transactions on Industrial Informatics*, *19*(1), 78-89.

Smith, JA., & Jones, LM. (2020). Adaptive meta-analysis frameworks integrating natural language processing for evidence synthesis. *Journal of Informetrics*, *14*(3), 311–325.

Stanimirović, P. S., Stupina, A. A., Ghorbani, S., & JABBARI, K. H. (2024). Investigating the cost stickiness behavior of organizations after the economic recession caused by the COVID-19 pandemic. *Journal of Infrastructure, Policy and Development*, *8*(7), 3864.

Statista. (2018). Revenues from the artificial intelligence (AI) market worldwide from 2016 to 2025. Retrieved April 15, 2020, from https://www.statista.com/statistics/607716/.

Van-Eck, N., & Waltman, L. (2009). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, *84*(2), 523–538.

Wang, P. (2021). Connecting the parts with the whole: Toward an information ecology theory of digital innovation ecosystems. *MIS Quarterly*, *45*(1).

Wang, Y., Zhou, Q., & Zhang, P. (2023). Blockchain and AI synergy in supply chain visibility: A framework and applications. *Supply Chain Forum: An International Journal*, *24*(2), 102-117.

Wuni, IY., Shen, GQP., & Osei-Kyei, R. (2019). Scientometric review of global research trends on green buildings in construction journals from 1992 to 2018. *Energy and Buildings*.

Yıldırım, F., Develi, EI., Meidute-Kavaliauskiene, I., Rostamzadeh, R., & Ghorbani, S. (2025). Symmetric encryption and cryptography algorithms in internet of things. *Pesquisa Operacional*, *45*, e295986.