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TRENDS AND FUTURE DIRECTIONS OF ARTIFICIAL IINTELEGENCE AND MACHINE LEARNING IN SUPPLY CHAIN RISK MANAGEMENT

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ABSTRAK

Studi ini bertujuan untuk memetakan tren perkembangan, struktur pengetahuan, dan arah penelitian masa depan untuk AI dan pembelajaran mesin dalam manajemen risiko rantai pasokan. Studi ini menggunakan pendekatan bibliometrik dengan data yang diambil dari Scopus untuk periode 2016–Maret 2026. Analisis dilakukan melalui ko-okurensi kata kunci, visualisasi jaringan, visualisasi overlay, dan visualisasi kepadatan menggunakan VOSviewer. Hasil menunjukkan bahwa publikasi tentang kecerdasan buatan dan pembelajaran mesin dalam manajemen risiko rantai pasokan telah meningkat secara signifikan, terutama setelah tahun 2021. Tema inti yang paling dominan meliputi kecerdasan buatan, pembelajaran mesin, rantai pasokan, dan ketahanan rantai pasokan. Sebaliknya, tema-tema baru yang muncul meliputi analitik prediktif, transformasi digital, kembaran digital, big data, blockchain, dan pembelajaran federasi. Temuan ini menunjukkan pergeseran fokus penelitian dari pendekatan analitis ke pendekatan yang lebih prediktif, adaptif, dan berbasis data. Studi ini menegaskan bahwa integrasi kecerdasan buatan dan pembelajaran mesin dalam manajemen risiko rantai pasokan masih memiliki ruang yang signifikan untuk perbaikan, khususnya dalam implementasi end-to-end, penjelasan, dan integrasi teknologi digital.

ABSTRACT

This study aims to map development trends, knowledge structures, and future research directions for AI and machine learning in supply chain risk management. This study uses a bibliometric approach with data taken from Scopus for the period 2016–March 2026. Analysis was conducted through keyword co-occurrence, network visualization, overlay visualization, and density visualization using VOSviewer. The results show that publications on artificial intelligence and machine learning in supply chain risk management have increased significantly, especially after 2021. The most dominant core themes include artificial intelligence, machine learning, supply chain, and supply chain resilience.In contrast, more recent emerging themes include predictive analytics, digital transformation, digital twins, big data, blockchain, and federated learning. These findings indicate a shift in research focus from an analytical approach to a more predictive, adaptive, and data-driven approach. This study confirms that the integration of artificial intelligence and machine learning in supply chain risk management still has significant room for improvement, particularly in end-to-end implementation, explainability, and digital technology integration.

Keywords: *Artificial intelligence; machine learning; supply chain risk management; supply chain resilience; bibliometric analysis*

1. INTRODUCTION

Global supply chains are currently facing greater complexity due to digitalization, cross-border integration, and the growing frequency of disruptions driven by demand volatility, logistics issues, and geopolitical uncertainty. These conditions require organizations to have end-to-end visibility and more adaptive response capabilities to survive in a dynamic business environment. In this context, Artificial Intelligence (AI) and Machine Learning (ML) are gaining increasing attention because they can improve predictive capacity, accelerate large-scale data processing, and support more responsive, data-driven decision-making (Baryannis et al., 2019; Culot et al., 2024). Similarly, the development of concepts such as the digital supply chain twin also shows great potential in monitoring disruptions and supporting real-time responses (Ivanov & Dolgui, 2021).

Nevertheless, supply chain risk management (SCRM) continues to face fundamental challenges. Modern supply chains are multi-tiered, highly interdependent, and exposed to unpredictable external events, thereby requiring a holistic, integrated approach (Ordibazar et al., 2025; Pan et al., 2025). On the other hand, traditional approaches in SCRM, such as risk matrices and risk priority numbers, remain semi-quantitative, rely on subjective judgment, and are limited in accurately capturing risk dynamics (Hill & Cole, 2025; Mukherjee et al., 2024). These limitations often make conventional approaches insufficiently fast and precise in detecting changes in risk patterns, especially in highly dynamic and uncertain environments (Balan et al., 2025). Therefore, a more predictive, adaptive, and data-driven approach is needed to improve SCRM's effectiveness.

In response to these limitations, AI and ML offer superior capabilities for identifying potential disruptions, learning from historical patterns, and providing real-time data-driven recommendations. Various studies have shown that implementing ML in SCRM can improve the speed of risk detection, predictive accuracy, and the quality of operational decision-making (Aljohani, 2023; Yang et al., 2023). Techniques such as time-series analysis, anomaly detection, and supervised learning also enable organizations to predict supplier failures, identify demand anomalies, and optimize risk mitigation strategies more systematically (Kang & Bhawna, 2025). More broadly, AI and ML have been used in various supply chain functions, including supplier selection, inventory control, transportation, and demand and sales estimation, demonstrating their role as critical tools in building supply chain resilience (Balan et al., 2025; Culot et al., 2024).

However, despite the rapid growth of AI applications in SCRM, the existing literature still exhibits significant limitations. Several studies confirm that research in this area remains fragmented, lacks end-to-end integration, and does not provide a truly comprehensive mapping of research themes, methods, and development directions (Ganesh & Kalpana, 2022; Yang et al., 2023). Existing research also tends to focus on specific cases or applications, thus not fully reflecting the evolution of AI and ML research in the SCRM context as a whole (Culot et al., 2024). Furthermore, aspects of supply chain interdependence, exposure to external events, model transparency, and interrelationships between risk stages have yet to be systematically explored (Ordibazar et al., 2025). In fact, AI-based SCRM automation is still in its infancy and lacks a widely established implementation framework (Das & Perona, 2025). These findings indicate a significant research gap in understanding the scientific landscape, research trends, and future directions of AI and ML in SCRM.

Based on these gaps, this study aims to systematically map the development of AI and ML research in supply chain risk management. Specifically, this research contributes to identifying publication trends, classifying key research themes, analyzing dominant methodological approaches, and formulating a future research agenda relevant to the dynamics of modern supply chain risk. The novelty of this research lies in its comprehensive synthesis, which not only describes the current state but also integrates multiple research dimensions to produce a more holistic, structured understanding of the role of AI and ML in SCRM.

The urgency of this research is heightened by rising global uncertainty and the need for organizations to build more resilient, adaptive supply chains. Therefore, the results of this study are expected not only to enrich the SCRM literature theoretically but also to provide practical implications for organizations, regulators, and policymakers in designing more effective, precise, and intelligent technology-based risk mitigation strategies (Ivanov & Dolgui, 2021).

2. MATERIALS AND METHODS

a. Research Design and Data Sources

This study uses a bibliometric approach to map trends, thematic structures, and research development directions in Artificial Intelligence (AI) and Machine Learning (ML) for Supply Chain Risk Management (SCRM). Bibliometric analysis is a quantitative method used to identify publication patterns, intellectual structure, and the evolution of a scientific field through science mapping and analysis of relationships between publications (Donthu et al., 2021). This approach is suitable for examining the development of research fields that are still growing and have a dynamic thematic structure (Lim et al., 2024).

The bibliographic data in this study were obtained from Scopus, the primary database. Scopus was selected for its widespread use in bibliometric studies. At the same time, differences in coverage across Scopus, Web of Science, and Dimensions underscore the importance of selecting data sources transparently and consistently in line with the research objectives (V. K. Singh et al., 2021). By centralizing data sources in a single database, the search and filtering process becomes more consistent and facilitates tracing publications relevant to AI and ML topics in SCRM (Donthu et al., 2021; Lim et al., 2024).

b. Article Search and Selection Strategy

The search was conducted in the Title, Abstract, and Keywords columns using the following strings: ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("supply chain" OR "supply chain management" OR "supply chain risk" OR "risk management" OR "risk assessment" OR "risk mitigation" OR "risk resilience"). This strategy was chosen to ensure the results accurately represent the research topic and avoid straying into less relevant areas (Donthu et al., 2021).

The overall flow of the article search and selection process is presented in Figure 1, while a detailed breakdown of the selection stages and the number of documents at each stage is shown in Table 1.

Table 1. Article Search and selection scheme

Article Search and Selection (Scopus)	
Stage 1: Database query Result: 2090 documents	TITLE-ABSTRACT-KEYWORD (("artificial intelligence" OR "machine learning" OR "deep learning") AND ("supply chain" OR "supply chain management") AND ("risk management" OR "supply chain risk" OR "risk assessment" OR "risk mitigation" OR "resilience"))
Stage 2: Limitations by year of publication and language. Result: 2032 documents	Limitation criteria: • Publication Year 2016 – Marc 2026 • Language: English
Stage 3: Limitations by document type and Source type Result: 1006 document	Limitation criteria: • Document type: Article, review. • Source type: Journal
Stage 4: Exclusions by subject area and removal of non-relevant articles Result: 585 documents	Exclusion criteria: • Subject area: Enviromental science, biochemistry, genetics and molecular biology, immunology and microbiology, health professions, medicine, materials science, chemistry, physics and astronomy, chemical engineering, arts and humanities, veterinary, nursing, and pharmacology, toxicology and pharmaceutics, etc • Remove keywords that are not relevant to the topic • Removal of duplicate and non-relevant article entries

The search period was limited to 2016 to March 2026, with the publication language English and document types journal articles and reviews. Based on the selection process shown in the flowchart and search table, the initial search phase yielded 2,090 documents. After limiting the documents by publication year and language, the total decreased to 2,032. Further restriction based on document type and publication source yielded 1,006 documents. In the final phase, irrelevant documents, duplicates, and articles not aligned with SCRM's AI and ML focus were removed, resulting in 585 articles for further analysis. This multistep selection process is crucial for maintaining dataset relevance and reducing noise in bibliometric analysis (Donthu et al., 2021; Lim et al., 2024).

c. Data Preprocessing and Bibliometric Analysis

Metadata exported from Scopus includes article titles, author names, publication year, journal source, keywords, abstract, and citation information. Prior to analysis, the dataset was carefully cleaned through data cleaning and term normalization, including matching keywords with similar meanings using a thesaurus file. This step is necessary because term inconsistencies can lead to keyword fragmentation and reduce the accuracy of theme mapping (Lim et al., 2024).

Bibliometric analysis was conducted using VOSviewer employing three main techniques. First, keyword co-occurrence and network visualization were used to identify frequently occurring keywords and map thematic clusters and relationships between concepts in the literature (Donthu et al., 2021; Du et al., 2024). Second, an overlay visualization was used to observe the development of research themes over time by publication year. Third, density visualization was used to assess the concentration and intensity of specific topic occurrences in the dataset. In this analysis, a minimum threshold of five keyword occurrences was set to ensure the analyzed keywords were truly representative of the thematic structure within the dataset. The analysis results were then used to identify dominant themes, interrelationships between topics, and the direction of AI and ML research development in SCRM.

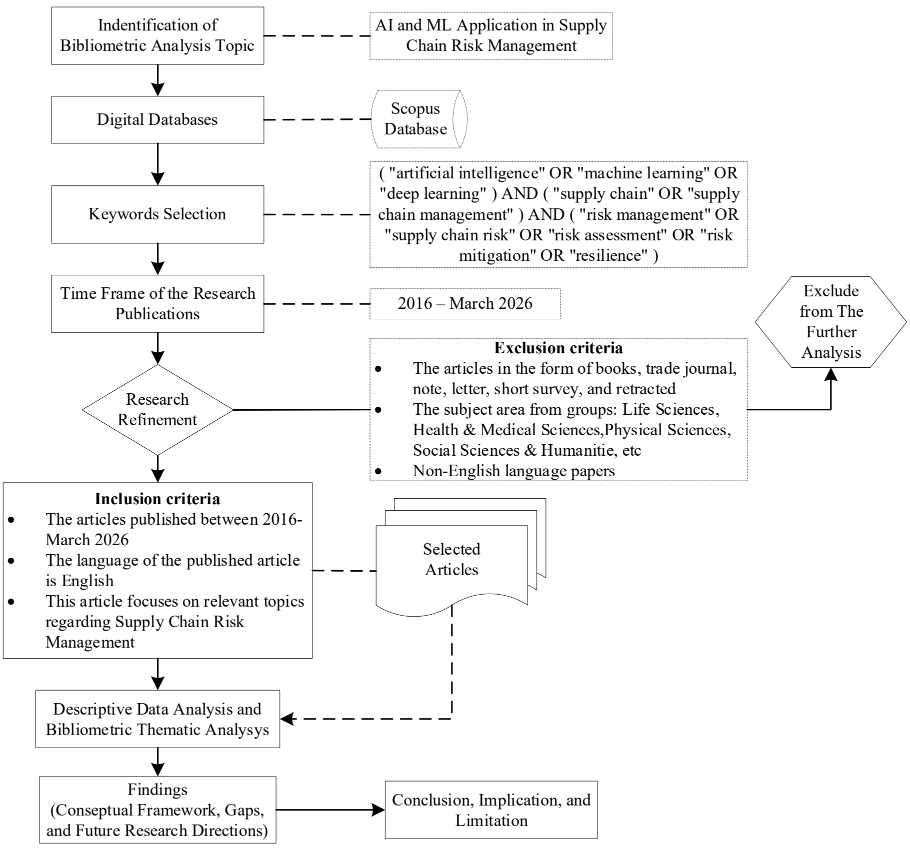
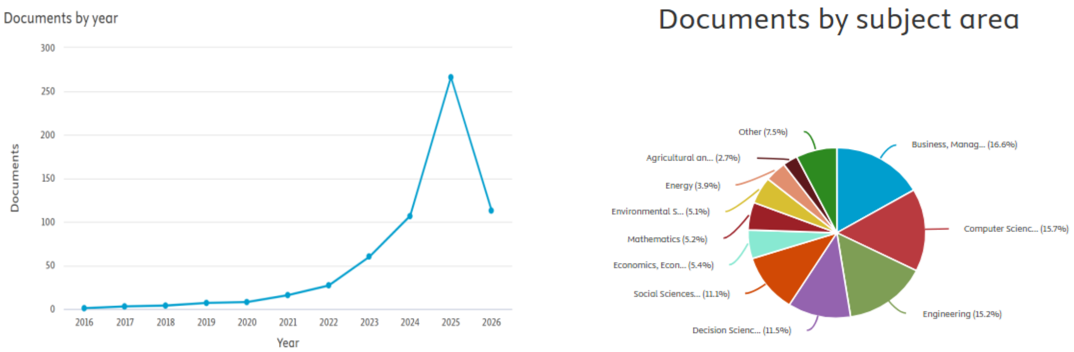


Figure 1. Flowchart of bibliometric methodology

3. RESULTS AND DISCUSSION

a. Publication Trends and Descriptive Profile

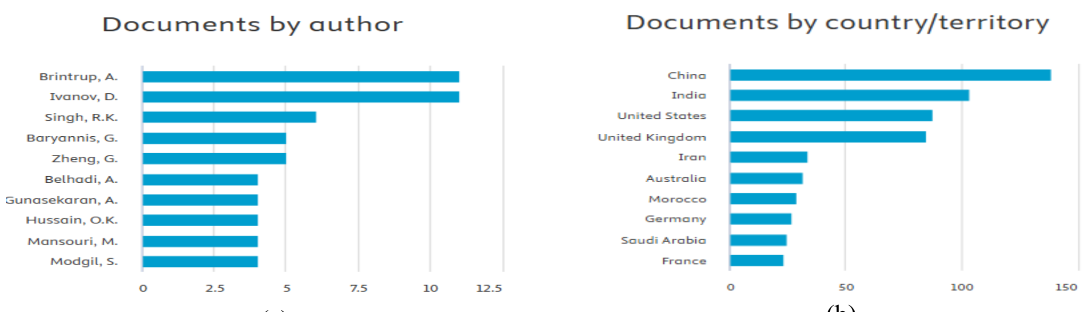
Based on the descriptive analysis, the number of publications on AI and ML in SCRM shows a significant growth trend during the 2016–March 2026 period. Figure 2(a) indicates that in the early phase, from 2016 to 2020, the number of publications was relatively low and increased gradually. However, since 2021, publication growth has accelerated markedly, followed by a sharp increase in the 2024–2025 period. The highest number of publications was recorded in 2025. Meanwhile, the number of publications in 2026 should be interpreted cautiously because the dataset only covers publications up to March 2026 and therefore does not represent a complete publication year. This pattern indicates a growing academic interest in the role of AI and ML in managing supply chain risks, particularly in increasingly uncertain, complex, and dynamic supply chain environments.



(a) (b)

Figure 2. (a) Trend in the number of research publications (2016 -March 2026); (b) Distribution of publication by subject area

In terms of disciplines, Figure 2(b) shows that this research is developing in a multidisciplinary way. The largest contributions come from Business, Management, and Accounting, followed by Computer Science, Engineering, and Decision Sciences. Furthermore, fields such as Social Sciences, Economics, and Mathematics also make significant contributions. This composition indicates that AI and ML studies in SCRM focus not only on technology or algorithm development but also encompass managerial aspects, decision-making, and economic and organizational implications. Thus, this field lies at the intersection of complementary technical and managerial approaches.



(a) (b)

Figure 3. (a) Authors with the highest number of publications; (b) Country with the highest number of publications

Regarding author productivity, Figure 3(a) shows that some researchers have more dominant contributions than others. Authors such as Brintrup and Ivanov occupy the top positions, followed by Singh, Baryannis, and Zheng. This indicates that the development of this field is still heavily influenced by a few key researchers who consistently contribute to shaping the direction and focus of research. The concentration of contributions among these few authors also indicates that the field of AI and ML in SCRM is still in its infancy, with a core research community playing a crucial role in advancing the literature.

Meanwhile, the distribution of publications by country in Figure 3(b) indicates that research in this field is global. China recorded the highest number of publications, followed by India, the United States, and the United Kingdom. Other countries, such as Iran, Australia, and several European countries, also contributed, albeit in smaller numbers. The dominance of these countries reflects significant investment and attention in developing AI technology and applying it to supply chains. Furthermore, this distribution demonstrates that supply chain risk and the use of intelligent technology are increasingly important cross-national concerns in the context of globalization.

Overall, this analysis of publication trends and descriptive profiles indicates that AI and ML research in SCRM is experiencing rapid growth, is multidisciplinary, and is driven by contributions from a diverse range of researchers and countries. These findings provide a solid foundation for further analysis of the knowledge structure, the evolution of research themes, and future research directions.

b. Structure of Scientific Knowledge in AI and Machine Learning in Supply Chain Risk Management

To identify the knowledge structure in this field, keyword co-occurrence analysis was used to map relationships among concepts in the AI and ML literature on SCRM. The resulting network visualization is presented in Figure 4.

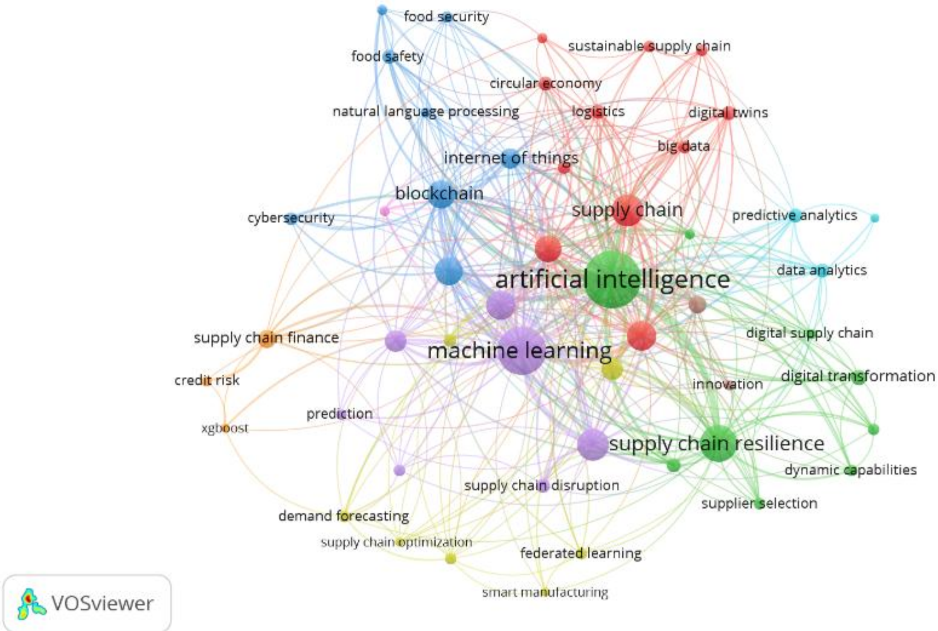


Figure 4. Network Visualization

The map shows that the terms artificial intelligence, machine learning, supply chain, and supply chain resilience occupy a central position in the network, demonstrating their role as core concepts in research development. These four terms have extensive links to various other themes, such as predictive analytics, digital transformation, big data, blockchain, the internet of things, digital twins, supplier selection, demand forecasting, cybersecurity, food safety, sustainable supply chain, and the circular economy. This interconnectedness demonstrates that AI and ML are no longer positioned solely as analytical tools but have evolved into key enablers in increasing visibility, supporting risk prediction, and strengthening adaptive supply chain response capabilities. This finding aligns with Culot et al., (2020), who demonstrated that the application of AI in the supply chain evolves through the integration of data requirements, technology implementation processes, and implications for organizational performance. Furthermore, Ivanov

& Dolgui, (2021) emphasized that digital technologies, such as AI and digital supply chain twins, enable greater visibility and real-time management of disruption risks.

Furthermore, the strong linkages between supply chain resilience, digital transformation, predictive analytics, big data, blockchain, IoT, and digital twins reflect a shift in research focus from operational efficiency to early detection, mitigation, and recovery from disruptions. In this context, Queiroz et al., (2022) demonstrate that digital technology plays a crucial role in enhancing supply chain resilience by increasing transparency and coordination among actors. Meanwhile, Dubey et al., (2020) suggest that the use of AI and data analytics increases visibility and agility, key elements in building supply chain resilience. Thus, the thematic structure depicted in Figure 1 demonstrates the interdisciplinary nature of this field. However, there remains room to strengthen the integration of technical approaches and managerial perspectives in the development of AI and ML for SCRM.

c. Temporal Evolution of Research Themes

After mapping the scientific knowledge structure onto the keyword co-occurrence network, an overlay visualization was used to interpret the development of research themes over time. In VOSviewer, node colors move from blue to green to yellow as scores increase, so yellow nodes represent newer themes, while blue nodes indicate themes earlier in the literature corpus. Thus, the overlay map not only shows the conceptual relationships between concepts but also the order in which they emerged and the temporal shifts in research focus.

Based on the resulting map (see Figure 5, the themes of artificial intelligence, machine learning, supply chain, and supply chain resilience appear at the core of the network, with a blue-green hue. This pattern indicates that these four concepts are the initial foundation for the development of AI and machine learning literature in supply chain risk management. This finding aligns with Culot et al., (2024), who demonstrated that AI in supply chain management evolves from issues of data and system requirements, technology implementation processes, integration between actors, and implications for performance. Singh et al., (2024) also emphasized that AI plays a crucial role in creating a more resilient supply chain by enabling transparency, optimizing procurement strategies, and mitigating the impact of disruptions.

In the transition phase, the themes of blockchain, the internet of things, big data, digital twins, sustainable supply chains, the circular economy, logistics, and cybersecurity are increasingly moving closer to the green-yellow spectrum. This shift demonstrates that the literature is no longer focused solely on AI and machine learning as analytical tools, but is beginning to shift toward digital infrastructure that enables comprehensive risk visibility, connectivity, and coordination. This developmental direction is consistent with (Ivanov & Dolgui, 2021), who position digital supply chain twins as a crucial mechanism for managing disruption risks and resilience in real time. Longo et al., (2023) also show that digital supply chain twins can enhance resilience and sustainability in the face of crises, while Zhao et al., (2023) demonstrate that supply chain digitalization positively impacts supply chain resilience and performance through the dynamic capabilities pathway.

The most recent themes on the map, which are typically colored yellow, include predictive analytics, data analytics, digital transformation, dynamic capabilities, supplier selection, demand forecasting, and federated learning. The emergence of these themes demonstrates a shift in research from simply understanding and mapping risk to using AI and machine learning for more predictive and prescriptive decision-making. In other words, the research focus is shifting from detecting disruptions to predicting, selecting the best response, and building adaptive capacity within the supply chain. This direction is reinforced by (Gabellini et al., 2025), who emphasize the importance of data, prediction, and decision support in intelligent digital twins for supply chain risk management. Sunmola & Baryannis, (2024) also note that AI offers significant opportunities to strengthen supply chain resilience by enabling a more responsive approach to disruptions.

Overall, the temporal evolution of this map reveals three major developmental stages. The first stage involves establishing the conceptual foundations of AI and machine learning in the supply chain. The second stage demonstrates the integration of digital technologies such as blockchain, IoT, big data, and digital twins to enhance transparency, visibility, and connectivity. The third, most recent, stage focuses on risk intelligence, utilizing AI and machine learning for predictive analytics, demand forecasting, supplier selection, and dynamic capabilities. These findings indicate that the field of supply chain risk management is shifting from a reactive to a proactive, adaptive approach, opening up a stronger research landscape for AI integration, supply chain resilience, and data-driven decision-making.

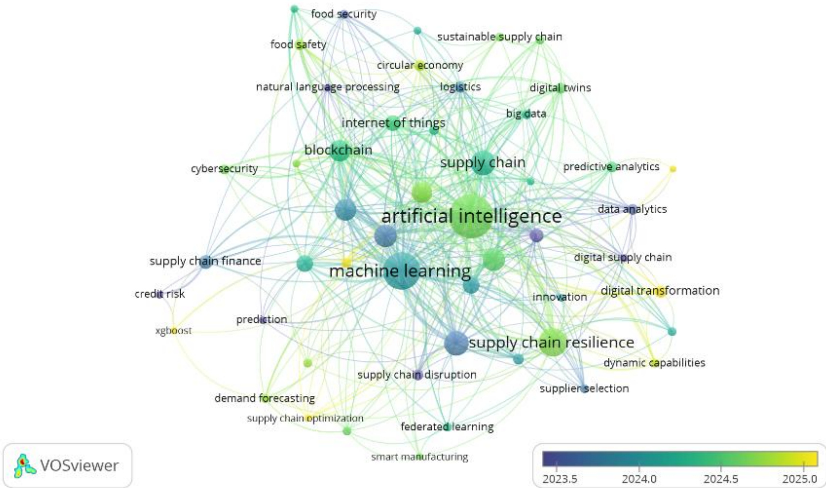


Figure 5. Overlay Visualization

d. Density Visualization and Research Concentration

After analyzing the structure of scientific knowledge and the temporal evolution of research themes, density visualization was used to examine the concentration of topics within the analyzed bibliometric dataset, namely 585 Scopus-indexed journal articles and review articles on AI and ML in Supply Chain Risk Management. In VOSviewer, the colors on the density map represent the density of items around a point: green-yellow areas indicate higher concentrations, while blue areas indicate lower concentrations. Thus, this visualization helps identify the most dominant themes and relatively underexplored areas within the analyzed field.

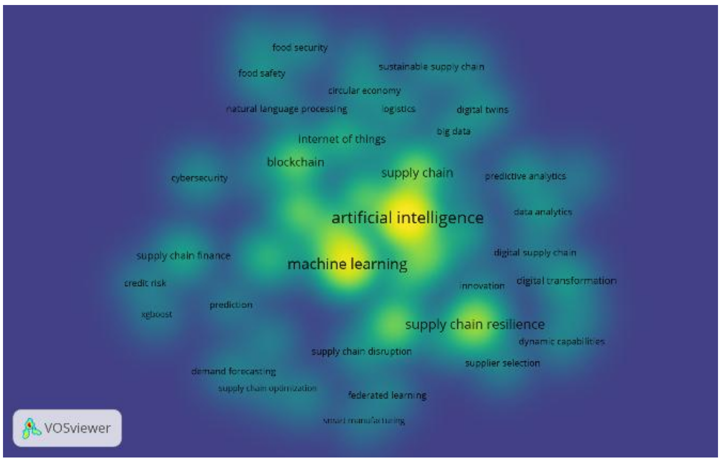


Figure 6. Density visualization

As shown in Figure 6, the strongest research focus is on artificial intelligence, machine learning, supply chain, and supply chain resilience. These four themes form a very clear center of density and can be interpreted as the core of the scientific discourse in the literature on AI and Machine Learning in Supply Chain Risk Management. This dominance indicates that AI and machine learning are no longer seen solely as technical approaches but are now key elements in the development of analytical, predictive, and adaptive supply chain capabilities. These findings are consistent with a systematic review by Toorajipour et al., (2021), which found that AI in supply chains is developing across logistics, production, marketing, and supply chain management. Furthermore, Culot et al., (2024) emphasized that AI research in SCM focuses on data and system requirements, technology implementation processes, interorganizational integration, and performance implications. Furthermore, Zamani et al., (2023) demonstrated that AI and big data analytics enhance supply chain resilience, particularly during the readiness, response, recovery, and adaptability phases.

Around this central density, a moderate concentration of topics, including blockchain, the internet of things, big data, digital twins, predictive analytics, digital transformation, sustainable supply chains, and the circular economy, is also evident. This pattern indicates a shift in focus from AI and machine learning as analytical tools to a broader digital technology ecosystem. In this context, digital technology supports transparency, visibility, and risk coordination in the supply chain. This direction aligns with Benhamou et al., (2026), who emphasized that digital twins in the supply chain have the potential to correct deviations in real time and anticipate and prevent disruptions, although operational implementation remains limited. In other words, the density of these digital themes indicates that the literature is moving beyond simply introducing technology to leveraging it for strengthening resilience and data-driven decision-making.

Meanwhile, themes such as supplier selection, demand forecasting, federated learning, cybersecurity, supply chain finance, and credit risk are located in relatively peripheral areas. This position indicates that these topics are still in their developmental stage and have not yet received as much research concentration as core themes. Substantively, this situation demonstrates that research opportunities remain wide open, particularly in integrating AI and machine learning into more specific decision-making processes in supply chain risk management. Thus, density visualization not only emphasizes the most established themes but also reveals research gaps that can be targeted to develop predictive methods, enhance risk mitigation, and advance more adaptive supply chain resilience strategies.

Overall, the density visualization results reinforce the findings in the previous subsection. While network visualization demonstrates the interconnectedness of concepts, and overlay visualization demonstrates the temporal dynamics of research themes, density visualization confirms the level of concentration and maturity of each theme. This map shows that the current literature remains heavily focused on AI, machine learning, and supply chain resilience. In contrast, themes such as federated learning and supply chain finance still warrant further exploration. Thus, density visualization provides a solid basis for formulating future research directions in this field.

e. Research Gaps and Future Research Directions

The synthesis of the three bibliometric visualizations shows that the knowledge structure in the field of AI and Machine Learning in Supply Chain Risk Management remains focused on artificial intelligence, machine learning, supply chain, and supply chain resilience as the primary research foundation. On the other hand, overlay visualization indicates a shift toward more advanced themes such as predictive analytics, digital transformation, dynamic capabilities, and federated learning. In contrast, density visualization confirms the dominance of the AI/ML–resilience theme in the existing literature. This pattern indicates that although the field has developed conceptually, gaps remain in practical implementation, technology integration, and end-to-end risk management. These findings align with recent studies showing that AI research in supply chain management still focuses on data requirements, implementation processes, and organizational performance, while its application in supply chain risk management still requires a more holistic and proactive approach (Culot et al., 2024; Ganesh & Kalpana, 2022; Yadav et al., 2024; Zamani et al., 2023).

Table 2 shows that research gaps in AI and Machine Learning in Supply Chain Risk Management lie not only in method development but also in conceptual integration and practical implementation. Based on network, overlay, and density visualization results, core themes such as AI, machine learning, and supply chain resilience have reached a relatively high level of maturity, while other themes are still developing gradually. This pattern indicates that the current literature remains dominated by technology-based approaches, which have not yet been fully integrated into a comprehensive risk management framework.

The main gaps lie in methodological aspects, particularly in explainability, model validation, and implementation in real-world contexts. This aligns with Culot et al., (2024), who emphasized that AI research in the supply chain still focuses on data and system requirements and has not fully accounted for the complexity of organizational decision-making. Furthermore, Ganesh & Kalpana, (2022) indicate that the application of AI in supply chain risk management is still in its early stages and requires a more holistic approach to support risk monitoring and predictive decision-making.

Table 2. Research gaps and future directions

Cluster Theme	Key Research Focus	Key Insight (Bibliometric Evidence)	Theoretical Implication	Methodological Gap	Future Research Direction
AI and Machine Learning Core	Application of AI and ML in supply chain risk analysis	Highest density and strongest connectivity in the network and density maps	AI is positioned as a foundational element of SCRM rather than merely an analytical tool	Limited explainability and poor generalizability of models	Development of explainable AI, robust ML, and cross-sector validation
Supply Chain Resilience	Resilience of supply chains under disruption	Strongly connected with AI, predictive analytics, and digital transformation	Shift from efficiency-oriented logic to a resilience-based paradigm	Lack of integrated models across readiness, response, and recovery phases	Development of simulation-based and scenario-based resilience models
Digital Technologies Integration	Blockchain, IoT, Big Data, and Digital Twins	Emerged strongly in the overlay map as recent themes	Digitalization acts as an enabler of visibility and risk coordination	Fragmented integration across technologies	Development of an integrated, real-time digital supply chain architecture
Predictive and Prescriptive Analytics	Demand forecasting, supplier selection, and data analytics	Displayed in yellow in the overlay map, indicating the most recent themes	Shift toward data-driven decision-making	Limited real-world implementation in strategic decision-making	Integration of AI into predictive and prescriptive decision support systems
Sustainable and Circular Supply Chain	Sustainability and circular economy	Connected to the core cluster but with lower density	Sustainability is gradually becoming embedded in SCRM	Sustainability is still treated separately from risk frameworks	Integrated models combining risk, resilience, and sustainability
Emerging and Peripheral Topics	Cybersecurity, federated learning, and supply chain finance	Located in peripheral and low-density areas	Emerging topics with high potential but still immature	Limited empirical evidence and practical validation	Empirical studies across industries and collaborative multi-actor approaches

From a technological perspective, integrating AI with blockchain, the internet of things, and digital twins is one of the most promising areas, yet implementation remains limited. Ivanov & Dolgui, (2021) demonstrated that digital supply chain twins can enhance real-time simulation and disruption management capabilities, while Zhao et al., (2023) emphasized that digitalization significantly contributes to supply chain resilience. However, most studies still discuss these technologies separately, necessitating an integrative approach to building adaptive, data-driven supply chain systems.

Furthermore, the sustainability dimension also reveals a conceptual gap. Although the themes of sustainable supply chains and the circular economy have emerged in the research landscape, their integration with risk management remains limited. Recent studies have shown that AI has significant potential to support sustainable supply chain management, particularly through increased efficiency and transparency (Yadav et al., 2024; Zamani et al., 2023). However, research that integrates risk, resilience, and sustainability aspects within a single analytical framework remains very limited.

Overall, future research directions should focus on developing models that are not only technically sophisticated but also practically relevant and integrative. This includes the development of explainable AI, the end-to-end integration of digital technologies, and the integration of risk, resilience, and sustainability dimensions into adaptive, data-driven decision-making systems (Culot et al., 2024; Ivanov & Dolgui, 2021; Zamani et al., 2023; Zhao et al., 2023).

4. CONCLUSION

This study aims to map the development, knowledge structure, and future research directions in AI and Machine Learning for Supply Chain Risk Management through a bibliometric analysis. The analysis shows that the core themes of artificial intelligence, machine learning, supply chain, and supply chain resilience dominate the literature in this field. Findings from the network visualization demonstrate that AI and machine learning have become the primary foundation for supply chain risk management research. In contrast, the overlay visualization indicates a shift in focus toward more advanced themes, such as predictive analytics, digital transformation, dynamic capabilities, and federated learning. Meanwhile, the density visualization confirms that research remains strongly concentrated on AI/ML and supply chain resilience.

Overall, the results of this study indicate that the field has evolved from a conceptual approach to a more predictive, adaptive, and data-driven one. However, there is still significant room for improvement, particularly in integrating digital technology, managerial perspectives, and actual implementation in supply chain risk management. Thus, this study confirms that AI and machine learning serve not only as analytical tools but also as key enablers for improving supply chain resilience and adaptability.

In terms of theoretical implications, this study enriches the literature by demonstrating that AI/ML-based supply chain risk management needs to be understood as the intersection of intelligent analytics, digital transformation, and supply chain resilience. In practice, the results can serve as a foundation for supply chain managers, policymakers, and industry players to develop risk-detection systems that are more proactive, transparent, and responsive to disruptions. Themes such as predictive analytics, digital twins, and digital transformation also offer opportunities to broaden the application of technology to support strategic decision-making.

This study has several limitations. First, the data were drawn solely from the Scopus database, so the results depend on its indexing scope. Second, this bibliometric analysis used specific keywords and thresholds, potentially overlooking relevant studies with different terminology. Third, this study focused on mapping the structure of the literature, thus failing to thoroughly assess the methodological quality or empirical impact of each study. Therefore, future research is recommended to use multiple databases, expand the search strategy, and combine bibliometric approaches with systematic literature reviews to produce a more comprehensive picture.

REFERENCES

Aljohani, A. (2023). Predictive analytics and machine learning for real-time supply chain risk mitigation and agility. *Sustainability*, *15*(20), 15088. https://doi.org/https://doi.org/10.3390/su152015088

Balan, G. S., Kumar, V. S., & Raj, S. A. (2025). Machine learning and artificial intelligence methods and applications for post-crisis supply chain resiliency and recovery. *Supply Chain Analytics*, *10*, 100121. https://doi.org/https://doi.org/10.1016/j.sca.2025.100121

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research*, *57*(7), 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Benhamou, L., Giard, V., & Lamouri, S. (2026). Digital twins in supply chain management: Scope and methodological issues. *International Journal of Production Economics*, *291*, 109842. https://doi.org/https://doi.org/10.1016/j.ijpe.2025.109842

Culot, G., Nassimbeni, G., Orzes, G., & Sartor, M. (2020). Behind the definition of Industry 4.0: Analysis and open questions. *International Journal of Production Economics*, *226*, 107617. https://doi.org/https://doi.org/10.1016/j.ijpe.2020.107617

Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions. *Computers in Industry*, *162*, 104132. https://doi.org/https://doi.org/10.1016/j.compind.2024.104132

Das, S. K., & Perona, M. (2025). Supply chain risk management automation: A literature review. *Electronic Markets*, *35*(1), 104. https://doi.org/10.1007/s12525-025-00844-1

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. . *Journal of Business Research*, *133*, 285–296.

Du, Q., Zhao, R., Wan, Q., Li, S., Li, H., Wang, D., Ho, C. W., Dai, Z., Chen, Y., & Shan, D. (2024). Protocol for conducting bibliometric analysis in biomedicine and related research using CiteSpace and VOSviewer software. *STAR Protocols*, *5*(3). https://doi.org/10.1016/j.xpro.2024.103269

Dubey, R., Gunasekaran, A., Bryde, D. J., Dwivedi, Y. K., & Papadopoulos, T. (2020). Blockchain technology for enhancing swift-trust, collaboration and resilience within a humanitarian supply chain setting. *International Journal of Production Research*, *58*(11), 3381–3398. https://doi.org/10.1080/00207543.2020.1722860

Gabellini, M., Regattieri, A., Bortolini, M., & Ronchi, M. (2025). Conceptualization and validation of an intelligent digital twin design framework for supply chain risk management. *International Journal of Information Management Data Insights*, *5*(2), 100365. https://doi.org/https://doi.org/10.1016/j.jjimei.2025.100365

Ganesh, D. A., & Kalpana, P. (2022). Future of artificial intelligence and its influence on supply chain risk management – A systematic review. *Computers & Industrial Engineering*, *169*, 108206. https://doi.org/https://doi.org/10.1016/j.cie.2022.108206

Hill, A., & Cole, R. (2025). Improving the risk matrix for supply chain risk management. *Continuity & Resilience Review*, *7*(2), 166–181. https://doi.org/10.1108/CRR-01-2025-0003

Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, *32*(9), 775–788. https://doi.org/10.1080/09537287.2020.1768450

Kang, P. S., & Bhawna, B. (2025). Enhancing supply chain resilience through supervised machine learning: supplier performance analysis and risk profiling for a multi-class classification problem. *Business Process Management Journal*, *31*(7), 2825–2848. https://doi.org/10.1108/BPMJ-03-2024-0174

Lim, W. M., Kumar, S., & Donthu, N. (2024). How to combine and clean bibliometric data and use bibliometric tools synergistically: Guidelines using metaverse research. *Journal of Business Research*, *182*, 114760. https://doi.org/https://doi.org/10.1016/j.jbusres.2024.114760

Longo, F., Mirabelli, G., Padovano, A., & Solina, V. (2023). The Digital Supply Chain Twin paradigm for enhancing resilience and sustainability against COVID-like crises. *Procedia Computer Science*, *217*, 1940–1947. https://doi.org/https://doi.org/10.1016/j.procs.2022.12.394

Mukherjee, S., De, A., & Roy, S. (2024). Supply chain risk prioritization: a multi-criteria based Intuitionistic Fuzzy TOPSIS approach. *International Journal of Quality & Reliability Management*, *41*(6), 1693–1725. https://doi.org/10.1108/IJQRM-07-2023-0214

Ordibazar, A. H., Hussain, O. K., Chakrabortty, R. K., Irannezhad, E., & Saberi, M. (2025). Artificial intelligence applications for supply chain risk management considering interconnectivity, external events exposures and transparency: a systematic literature review. *Modern Supply Chain Research and Applications*, *7*(2), 148–179. https://doi.org/10.1108/MSCRA-10-2024-0041

Pan, H., Cheng, M., Wang, R., Zou, N., & Liu, D. (2025). Digital transformation and supply chain resilience in Chinese manufacturing: the mediating role of supply chain risk. *Asia Pacific Journal of Marketing and Logistics*, 1–17. https://doi.org/https://doi.org/10.1108/APJML-01-2025-0059

Queiroz, M. M., Ivanov, D., Dolgui, A., & Fosso Wamba, S. (2022). Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review. *Annals of Operations Research*, *319*(1), 1159–1196. https://doi.org/10.1007/s10479-020-03685-7

Singh, R. K., Modgil, S., & Shore, A. (2024). Building artificial intelligence enabled resilient supply chain: a multi-method approach. *Journal of Enterprise Information Management*, *37*(2), 414–436. https://doi.org/10.1108/JEIM-09-2022-0326

Singh, V. K., Singh, P., Karmakar, M., Leta, J., & Mayr, P. (2021). The journal coverage of Web of Science, Scopus and Dimensions: A comparative analysis. *Scientometrics*, *126*(6), 5113–5142. https://doi.org/10.1007/s11192-021-03948-5

Sunmola, F., & Baryannis, G. (2024). Artificial Intelligence Opportunities for Resilient Supply Chains. *IFAC-PapersOnLine*, *58*(19), 813–818. https://doi.org/https://doi.org/10.1016/j.ifacol.2024.09.195

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

Yadav, A., Garg, R. K., & Sachdeva, A. (2024). Artificial intelligence applications for information management in sustainable supply chain management: A systematic review and future research agenda. *International Journal of Information Management Data Insights*, *4*(2), 100292. https://doi.org/https://doi.org/10.1016/j.jjimei.2024.100292

Yang, M., Lim, M. K., Qu, Y., Ni, D., & Xiao, Z. (2023). Supply chain risk management with machine learning technology: A literature review and future research directions. *Computers & Industrial Engineering*, *175*, 108859. https://doi.org/https://doi.org/10.1016/j.cie.2022.108859

Zamani, E. D., Smyth, C., Gupta, S., & Dennehy, D. (2023). Artificial intelligence and big data analytics for supply chain resilience: a systematic literature review. *Annals of Operations Research*, *327*(2), 605–632. https://doi.org/10.1007/s10479-022-04983-y

Zhao, N., Hong, J., & Lau, K. H. (2023). Impact of supply chain digitalization on supply chain resilience and performance: A multi-mediation model. *International Journal of Production Economics*, *259*, 108817. https://doi.org/https://doi.org/10.1016/j.ijpe.2023.108817