AI-Enabled Decision Support Systems for Supply Chain Management: A Systematic Literature Review

BURCU ELİF BÜLBÜL, ESİN MUKUL, NAZLI GÖKER
Industrial Engineering Department,
Galatasaray University,
Besiktas, 34349, Istanbul,
TÜRKİYE

Abstract: - This work outlines the review of the role of Artificial Intelligence (AI) in improving Decision Support Systems (DSS) for value chain management and its planning. Complex and uncertain environment of global value chains have diminished the effectiveness of conventional approaches, recommending AI-allowed DSS for more adaptive and data-driven decision-making procedures. These DSSs enhance forecasting robustness, resource allocation, and strategic as well as operational decisions. The related researches focus on the key AI technologies namely machine learning, predictive analytics, and optimization frameworks. They improve decision making effectiveness in areas like reverse logistics and recovery planning while also supporting goals. AI also brings transparency, trust and accountability into decision making processes. In addition AI-powered decision support systems help create resilient and competitive value chains. Still there are challenges. These include system integration and the need, for more human-centered and sustainability-focused designs.

Key-Words: - Artificial Intelligence, decision support systems, digital technologies, literature review, supply chain management, systematic review.

Received: September 3, 2026. Revised: September 24, 2026. Accepted: October 4, 2026. Published: November 13, 2026.

1 Introduction

Supply chain management (SCM) possesses a significant role in organizing material, information, and financial flows across complicated and global networks. Recently, increasing demand variability, multi-tier supplier structures, and improving sustainability, and hence resilient value chains have dealt with the complex supply chain decision-making processes. Under these circumstances, conventional analytical techniques and deterministic planning tools have become inadequate to cope with uncertain, nonlinear supply chain structure, and rapid environmental changes [1], [2].

Rapid advances in Artificial Intelligence (AI) have made decision support systems (DSS) key enablers of more adaptive, data-driven value chain management. AI-supported DSS incorporates tools named as machine learning, predictive analytics, optimization models to have improved forecasting robustness, resource allocation, and strengthened operational processes. In addition, these systems provide improved decision quality in terms of strategic, tactical, and operational levels of value chain planning [3].

Although the rapid improvements of AI applications in SCM continue, the existing literature remains incomplete. Many papers concentrate on isolated decision problems or specific AI tools without converting them into clear DSS structure. In addition, significant components namely explainability, human-focused design, and sustainability are generally seen as secondary aspects rather than integral properties of DSS. This disintegration limits the practical applicability, transparency, and long-term effect of AI-integrated DSS. Particularly, important gaps are faced with system-level integration, human–AI interaction, and the integration of sustainability as a maim decision goal [4], [5].

To deal with these limitations, this work proposes a systematic synthesis of AI-supported decision aids in value chain management. Throughout the literature, the paper makes an analysis of existing contributions from descriptive, analytical, and thematic aspects. Specifically, it observes (i) the different types of value chain decision problems defined, (ii) the AI tools and methodological frameworks applied, (iii) the design and integration degree of DSS structures, and (iv) the extent to which explainability, sustainability, and human–AI collaboration are included. Besides, the objective of this paper is to employ a systematic understanding of

AI-supported DSS and to indicate the research gaps and future research directions for intelligent and sustainable value chain decision-making procedure.

In order to support this analysis, research questions are created via a systematic literature review:

RQ1. In the current literature, what varieties of decision-making challenges related to value chain management are tackled by AI-enhanced decision support systems?

RQ2. What AI instruments and methodological structures exist? How can they be systematically organized?

RQ3. In what ways are the frameworks for AI-enhanced decision support systems formulated, and how effectively do they facilitate tactical and operational choices?

RQ4. How do current decision-making systems emphasize attributes such as explainability, reliability, and transparency? What framework enhances managerial understanding and acceptance?

RQ5. To what degree are considerations of sustainability, resilience, and life-cycle perspectives integrated into AI-enhanced decision support systems?

The remaining parts of the paper are organized as follows. Section 2 gives the conceptual background of AI-supported DSS in value chain management. Section 3 explains the literature review about the subject. Section 4 outlines the results related to the research questions. The final section delineates the conclusions and outlines directions for future research.

2 Supply Chain Management with AI-Supported Decision Support Systems

Modern value chains work in complicated and vague environments with the presence of globalization, multi-tier networks, demand variability, and sustainability and resilience needs. Although global sourcing and lean applications have enhanced efficiency, they have also augmented vulnerability to disruptions [6], [7]. In consequence, conventional deterministic planning models are now insufficient to keep up with nonlinear properties and real-time variations. They create a requirement for more adaptive DSS [8]. With the digitalization of value chain procedures and the augmenting availability of operational data, DSS has become more data-intensive system. Besides, traditional DSS remains insufficient in order to cope with uncertain and complex supply chains.

DSS helps supply chain decisions plan inventory and logistics processes [9], however, traditional systems were limited by rule-based frameworks and static assumptions. The incorporation of AI led us to have more intelligent and adaptive DSS. Machine learning, predictive analytics, and optimization improve forecasting and operational decisions by modeling complex and uncertain environments [5], [10]. Hybrid approaches combining AI with fuzzy logic and multi-criteria decision-making methods enhance decision quality [11], [12], [4], [7].

In recent years, researchers also focus on sustainable and human–AI collaboration systems. AI-supported DSS contributes to low-carbon and resilient value chain design [13], [14], thus AI improves transparency and trust [4]. In similar manner, human-focused approaches note the significance of combining human judgment with AI [3]. In addition, these developments led to AI-supported DSS possessing a critical role for next-generation value chain management. In such supply chain, intelligent, transparent, and sustainability-focused decision-making is essential for long-term competitiveness and resilience.

3 Literature Review

This study uses a structured and systematic literature review approach to identify classify and synthesize research on AI–supported DSS, in supply chain management. Than looking at individual studies alone the review follows a thematic and table‑driven synthesis to capture methodological, technological and application‑oriented characteristics of the literature.

In this section the review process and review results are presented.

3.1 Review Process

The review process followed known systematic review guidelines. This study was conducted to ensure clarity and reproducibility of the work, as well as to facilitate an understanding of the methods employed. A comprehensive search was carried out using the Web of Science database, incorporating combinations of keywords related to artificial intelligence-based DSS and supply chain management. The main search string included terms, like (“ intelligence" OR "machine learning”) AND (“decision support system" OR "decision support systems" OR "intelligent decision-making”) AND (“supply chain" OR "logistics" OR "supply chain management”). Only English-language papers were included to keep things consistent.

Clear inclusion and exclusion criteria were applied to refine the dataset. Inclusion and exclusion criteria are as follows:

Inclusion criteria:

- Peer-reviewed journal articles or conference papers,
- Studies explicitly addressing AI-supported DSS,
- Research is situated in supply chain management or closely related domains,
- Conceptual, methodological, or empirical studies,
- Full-text availability.

Exclusion criteria:

- Non-peer-reviewed articles (e.g., editorials, white papers),
- Studies focusing solely on AI algorithms without a decision support perspective,
- Articles unrelated to supply chain decision-making,
- Duplicate publications.

Following the PRISMA protocol shown in Figure 1, an initial screening yielded 142 studies. After removing duplicates and applying screening and eligibility criteria, a final sample of 33 peer-reviewed studies was selected for in-depth analysis. These studies form the basis for the descriptive and technical classifications presented in the subsequent sections.

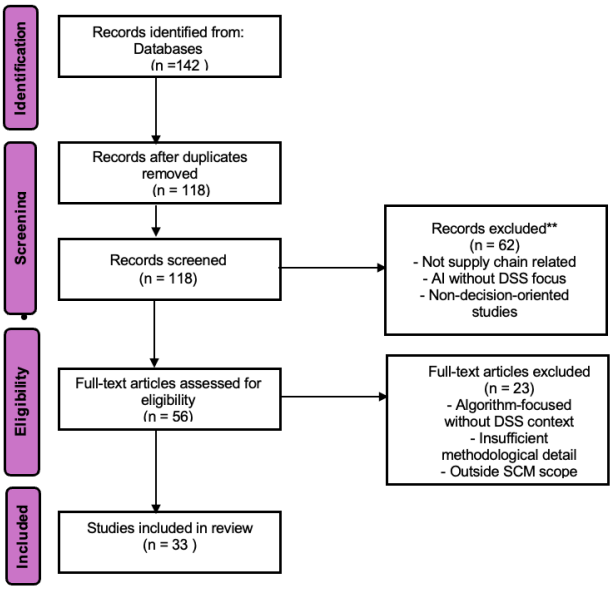


Fig. 1: A diagrammatic representation of the PRISMA review process
Source: created by the authors

3.2 Review Results

Table 1 (Appendix) and Table 2 summarize the findings of the literature review. Table 1, in the Appendix shows a list of the studies that were looked at. It includes the year each study was published what the study aimed to achieve the industry or field where it was applied the part of sustainability it focused on and whether the study used a DSS approach. Table 2 gives a breakdown. It lists the intelligence methods used the ways the studies were conducted and the types of analysis applied in AI-supported DSS. When taken together, these tables present an overview of how artificial intelligence-enabled DSS are examined across different supply chain environments, in the context of various decision-making problems, and through diverse research methodologies.

Table 2. Studies about AI-supported DSS in supply chain with technique details

Year	Author(s)	AI Type	Used Approach
2009	[9]	Multi-AI DSS	CBR, MAS, fuzzy inference
2019	[11]	Neuro-Fuzzy DSS	ANFIS, EOQ optimization
2019	[17]	Predictive AI	Regression, optimization
2021	[12]	Hybrid AI–DSS	Fuzzy MCDM, optimization, game theory
2021	[6]	Real-time AI DSS	Predictive analytics, scheduling optimization
2021	[15]	AI-based DSS (Retail)	Predictive analytics, RL optimization
2022	[18]	AI-based DSS (Review)	SLR, classification, content analysis
2022	[8]	Predictive AI (Review)	Bibliometric mapping
2022	[16]	Explainable AI DSS	Causal modelling, sensitivity analysis
2024	[10]	AI-driven operations	Qualitative coding
2025	[5]	Predictive AI (Review)	RF, SVM, ANN, CNN1D, Fuzzy–Bayesian
2025	[4]	Trustworthy AI	Link prediction, ontology reasoning
2025	[3]	Human-centric AI DSS	Interviews, sensemaking analysis
2025	[13]	Sustainability AI DSS	Multi-objective modelling, meta-heuristics
2025	[2]	Sustainability AI (Review)	SLR, sustainability classification
2025	[14]	Low-carbon AI DSS	SLR, content analysis
2025	[7]	Knowledge-based AI DSS	Scenario reasoning

Source: created by the authors

A comprehensive review of the literature highlights aspects and gaps regarding AI-powered DSS for supply chain management. From an industry perspective most research focuses on the

manufacturing and logistics sectors, where clear processes and easy access to data facilitate the use of AI‑powered DSS. In contrast sectors such as construction, machinery and equipment and hospitality and tourism remain largely unaddressed; this indicates a bias toward data‑rich environments and a lack of diversity, in how AI‑powered DSS can be implemented.

Methodologically, data-driven forecasting approaches—specifically machine learning and deep learning techniques such as ANN, RF, SVM, CNN, and LSTM—are frequently employed in the literature. These models demonstrate strong capabilities in determining non-linear connections and managing uncertainty, making them widely used for forecasting, lead-time estimation, and operational optimization [5], [15]. A major limitation, though, is that these techniques are frequently employed as individual analytical instruments instead of being incorporated into broader decision support system architectures. As a result, a considerable amount of the research focuses more on the precision of computations instead of converting results into practical insights for management.

A smaller but important stream of research employs hybrid and uncertainty-aware approaches, including fuzzy logic, neuro-fuzzy systems, Bayesian networks, and multi-criteria decision-making methods, which are particularly relevant in complex and ambiguous decision contexts [11], [16]. Figure 2 shows the distribution of AI techniques. In addition, emerging knowledge-based and explainable AI approaches, such as knowledge graphs, graph neural networks, and neuro-symbolic reasoning, offer promising avenues for enhancing transparency and trust. Nevertheless, these approaches remain largely conceptual or experimental and have not yet been widely operationalized [4], [7].

From a decision support perspective, the analysis reveals that only a subset of studies adopts a fully integrated DSS approach, incorporating scenario analysis, alternative evaluation, and managerial interpretation [3], [10]. A significant portion of the literature focuses primarily on technical model performance, with limited attention to system design, user interaction, and organizational decision processes. This indicates a fundamental gap between AI model development and practical decision support implementation.

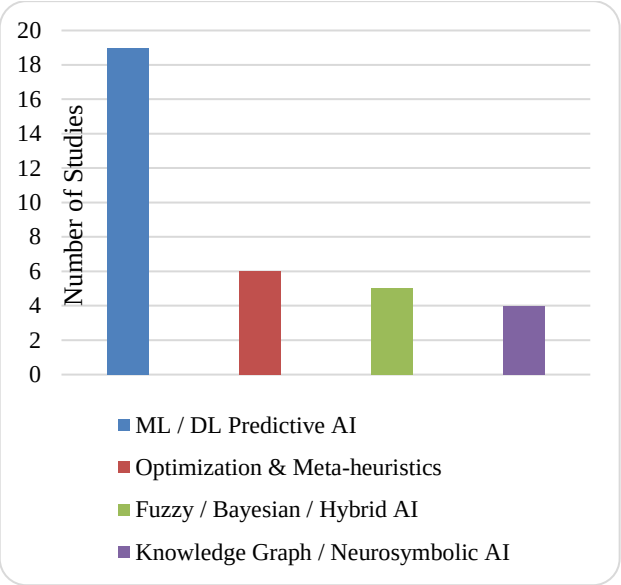


Fig. 2: Distribution of AI techniques used in AI-supported DSS
Source: created by the authors

Additionally, even though they are becoming more prevalent, sustainability and resilience issues are usually handled as secondary goals rather than being included into DSS systems as fundamental decision criteria [12], [14]. In a similar vein, human-centric viewpoints are still lacking, with the majority of AI-DSS being viewed as automated tools rather than cooperative systems that combine AI and human judgment. Despite their significance for management adoption and efficient decision-making, issues of explainability, transparency, and trust are also not fully addressed.

The results show a difference in what is being published right now. Most of the work is focused on how AI can predict things. But there isn't progress, in how AI systems work together how they can explain themselves how sustainable they are and how they can work with people. This shows that future research should not just look at AI doing one task at a time. Instead it should focus on creating systems that are open easy to understand and built around people. These systems need to handle the important needs of today's supply chains.

3.3 Key Technical Insights

A number of significant insights about the state of AI-supported DSS in supply chain management are revealed by the technical synthesis [13-15].

- *Dominance of predictive AI:* The literature is dominated by machine learning and deep learning models; these studies tend to focus more on operational optimization and forecasting rather than on decision-oriented system design.

- *Limited DSS integration:* Many artificial intelligence techniques, which have been integrated to only a limited extent into comprehensive DSS designs, are used as standalone analytical tools.
- *Underutilization of uncertainty-aware methods:* Techniques such as fuzzy logic, Bayesian networks, and hybrid intelligent systems are still underutilized, despite being well-suited for addressing uncertainties in expert-driven decision-making contexts.
- *Emergence of explainable AI:* Knowledge-based and explainable artificial intelligence techniques—such as knowledge graphs and causal models—are attracting increasing interest, even though they largely remain at a conceptual level and have not yet been sufficiently operationalized.
- *Weak human–AI collaboration:* The majority of implementations place a low priority on interpretability, sensemaking, and human-centered decision support in favor of automation and predictive accuracy.

When combined, these results show that the current supply chain management AI-DSS literature is distinguished by strong methodological sophistication in predictive analytics but little advancement in system-level integration, sectoral diversity, and the creation of human-centric and explainable design principles.

These trends clearly highlight the need for a more comprehensive viewpoint, which this study attempts to provide by putting forth a conceptual framework that unifies human decision-making, DSS systems, and AI capabilities.

Therefore, the goal of this study is to methodically locate, categorize, and evaluate academic research that looks at the development, use, and consequences of AI-supported supply chain management DSS. The review concentrates on AI approaches, DSS structures, explainability, sustainability, and human–AI cooperation, all of which are guided by the research issues.

4 Findings and Discussion

The significant patterns, imbalances, and implications for AI-supported DSS in supply chain management are highlighted in this part, which summarizes the key findings of the systematic literature study in connection to the research topics.

- ***RQ1: Supply Chain Decision Problems:*** Although a variety of supply chain decision-making issues are covered in the examined research, operational and tactical levels are the main focus. The majority of the literature focuses on delivery delays, routing, and disruption management in logistics and transportation environments [5, 6, 9]. The majority of supply chains are manufacturing-oriented, with research concentrating on lifecycle analysis, production planning, and analytics-driven decision support [8], [13], [19], and [20]. There is a glaring sectoral mismatch, though, as retail apps are still scarce and industries like construction, equipment, and hospitality are hardly present.
- ***RQ2: AI Techniques and Methodological Approaches:*** Data-driven predictive AI techniques are clearly in the lead, according to the report. The widespread usage of machine learning and deep learning techniques, including ANN, RF, SVM, CNN, and LSTM, is indicative of their efficacy in predicting and optimization applications [5], [8]. While knowledge-based and graph-oriented approaches are still rare and mostly experimental, hybrid approaches that combine AI with optimization or fuzzy logic are present but less prevalent [4], [11]. Predictive accuracy is generally prioritized in the literature, with prescriptive and explainable decision-making receiving comparatively less emphasis.
- ***RQ3: DSS Design and Integration:*** Just about half of the research explicitly adopt a DSS approach to system architecture, integrating AI models into decision support frameworks that allow management interpretation and scenario analysis [3], [15], and [21]. A substantial amount of the research is still algorithm-centric, focusing on model performance with little concern for user interface, system architecture, or decision-making processes. This implies that supply chain applications do not have fully integrated, end-to-end DSS infrastructures.
- ***RQ4: Explainability and Trustworthiness:*** Only a small percentage of studies address explainability and transparency, whereas the majority rely on black-box AI models. Although some studies use explainable AI methods like neurosymbolic approaches or Bayesian reasoning [4], [16], the general focus is still on prediction performance rather than interpretability. This disparity makes it difficult for managers to trust AI-supported DSS in the real world.
- ***RQ5: Sustainability and Resilience:*** Sustainability and resilience considerations are evident, but they are not yet central to the literature. Resilience-oriented, low-carbon, or lifetime decision support is used in very few

studies [12], [14], often in response to exogenous disturbances like as the COVID-19 pandemic [6]. However, most studies focus on efficiency and forecast accuracy, treating sustainability as a secondary objective rather than a crucial component of DSS design.

When combined, the results show a recurring pattern: whereas the literature shows significant technical progress in predictive AI, system-level integration, sectoral variety, explainability, and sustainability-oriented design are still lacking. This disparity emphasizes the need for a change to more comprehensive, open, and human-centered AI-supported DSS frameworks that can handle the intricate and strategic requirements of contemporary supply chains.

5 Conclusion and Future Directions

The literature currently in publication is mostly focused on operational and tactical decision issues in manufacturing and logistics environments, according to this study's methodical synthesis of research on AI-DSS in supply chain management. Despite the dominance of predictive AI algorithms, their practical effect and managerial significance are restricted due to their poor integration into comprehensive DSS infrastructures.

The paper makes a theoretical contribution by emphasizing the need for integrated, understandable, and human-centric AI-DSS frameworks by framing AI as an embedded part of DSS rather than a stand-alone analytical tool. Limited industry variety, inadequate end-to-end DSS integration, a lack of focus on explainability and reliability, a marginal inclusion of human judgment, and the handling of sustainability as a secondary rather than primary goal are some of the major weaknesses that have been found. These gaps highlight structural constraints that impede the prudent and strategic use of AI-DSS in intricate supply chain settings.

Future research should focus on creating an integrated AI-supported DSS that addresses operational, tactical, and strategic decision levels. A focus on explainable and trustworthy AI methods, such as causal modeling, knowledge graphs, and neuro-symbolic reasoning, is essential to increasing transparency and managerial trust. Additionally, resilience, sustainability, and life-cycle perspectives must be taken into account while making judgments. In the end, adopting a human-centric, socio-technical design perspective that promotes collaboration between human decision-makers and AI systems is one of the most crucial methods to develop intelligent, moral, and sustainable supply chain decision-making.

Acknowledgement:
This work has been supported by the Scientific Research Projects Commission of Galatasaray University FBA-2026-1334. This paper is dedicated to the memory of Prof. Dr. Y. Esra Albayrak, whose guidance, inspiration, and lasting impact on our academic development will never be forgotten.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

References:

[1] 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.

[2] Chowdhury, S., Ren, S., & Jnr, R. G. R. (2025). Leveraging artificial intelligence to facilitate green servitization: Resource orchestration and Re-institutionalization perspectives. International Journal of Production Economics, 281, 109519. https://doi.org/10.1016/j.ijpe.2025.109519.

[3] Hao, X., Demir, E., & Eyers, D. (2025). Beyond human-in-the-loop: Sensemaking between artificial intelligence and human intelligence collaboration. Sustainable Futures, 10, 101152. https://doi.org/10.1016/j.sftr.2025.101152.

[4] Kosasih, E. E., & Brintrup, A. (2025). Towards trustworthy AI for link prediction in supply chain knowledge graph: a neurosymbolic reasoning approach. International Journal of Production Research, 63(6), 2268-2290. https://doi.org/10.1080/00207543.2024.2399713.

[5] Müller, N., Burggräf, P., Steinberg, F., Sauer, C. R., & Schütz, M. (2025). An analytical review of predictive methods for delivery delays in supply chains. Supply Chain Analytics, 11, 100130. https://doi.org/10.1016/j.sca.2025.100130.

[6] Alswailem, O. A., Horanieh, B. K., AlAbbad, A., AlMuhaideb, S., AlMuhanna, A., AlQuaid, M., ... & AbuSalah, A. (2021). COVID-19 intelligence-driven operational response platform: experience of a large tertiary multihospital system in the Middle East. Diagnostics, 11(12), 2283. https://doi.org/10.3390/diagnostics11122283.

[7] Rolf, B., Mebarki, N., Lang, S., Reggelin, T., Cardin, O., Mouchère, H., & Dolgui, A. (2022). Using knowledge graphs and human-centric artificial intelligence for reconfigurable supply chains: A research framework. IFAC-PapersOnLine, 55(10), 1693-1698. https://doi.org/10.1016/j.ifacol.2022.09.641.

[8] Meidute-Kavaliauskiene, I., Taşkın, K., Ghorbani, S., Činčikaitė, R., & Kačenauskaitė, R. (2022). Reviewing the applications of neural networks in supply chain: Exploring research propositions for future directions. Information, 13(5), 261. https://doi.org/10.3390/info13050261.

[9] Tse, Y. K., Chan, T. M., & Lie, R. H. (2009). Solving complex logistics problems with multi-artificial intelligent system. International Journal of Engineering Business Management, 1(1), 37–48. https://doi.org/10.5772/6781.

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

[11] Sremac, S., Kazimieras Zavadskas, E., Matić, B., Kopić, M., & Stević, Ž. (2019). Neuro-fuzzy inference systems approach to decision support system for economic order quantity. Economic research-Ekonomska istraživanja, 32(1), 1114-1137. https://doi.org/10.1080/1331677X.2019.1613249.

[12] De Oliveira, F. J. B., Ferson, S., & Dyer, R. (2021). A collaborative decision support system framework for vertical farming business developments. International Journal of Decision Support System Technology (IJDSST), 13(1), 34–66. https://doi.org/10.4018/IJDSST.2021010103.

[13] Pourhejazy, P., & Solvang, W. D. (2025). Exploring the role of Artificial Intelligence in life-cycle-related studies. IFAC-PapersOnLine, 59(10), 2479-2484. https://doi.org/10.1016/j.ifacol.2025.09.417.

[14] Vishwakarma, A. K., Patro, P. K., & Acquaye, A. (2025). Applications of AI to low carbon decision support system for global supply chains. Cleaner Logistics and Supply Chain, 17, 100261. https://doi.org/10.1016/j.clscn.2025.100261.

[15] Vazquez-Noguerol, M., Comesaña-Benavides, J., & Del Río-Rama, M. (2021). How can e-grocers use artificial intelligence based on technology innovation to improve supply chain management? Sustainability, 13(4), 2327. https://doi.org/10.1007/978-3-030-78288-7_14.

[16] Kliangkhlao, M., Pongpullponsak, A., & Kachitvichyanukul, V. (2022). The design and development of a causal Bayesian networks model for the explanation of agricultural supply chains. *IEEE Access*, *10*, 86813–86823. https://doi.org/10.1109/ACCESS.2022.3199353.

[17] 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.

[18] Vazquez-Noguerol, M., Comesaña-Benavides, J. A., Poler, R., & Prado-Prado, J. C. (2022). An optimisation approach for the e-grocery order picking and delivery problem. *Central European Journal of Operations Research*, *30*(3), 961–990. https://doi.org/10.1007/s10100-020-00710-9.

[19] Kaur, I., & Hassan, I. U. (2026). A bibliometric analysis and management of big data and machine learning research: Current trends and future directions. In Emerging Trends in Industrial Engineering and Management (pp. 135-148). CRC Press. https://doi.org/10.1201/9781003512585-11.

[20] Dehaghani, M. N., Korõtko, T., & Rosin, A. (2025). Ai applications for power quality issues in distribution systems: A systematic review. IEEE Access, 13, 18346-18365. https://doi.org/10.1109/ACCESS.2025.3533702.

[21] Abdildayeva, A., Shayakhmetova, A., & Duisen, A. (2026). Bayesian Networks and AI in COPD Predictive Modeling: Automating Reporting and Decision Support with NLP. WSEAS Transactions on Business and Economics, 23, 123–129. https://doi.org/10.37394/23208.2026.23.11.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Creative Commons Attribution License 4.0 (Attribution 4.0 International, CC BY 4.0)

This article is published under the terms of the Creative Commons Attribution License 4.0
https://creativecommons.org/licenses/by/4.0/deed.en_US

APPENDIX

Table 1. Studies about AI-supported DSS in the supply chain

Year	Author(s)	Aim of the Study	Used Technology	Application Area (Country)	Application Sector	DSS (+/-)
2009	[9]	Multi-AI systems for logistics	CBR, MAS, ANN, Fuzzy	Global	Logistics & Transportation	+
2019	[11]	Neuro-fuzzy DSS for SCM	Neuro-Fuzzy ANFIS	Global	Manufacturing	+
2021	[17]	AI-supported SCM modeling	ML models	Global	Manufacturing	-
2021	[12]	Collaborative DSS for vertical farming	Fuzzy, ML, DSS	UK / Global	Manufacturing	+
2021	[6]	AI-driven COVID-19 response platform	ML, DL, Big Data, DSS	Saudi Arabia	Logistics & Transportation	+
2021	[15]	AI for e-grocers SCM	AI, ML, DL	Spain	Retail	+
2022	[18]	AI-based DSS in e-grocery	AI, ML, DL, GA, DSS	Spain	Retail	+
2022	[8]	Neural networks in SCM	ANN, ML	Global	Manufacturing	+
2022	[16]	Causal Bayesian DSS for SCM	Bayesian Networks, DSS	Thailand	Manufacturing	+
2024	[10]	AI-driven operations transformation	AI, Analytics	Global	Manufacturing	-
2025	[5]	Predictive methods for delivery delay management	ML models, ERP data	Global	Logistics & Transportation	+
2025	[4]	Trustworthy AI for SC knowledge graphs	Knowledge Graphs, GNN, Neurosymbolic AI	Global	Logistics & Transportation	-
2025	[3]	Human–AI sensemaking in SCM	ML, NLP	UK / Multi-country	Logistics & Transportation	+
2025	[13]	AI-supported life-cycle DSS	AI, ML, Optimization	Global	Manufacturing	+
2025	[2]	AI for sustainable supply chains	AI, ML, DSS	Global	Manufacturing	+
2025	[14]	Low-carbon AI DSS	AI, ML, DL, DSS	Global	Manufacturing	+
2025	[7]	Reconfigurable SC with KG & HCAI	Knowledge Graphs, AI	EU	Logistics & Transportation	+

Source: created by the authors