Artificial intelligence in supply chain management: A systematic literature review

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Abstract

Today's world is already moving towards being completely digital. This is where artificial intelligence (AI) comes into play, optimizing supply chain management (SCM) systems by improving efficiency, resilience, and cost-effectiveness. Despite the richness of prior studies, there is limited research that extensively reviews the extant findings to present an overview of the different facets of this area. This research seeks to address this gap through a systematic review of 65 studies obtained from the Scopus database across a wide range of years. It was found in the review that AI has the potential in areas such as real-world scenarios, problem-solving, speed of operations and sustainable supply chains. A conceptual framework is proposed to validate the link between AI technologies and SCM performance measures. The findings highlight new research directions to enhance supply chain agility, transparency, and creativity.

Mots-clés: Intelligence Artificielle ; Gestion de la Chaîne d'Approvisionnement ; Résilience ; Agilité ; Performance Opérationnelle.

Keywords: Artificial Intelligence ; Supply Chain Management ; Resilience ; Agility ; Operational Performance.

1 Introduction

Artificial Intelligence (AI) refers to the ability of machines and computer systems to perform tasks that typically require human intelligence, such as learning from data, reasoning, problem-solving, decision-making, and language understanding (Russell & Norvig, 2021). AI systems rely on advanced algorithms, statistical models, and computational power to analyze vast amounts of data, recognize patterns, and make automated or semi-automated decisions without direct human intervention (Goodfellow, Bengio, & Courville, 2016), AI can be divided into two main categories: Narrow AI: This type of AI is designed for specific tasks, such as speech recognition (e.g., Siri, Alexa), recommendation systems (e.g., Netflix, Amazon), fraud detection, and demand forecasting in supply chains. It is the most widely used form of AI today (Kaplan & Haenlein, 2019). General AI (AGI): Unlike Narrow AI, AGI is capable of reasoning, learning, and adapting across a wide range of tasks, similar to human intelligence. While AGI was once considered theoretical, recent advancements in multimodal AI models and self-improving neural networks suggest that AGI is becoming increasingly viable (Goertzel, 2024; Bommasani et al., 2023). Recent advancements in machine learning, deep learning (DL), and natural language processing (NLP) have significantly expanded AI's capabilities, enabling more complex applications in various industries, including supply chain management. These technologies allow AI systems to continuously refine their predictions and decision-making processes, making AI a powerful tool for optimizing decision-making, reducing operational inefficiencies, and enhancing overall business performance (LeCun et al., 2014).

While AI in SCM has gained increasing attention, the field remains highly fragmented, with diverse methodologies and applications. Given the rapid evolution of AI technologies and their integration into supply chains, this study takes an exploratory approach to map existing literature, identify key trends, and highlight research gaps. Rather than relying on a single theoretical framework, this review provides a broad synthesis of emerging research, allowing for a more flexible and adaptive understanding of AI's role in supply chain management.

This study aims to consolidate existing knowledge, identify research opportunities, and propose a framework for future investigations. Using evidence-based methodologies, we analyze scholarly contributions to uncover trends, challenges, and best practices associated with AI in supply chain operations. By doing so, we aim to provide valuable insights for researchers and practitioners seeking to navigate the evolving landscape of AI-driven SCM. Our systematic literature review (SLR) builds upon the findings of previous studies and extends them in two significant ways: (a) it incorporates the most recent state-of-the-art research on AI applications in SCM by including studies published up until December 2024, and (b) it adds a new layer of understanding to the accumulated knowledge in this field. Previous reviews have primarily focused on performance metrics associated with Big Data in SCM (e.g., Kamble and Gunasekaran, 2020), bibliometric analysis (Mishra et al., 2018), and levels of analytics used (Nguyen et al., 2018). Our review, however, shifts the lens to AI's impact on SCM, emphasizing efficiency, resilience, and cost-effectiveness. Specifically, We address the following research questions: **RQ1.** *What are the emerging trends, key findings, and gaps identified in AI applications in supply chain management?* **RQ2.** *How can research and practice in this domain evolve to meet future needs?* These research questions are systematically addressed using a rigorous review protocol informed by Denyer and Tranfield’s (2009) three-stage process. To answer **RQ1**, we present detailed research profiling, including data on publication trends, citation metrics, and geographic distribution. Additionally, we organize the findings under key themes that capture AI’s role in enhancing supply chain performance while critically analyzing the research gaps and limitations in the current body of literature. **RQ2** is addressed by offering recommendations for future research, proposing a conceptual framework, and discussing practical implications for supply chain professionals.

2 Review methodologie

Aligned with the recent systematic literature reviews conducted by Denyer and Tranfield (2009), this research follows a three-stage process: defining the study's objectives and outlining the search strategy, gathering data based on the established search approach, and presenting the findings through research profiling, as detailed below.

2.1 Definition of the research objectifs and search protocol

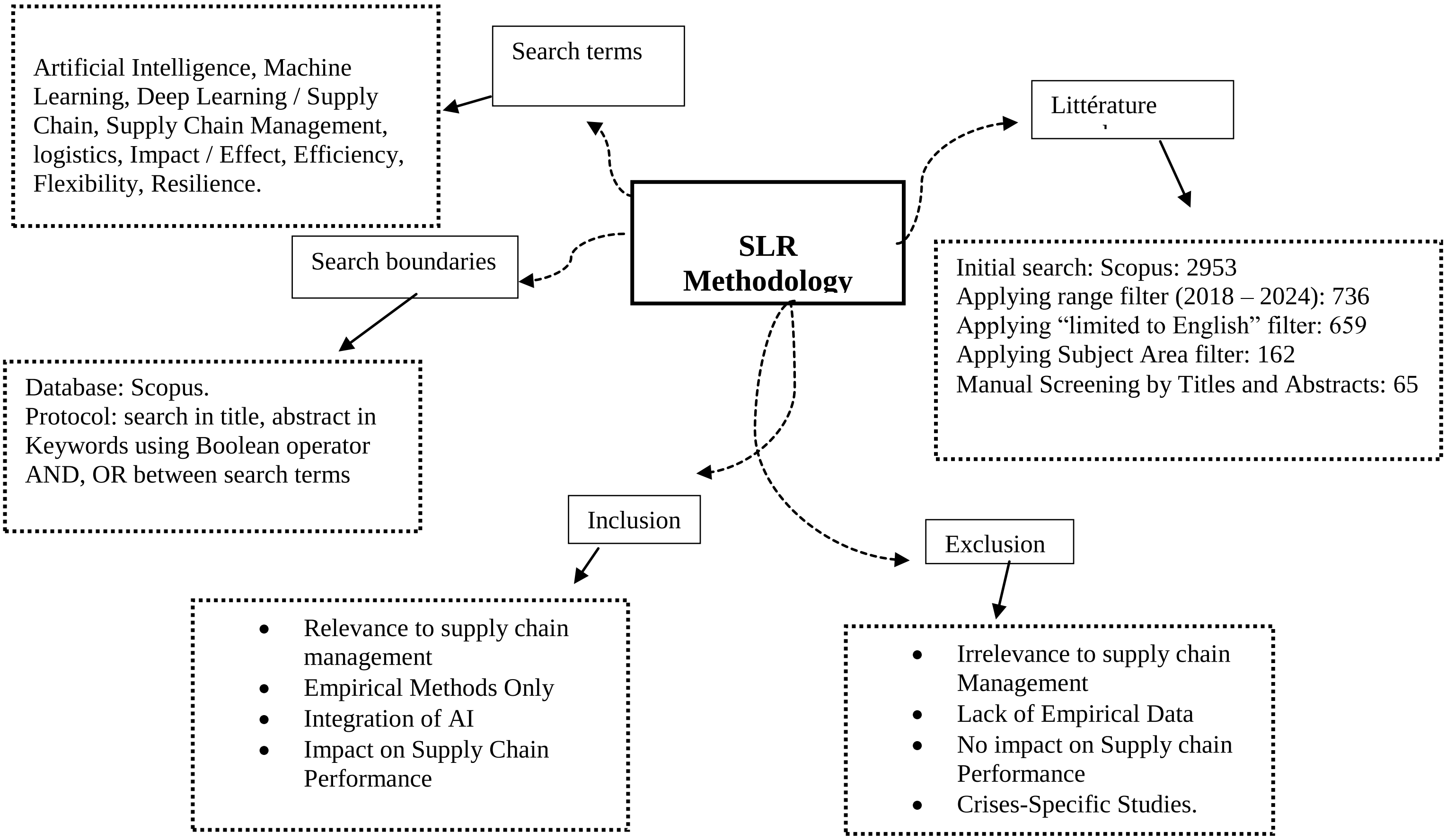
Using a SLR helps to set the conceptual bounderies of the study (Behera, Bala, and Dhir 2019), In this study we seek to obtain data on what is already published on
AI applications in SCM and its impact on SCM performance metrics like efficiency, resilience, cost effectiveness and likely gaps in research to be covered in the future.

The aims are set to inform on the present status of AI integration, benefits and issues experienced in SCM while at the same time suggesting research pathways needed to grow the body of knowledge in that area. Scopus was chosen as first choice database because of its coverage, quality and efficient advanced searching parameters (Schotten et al., 2018; Visser et al ., 2020). There was a structured search approach followed that comprised of filters and sets of rules for manual elimination and inclusion screening. This methodology made it easy to identify important and relevant articles that were in line with the objectives of the review.

2.2 Data gathering

Using Scopus as our databases, we conducted our search using the selected keywords combination of "Artificial Intelligence" OR ai OR "Machine Learning" OR "Deep Learning») AND («Supply Chain" OR "Supply Chain Management" OR logistics AND «Impact" OR "Effect" OR "Efficiency" OR "Flexibility" OR "Resilience) on December 01, 2024. The search resulted in a preliminary total of 2953, after applying the range filter we found 736 articles from: 2018 to 2024, The year 2018 marks a significant turning point in the adoption and advancement of AI technologies, particularly in SCM, for example, Toorajipour et al. (2021) highlighted that post-2018, AI technologies such as machine learning and optimization algorithms became integral to enhancing decision-making across supply chains, Similarly, Zamani et al. (2023) emphasized how advancements in AI and big data analytics since 2018 have driven supply chain resilience and efficiency. Hangl et al. (2022) also noted that the period after 2018 witnessed accelerated AI integration in SCM due to a combination of technological innovations and shifting industry priorities. then we limited the language to English, wish lead the search to only 659 articles, then the subject areas limited to only "Decision science" and "Business, management and accounting" in result it last 162 articles for further manual review, then a manual screening process was conducted to ensure the relevance and quality of the selected studies. Each abstract was thoroughly reviewed, and only articles meeting the predefined inclusion criteria and free from any exclusion criteria, shown in figure 1, were selected for further analysis, leaving us with a final tally of 65 studies for review;

Figure 1. Study selection process.



2.3 Summary Statistics and Study Attributes

The summary statistics presented below include the number of publications by year, average citations per year, the geographic scope of the studies.

Figure 2 illustrates that the annual output of scientific research on AI and SCM has been steadily growing, with a slight peak in 2019, followed by a significant surge from 2021 to 2024. This trend underscores the increasing relevance and importance of this topic in recent years.

Figure 2: Growth of AI and SCM Research (2018-2024)

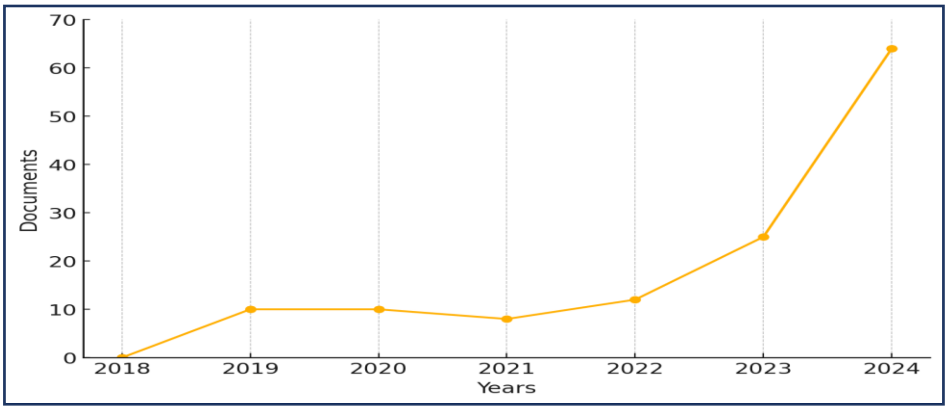
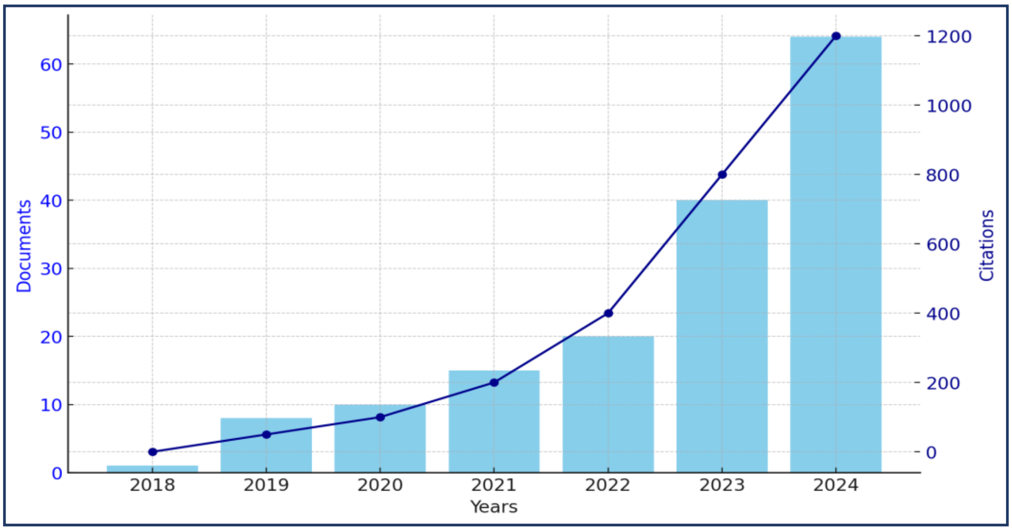


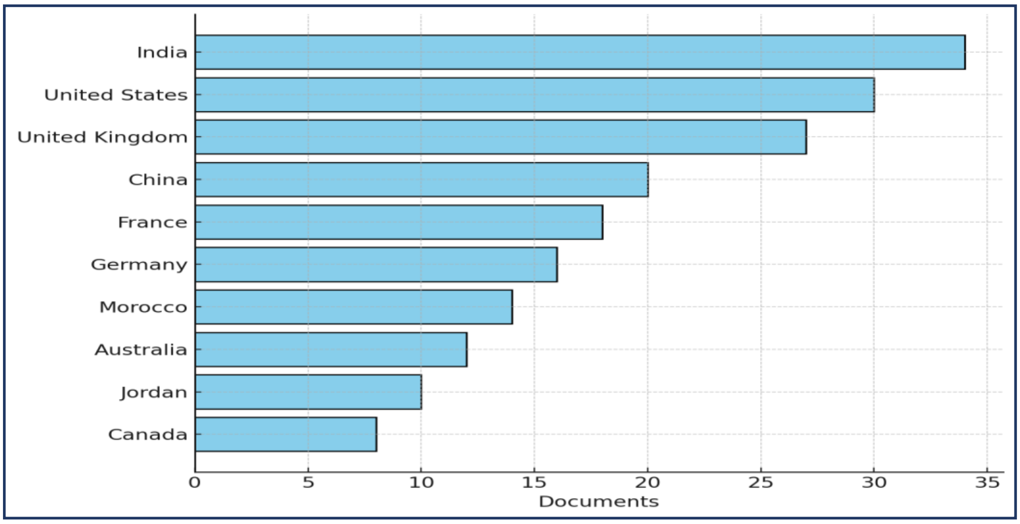
Figure 3 displays the average citations per year for articles published in this domain. The highest average citation per year is observed in 2024, reaching 1,200.

Figure 3: Average Citations per Year for AI and SCM Article



In addition, Figure 4 highlights the geographical distribution of contributions, with India and the United States leading in the number of studies within our sample.

Figure 4: Geographical Distribution of AI and SCM Research Contributions



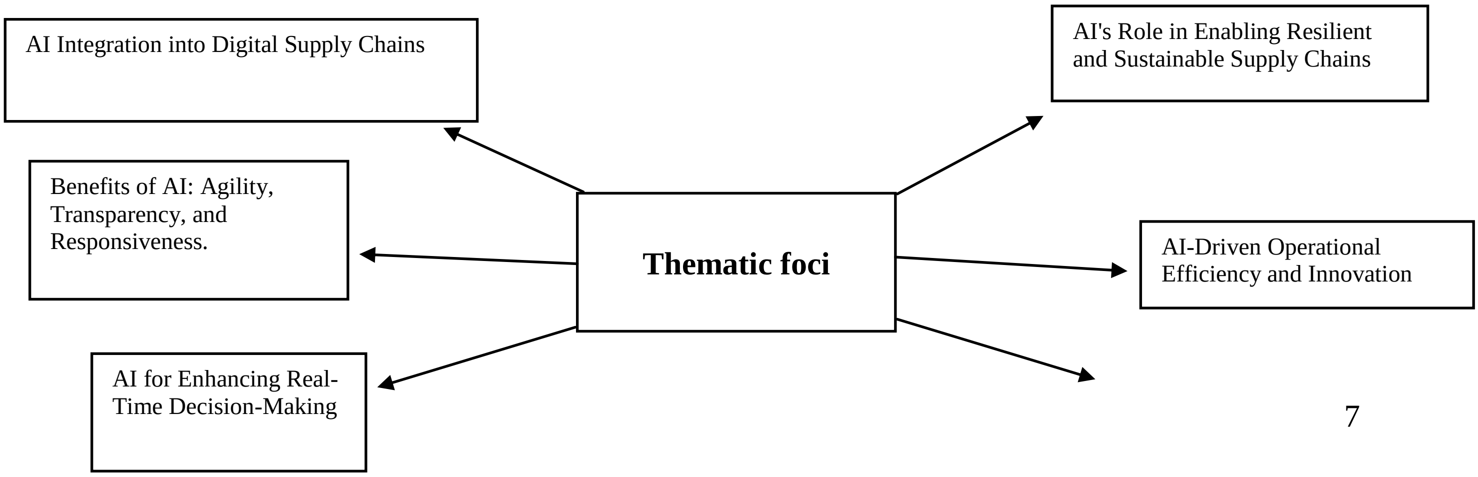
2.4 The manual screening

For the manual screening process, we systematically examined the abstracts of 162 articles retrieved from the Scopus database. Each abstract was carefully read in full to ensure a comprehensive understanding of the study's research objectives and key findings. This approach was essential to minimizing the risk of misinterpreting the study's relevance to our research objectives. We excluded 97 articles that did not meet the pre-established inclusion criteria or that satisfied any of the exclusion criteria, leaving us with 65 articles for further analysis.

3 Identification of key themes

The selected 65 articles were then imported into Nvivo 14, we used Nnvivo 14 to perform open coding on the content of the articles. During the open coding process, we identified relevant text segments that reflected key themes, concepts, or patterns related to AI in SCM. These segments were assigned specific codes based on their content, and these codes were subsequently categorized into broader themes.Through this process, six final thematic foci were identified. These themes represent the most significant trends and insights that emerged from the analysis of the 65 articles as shown in figure 5.

Figure 5 : Thematic foci of research on IA application on SCM.



3.1 AI Integration into Digital Supply Chains

AI has revolutionized supply chain operations by integrating tools as Customer Relationship Management (CRM) systems, mobile devices, and Radio-Frequency Identification (RFID) technologies to enable real-time data sharing, better inventory management, and streamlined manufacturing, boosting responsiveness and competitiveness (Feldt et al., 2019). Combining AI with blockchain enhances transparency, sustainability, and trust by optimizing data handling and securing traceability (Tsolakis et al., 2024). Strategically, AI optimizes transportation costs, logistics cycles, and inventory decisions, helping businesses meet goals and adapt to market changes (Kitzmann et al., 2024). It also enhances collaboration via big data analytics platforms, improving decision-making and omnichannel operations, particularly in healthcare (Bag et al., 2022). AI-driven tracking systems increase supply chain security and transparency by detecting fraud, predicting delays, offering real-time visibility and fostering customer trust (Tamym et al., 2021). Additionally, AI-powered robots automate tasks, improve logistics, and boost agility with the support of organizational readiness (Shamout et al., 2022).

3.2 Benefits of AI: Agility, Transparency and Responsiveness

Machine learning promotes the complex automation of business processes within supply chains. Organizations are able to handle inventory and respond to dynamism in market conditions. Furthermore, robotic process automation (RPA) and automated guided vehicles (AGVs) improve efficiency in workflow automation and material handling tasks. Combined with IoT devices, such as smart sensors, the use of blockchain technology guarantees the traceability and real time supervision of products. This combination is especially useful for the pharmaceutical industries because of the importance of compliance and quality assurance in this industry, (Bag et al., 2022). Predictive modelling assesses risks and further, digital twins enable improved strategies for the aftermath of disruptions. Other signal metrics such as news and social media can also be used to create awareness of disruptions. This is made possible through NLP tools (Al-Zaqeba et al, 2022; Shamout et al, 2022). However, most of these technologies and business processes will depend on the existence of a well-defined IT structure with proper strategies (Sharabati et al, 2024).

3.3 Integration of Machine Learning and Mathematical Models in SCM

Advanced deep learning models, like Eagle Strategy Slime Mould Algorithm-General Regression Neural Network (ESSMA-GRNN), significantly improve lead-time predictions, outperforming traditional methods in metrics such as Mean Squared Error (MSE) and Explained Variance, enabling efficient delivery planning (Fri, 2024). Machine learning (ML) enhances supply chain resilience through digital twins, particularly in the Fast-Moving Consumer Goods (FMCG) sector, improving visibility, inventory management, and adaptability to disruptions (Singh et al., 2024). In multimodal logistics, ML with models like SARIMA optimizes network design, reducing costs, environmental impacts, and enhancing resilience (Rekabi et al., 2024). Combining blockchain and ML improves procurement by enhancing traceability, transparency, and supplier selection, using approaches like Mixed-Integer Nonlinear Programming (MINLP) to reduce disruptions and improve information flow (Yadav & Singh, 2024). ML techniques, such as discrete wavelet transformation with multi-gene genetic programming (DWT-MGGP), mitigate the bullwhip effect in inventory control, providing robust demand forecasting and improving inventory management under uncertainty (Jaipuria & Mahapatra, 2019).

3.4 AI for Enhancing Real-Time Decision-Making

As mentioned by Feldt et al. (2019), the autonomous systems have alleviated decision making bottlenecks, decreased lead and production times, and ameliorated autonomous responsiveness in supply chains. For instance, Fri (2024) states that the use of ESSMA-GRNN models greatly increases the accuracy of lead-time estimates by dealing with large amounts of data, which enables precise scheduling. The inputs into logistics systems are certainly optimized through predictive analytical approaches, where Convolutional Neural Network-Long short-Term Memory (CNN-LSTM) models allow for solutioning under uncertainty in a sustainable and economically reasonable manner (Oguntola et al., 2024). Furthermore, Melançon et al. (2021) have stated that risk management systems will be able to increase service levels by predicting the risk of such levels weeks in advance, enabling service disruptions to be mitigated proactively. In addition, Tamym & Moh (2021) showed that AI supply chain tracking systems assist in greater supply chain visibility and effective inventory management through real time responses and reduced inefficiencies.

3.5 AI's Role in Enabling Resilient and Sustainable Supply Chains

Since AI's analytical function recognizes the problem areas and allows managers to reorient strategies, when necessary, it has decreased operational costs. Total Interpretive Structural Modeling (TISM) based on Organizational Information Processing (OIPT) establishes that AI facilitates scenario planning and contingency planning which are useful for firms dealing with disruptions (Singh et al., 2024; Belhadi et al., 2024). AI aids in supply chain trust and cooperation by assisting businesses in timely making information available, thus bettering networks and providing stability during shielding crisis (Ali et al., 2024). In addition to resilience, AI enables SCM to be more sustainable through efficient use of resources resulting in less waste and better recyclability. For instance, in the processes of procurement and of production, AI systems can perform real time monitoring, thus averting overproduction and wastage of resources (Sinha et al., 2024). Both IoT and blockchain technologies have made supply chains more transparent, so together with AI they make predictability and accountability more available aiming at the balance between sustainability and resilience and at the same time providing a leap forward in supply chains nowadays (Wu et al., 2024).

3.6 AI-Driven Operational Efficiency and Innovation

AI has transformed operations by improving efficiency and decision-making. Monte Carlo tree search approach (MCTS) enhances inventory management, cutting costs and reducing the bullwhip effect (Preil & Krapp, 2022). Integration with ML and digital twins strengthens supply chain resilience and analytics, ensuring consistency in volatile conditions (Singh et al., 2024). In predictive modeling, AI improves forecasting accuracy, with models like Logistic Regression and Decision Trees optimizing resource-sensitive domains, such as blood inventory management (Sakib et al., 2023). AI also drives innovation, reshaping business models and enhancing agility, transparency, and responsiveness through frameworks like diffusion of innovations (DOI) and Technology-Organization-Environment (TOE) (Sharabati et al., 2024). The combination of AI and Blockchain Technology (BCT) enables sustainable supply chains, optimizing operations and monetizing data, as demonstrated in the tuna fish supply chain (Tsolakis et al., 2024). AI further bolsters resilience by supporting dynamic capabilities like disruption sensing and adaptation, fostering continuous innovation (Pal et al., 2024).

4 Gaps and potential research questions

We conducted a systematic review of the extant literature to present a research profile and the thematic foci of AI applications in SCM. A critical analysis of this research profile and the six identified themes revealed significant gaps in the literature, particularly regarding the integration of AI technologies, their real-world validation, and their potential to enhance supply chain resilience, efficiency, and sustainability. These gaps highlight opportunities for future academic research that can address these shortcomings, support effective managerial decision-making, and pave the way for practical advancements in AI-driven SCM. In turn, these insights form the basis for proposing a conceptual framework, as illustrated in Figure 6, figure 7 and figure 8, aimed at guiding future exploration and application in this field.

4.1 Gaps in the research profile

The selected studies exhibit notable limitations in their research designs, encompassing aspects such as the theoretical focus without practical validation, the predominant emphasis on predictive over prescriptive analytics, insufficient integration of environmental sustainability metrics, and a lack of diverse data sources.

4.1.1 Theoretical Models Lacking Real-World Testing

A number of studies do formulate theoretical frameworks but do not furnish room for practical implication. As example are, Ismail, M.M., et al. (2024) who developed a multi-criteria decision-making model to effectively increase resilience of supply chains but did not test it in different real-world scenarios. Barhmi, A., et al. (2024), on the other hand, proposed a digital learning orientation framework, yet solely relied on survey results without validating their findings against actual industry practice. Also, Belhadi, A., et al. (2024) examined the role of AI in supply chain performance enhancing capabilities, but within the strategy proposed no case studies were provided to support the real benefits AIs may offer. The same is true for Pal, T., et al. (2024) and Long, L.N.B., et a. (2024), both who did highlight relevant theoretical aspects but did not support them with practical implementations into existing organizational structures for various industries.

4.1.2 Insufficient Emphasis on Predictive vs. Prescriptive Analytics

Despite the broad appeal of predictive analytics, prescriptive analytics providing decision alternatives has not been given much attention. Sinha, P., et al. (2024) explored AI in sustainability in the apparel business, but failed to suggest any prescriptive measures for these stakeholders. Wyrembek, M., et al (2024), predicted some supply chain delays, but did not suggest the steps to be taken to reduce these delays. According to Pandey, H., et al. (2024) and Bag, S., et al. (2022), there was excessive reliance on data analytics without consideration of how predictions would be converted to prescriptions that would advance the operations of the company.

4.1.3 Insufficient Attention to Environmental Sustainability

Despite advancements in AI and ML, few studies adequately address their environmental implications in supply chain management. Ismail, M.M., et al. (2024), proposed a sustainable resilience framework using multi-criteria decision-making but did not evaluate the carbon footprint of these solutions. Rekabi, S., et al. (2024), introduced a dry port-seaport logistics network with Industry 5.0, yet its environmental objectives were secondary to cost and resilience goals. Long, L.N.B., et al. (2024), also presented a low-carbon performance framework but emphasized operational efficiency over sustainability metrics.

4.1.4 Limited Diversity in Data Sources

A number of investigations base their conclusions on a single narrow approach and hence their conclusions are difficult to generalize. Allahham, M., and others (2024), limited their analysis to questionnaires filled out by only 420 managers and did not utilize real time or third-party data sets. Muñoz-Villamizar, A and others (2024), introduced web harvesting as a tool to examine food prices in Brazil but only detached data of one company and its competing companies. Ali, A.A.A., and others (2024), on the other hand employed an identical strategy by appealing to 542 people across various industries to fill out questionnaires and did not incorporate any operational or transactional data into the analysis. Al-Banna, A and others (2024) have investigated Industry 4.0 strategies but again did not cross check their frameworks with a wider array of datasets.

4.2 Gaps related to thematic foci

The critical analysis of the above themes has allowed us to identify various gaps in the prior literature. We have thus classified these gaps into two categories:

4.2.1 Gaps in AI and Blockchain Integration: Practical Frameworks and Collaboration Insights

While there are economists and researchers that see a theoretical gap in AI and Blockchain integration, research evidence suggests otherwise. Economists like Feldt et al. (2019) discuss value advancing elements such as traceability and transparency but fall short in suggesting any form of implementation, Tsolakis et al. (2024) were also able to propose an AI and a blockchain model, however, this too was merely a simulation and therefore not viable to be used. AI was explored further in the context of the healthcare supply chain by Bag et al. (2022) but again in this case no insight was provided for the manufacturing or retail sectors. Relevant Still are the ample gaps in understanding the role that AI can play in promoting cooperation across supply chain networks. Such as in the case of Bag et al. (2022) where they focused more on AI facilitated data sharing applications in the healthcare setting while ignoring its relevance throughout the entire supply chain. Other authors like Shamout et al. (2022) expanded the scope of AI tools like robotics in inter organizational communication, with no address of its relevance in cross functional collaboration. Lastly while Feldt et al (2019) did discuss the relevance of AI within the context of augmentation or promotion of collaboration the current evidence available does not support that claim.

4.2.2 Gaps in Digital Twin Applications and Cost Efficiency Analysis

While much of AI research focuses on predictive analytics, the role of digital twins in simulation-based risk mitigation is underexplored. Oguntola et al. (2024) highlighted AI's logistics predictions but omitted physical testing using AI-enabled digital twins. Similarly, Trautmann et al. (2024) showcased IoT's real-time visibility without applying digital twins for supply chain recovery. Shamout et al. (2022) referenced digital twins but lacked empirical validation. Existing studies often prioritize supply chain responsiveness but overlook cost-efficiency trade-offs. For instance, Al-Zaqeba et al. (2022) addressed early risk detection but ignored cost implications. Sharabati et al. (2024) examined agility benefits without assessing implementation costs, and Tsolakis et al. (2024) discussed blockchain-AI integration without considering Return On Investment (ROI) as a decision-making factor. Singh et al. (2024) integrated resilience into digital twins but failed to link them to demand balancing. Meanwhile, Jaipuria and Mahapatra (2019) applied Multi-Gene Genetic Programming (MGGP) to traditional inventory systems, and Rekabi et al. (2024) assessed logistics frameworks without addressing inventory oscillations due to demand shifts.

4.3 Potential research questions

Table.1 Theme-based research questions.

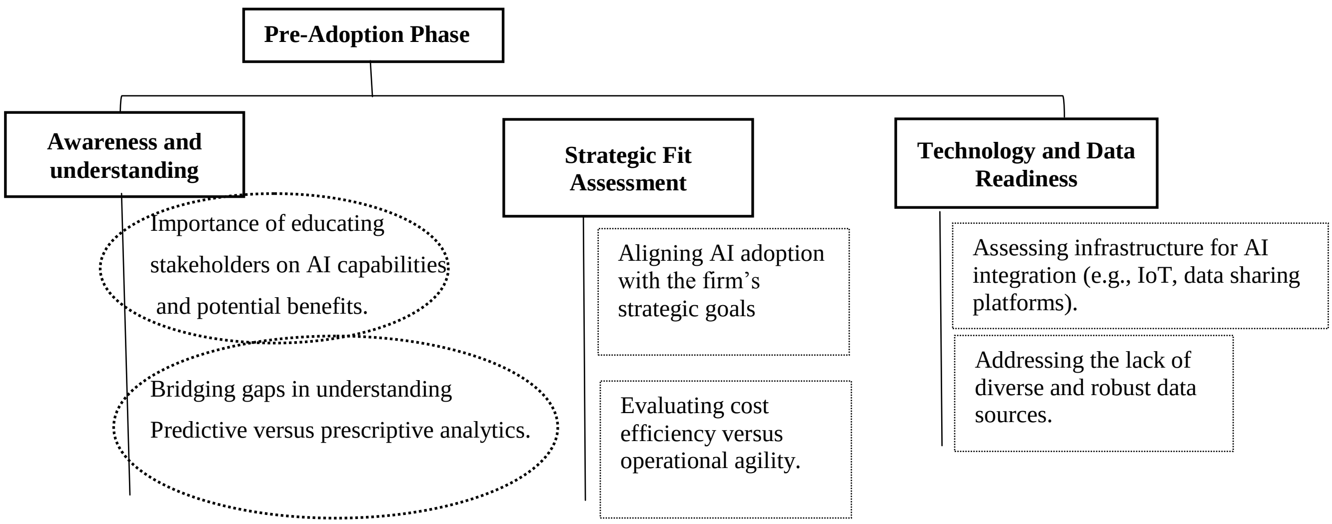
Thematic foci	Potential research questions
AI Integration into Digital Supply Chains	1. How can AI and blockchain technologies be effectively integrated to enhance transparency and trust within digital supply chains? 2. What are the challenges and enablers of AI-powered collaborative platforms for cross-industry supply chain networks? 3. How can AI-based tracking systems balance customer satisfaction and operational efficiency in dynamic supply chains? 4. What role do AI-powered autonomous robots play in increasing supply chain agility, and what factors influence their successful adoption? 5. How can AI and IoT integration optimize real-time data sharing in complex supply chain ecosystems?
AI's Role in Enabling Resilient and Sustainable Supply Chains	1. How does AI-driven predictive analytics improve supply chain resilience in the face of dynamic disruptions? 2. What strategies can be employed to integrate sustainability metrics into AI-enabled supply chain frameworks? 3. How does AI-driven collaboration impact trust and transparency in multi-stakeholder supply chains?
AI-Driven Operational Efficiency and Innovation	1. What factors contribute to the successful deployment of AI and blockchain technologies in creating monetized supply chains? 2. How do AI-driven dynamic capabilities (e.g., sensing, seizing, and transforming) support resilience and innovation in supply chains? 3. What are the comparative benefits of AI in predictive modeling versus traditional methods in supply-sensitive domains? 4. How can advanced robotics combined with AI redefine operational strategies in logistics?
Benefits of AI: Agility, Transparency, and Responsiveness	1. How can AI-enabled digital twins support responsiveness to supply chain disruptions? 2. What are the critical factors influencing the adoption of cloud-based AI tools in enhancing supply chain interoperability?

AI for Enhancing Real-Time Decision-Making	1. What are the most effective deep learning models for lead-time prediction in supply chains, and how do they outperform traditional methods? 2. How can AI-powered predictive analytics optimize logistics networks under uncertainty?
Integration of Machine Learning and Mathematical Models in SCM	1. How do hybrid models like ESSMA-GRNN outperform traditional methods in lead-time prediction for modern manufacturing? 2. What are the benefits of integrating ML-enabled digital twins with mathematical models in supply chain risk management? 3. How does the combination of ML and blockchain address challenges in supplier selection and procurement transparency?

5 Framework development

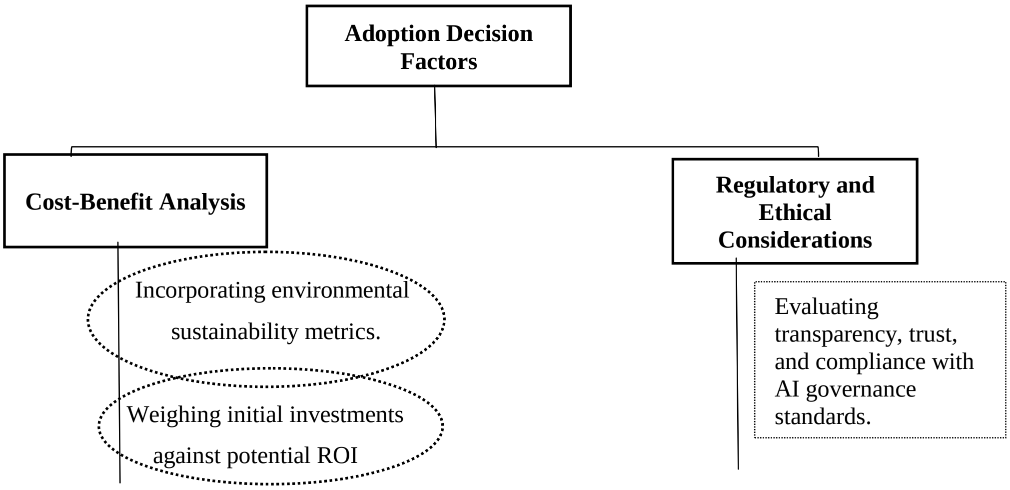
We have structured an idea to aid in understanding the integration of AI into SCM by filling the gaps that have been identified in the previous studies, it elucidates the pivotal areas of consideration that help in merging AI during the further stages of SCM integration as shown in Figure 6; figure 7 and figure 8.

Figure 6. Pre-Adoption Phase



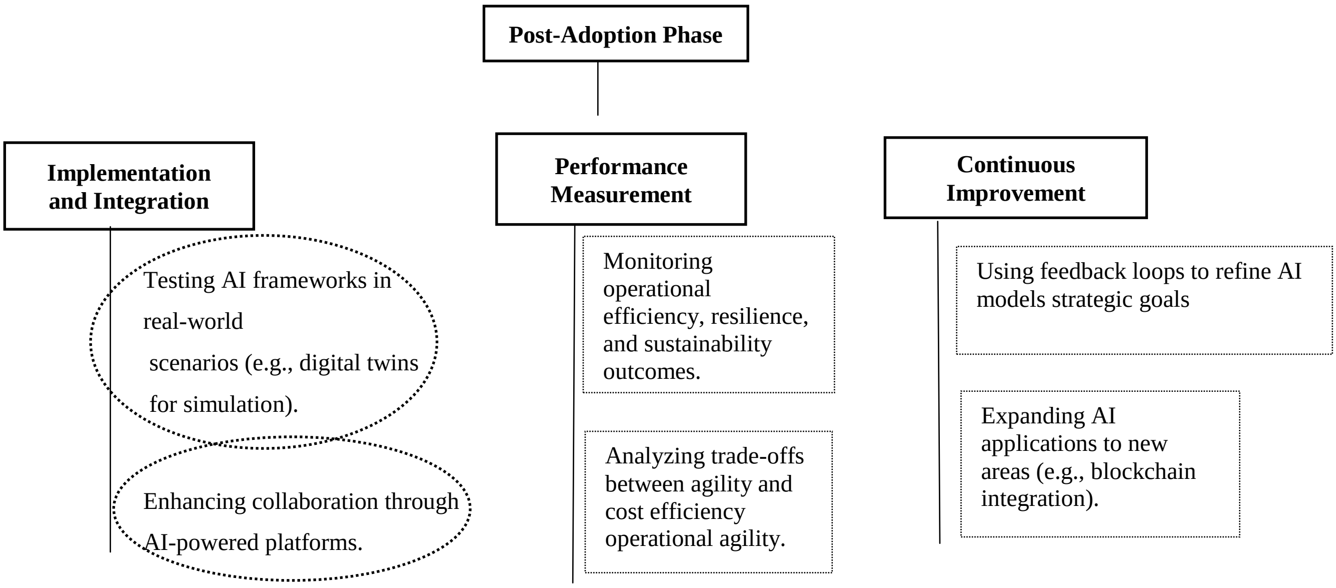
The pre-adoption phase stage of the framework under consideration explains the factors that shape a firm's intention to adopt AI in supply chain management. Such elements involve awareness and education on other AI technologies for non-experts which allows them to comprehend AI's abilities such as predictive and prescriptive analytics. The framework also suggests that firms with an existing combination of organizational goals and AI capabilities tend to adopt more. This combination encompasses technology, such as flexibility versus cost effectiveness and data scope, readiness in terms of technology infrastructure, and information domain. For instance, Ismail et al. (2024) proposed a multi-criteria decision-making model but did not attempt to implement it in practice, which pointed towards lack of advance during the adoption phase, the framework describes technological readiness and data as factors that facilitate the process of adoption, like facilitating AI and IoT devices. However, gaps that exist in the literature such as the pursuit of limited diversification of data sources (Allahham et al., 2024) and insufficient prescriptive-predictive analytical effort (Sinha et al., 2024; Pandey et al., 2024) point out the need for preparatory needs. Such as the constant dependence on one data source, as observed by Muñoz-Villamizar (2024).

Figure.7 Adoption Decision Factors



The adoption decision Factors, on the other hand, postulates that a cost-benefit analysis is among the best predictors of a firm's readiness to take on AI. The anticipated adoption of AI includes, among others, business profitability, improvement in productivity and enhanced ability to monitor environmental sustainability metrics. Rekabi et al. (2024) dealt with sustainability, but did not put environmental goals first before operational goals, which indicates a certain gap for companies to grasp. Also, the importance of weighing initial investments against ROI to ensure a strategic alignment of resources with expected outcomes. Moreover, governance norms of AI, trust and transparency as well as ethical principles of compliance need to be catered as in Bag et al. (2022) and Shamout et al. (2022).

Figure.8 post-Adoption phase



The post-adoption phase focuses on embedding AI into operational processes to ensure sustained value in SCM. This stage emphasizes integrating AI with IoT and blockchain to enhance transparency, visibility, and collaboration, addressing gaps left by theoretical frameworks lacking real-world validation. Practical tools like digital twins and simulations are key to mitigating inefficiencies and predicting disruptions. Performance measurement is central, encouraging firms to track AI's impact on efficiency, resilience, and sustainability. By evolving from predictive to prescriptive analytics, AI applications can provide actionable decisions in real time. Ongoing evaluation allows businesses to balance agility and cost-efficiency, optimizing AI-driven SCM. Feedback loops drive continuous improvement, with AI models further enhanced and expanded into new domains. Integration with blockchain promotes innovation and sustainability, supporting environmentally friendly supply chains and business growth.

6 Conclusion

This review synthesizes findings from 65 papers, highlighting AI's transformative role in enhancing decision-making, responsiveness, and enterprise capabilities in global supply networks. AI significantly impacts six areas: digital platform integration, real-time decision-making, operational performance, machine learning tools, reactiveness, and sustainability. AI reduces lead times, errors, and risks while optimizing logistics and visibility. However, a notable gap exists in transitioning AI models from theory to practical applications, as well as in validating AI frameworks through empirical testing. The review identifies an overemphasis on predictive analytics, with insufficient focus on prescriptive solutions. While AI effectively detects and predicts supply chain problems, more research is needed to develop systems that provide actionable strategies. The proposed framework addresses AI integration across pre-adoption, adoption, and post-adoption phases, emphasizing strategy alignment, cost-benefit analysis, and continuous improvement. Despite AI's evident potential in SCM, research must address gaps in multisectoral collaboration and practical implementation. Expanding AI's role from prediction to actionable policy solutions is key to fully harnessing its benefits.

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