African Scientific Journal
ISSN : 2658-9311
Vol : 03, Num 35 Avril 2026

Advancing Supply Chain Management through Artificial Intelligence: Conceptual studies

Vers une optimisation avancée de la gestion de la chaîne logistique par l'intelligence artificielle : cadre conceptuel.

Auteur 1 : Dr Rabii EL GOMRI
Auteur 2 : Dr DIFTAR Abdelhakim

Rabii EL GOMRI, Research Professor;
Research-Lab; Higher Institute of Transport and Logistics
(ISTL- Casablanca, Morocco).

DIFTAR Abdelhakim, Research Laboratory in Development Economics and Governance of Organizations (LAREDGO). Hassan II University of Casablanca - Morocco.

Déclaration de divulgation : L'auteur n'a pas connaissance de quelconque financement qui pourrait affecter l'objectivité de cette étude.

Conflit d'intérêts : L'auteur ne signale aucun conflit d'intérêts.

Pour citer cet article : EL GOMRI .R & DIFTAR .A (2026) «Advancing Supply Chain Management through Artificial Intelligence: Conceptual studies », African Scientific Journal « Volume 03, Num 35 » pp: 1679 – 1698.

DOI : 10.5281/zenodo.20085740

Abstract

This article investigates how artificial intelligence (AI) is reshaping supply chain management (SCM) through concrete and operational applications. AI enhances the efficiency of data collection and analysis while significantly strengthening decision-making processes and advanced modeling capabilities (Ivanov & Dolgui, 2020). Techniques such as machine learning and Big Data analytics provide robust and scalable solutions to complex supply chain challenges, including demand forecasting, inventory management, and logistics flow optimization (Chopra & Meindl, 2020; Kamble, Gunasekaran & Gawankar, 2020). The integration of these technologies also contributes to improving supply chain resilience in the face of increasing disruptions and uncertainty (Christopher & Peck, 2004). Moreover, AI enhances end-to-end supply chain visibility through the use of natural language processing (NLP) techniques and intelligent agents, enabling more proactive and informed managerial decisions (Mikalef et al., 2020). Nevertheless, several challenges persist, particularly concerning algorithmic transparency, data governance frameworks, and ethical implications related to AI deployment (LeCun, Bengio & Hinton, 2015). The article concludes by proposing strategic perspectives for the effective adoption of AI in SCM, while emphasizing the critical challenges associated with its operational implementation.

Keywords: Artificial intelligence (AI); Supply chain management (SCM); Big Data analytics; Machine learning; Supply chain optimization; Supply chain resilience.

Introduction

Supply chain management (SCM) is a critical domain for the efficient functioning of firms and global economies. By coordinating the flow of products, information, and financial resources across complex networks of organizations, SCM seeks to optimize supply chain performance while minimizing costs and meeting customer demand (Christopher, 2016). With globalization and the increasing expectations of consumers, supply chains have become progressively more complex, making SCM research essential for developing strategies and models capable of addressing these challenges.

Traditionally, SCM research has relied on quantitative methodologies such as mathematical programming, stochastic simulation, and statistical analysis (Silver, Pyke & Thomas, 2017). Although these approaches have led to significant advancements, they are often limited in their ability to process large volumes of heterogeneous data and to model dynamic and uncertain environments. For instance, demand forecasting and inventory optimization represent complex problems influenced by multiple factors, including consumer behavior, economic fluctuations, and logistical disruptions (Chopra & Meindl, 2020). These challenges underscore the need for new research approaches capable of more effectively capturing the complexity and uncertainty inherent in SCM.

Artificial intelligence (AI) has emerged as a powerful tool to address these challenges and to fundamentally transform SCM research. Advances in machine learning, Big Data analytics, and deep learning provide researchers with new opportunities to investigate complex supply chain phenomena in a more comprehensive and precise manner (LeCun, Bengio & Hinton, 2015). For example, neural networks and machine learning algorithms enable the development of robust predictive models for inventory management and resource planning, while real-time data analytics support the rapid identification of and response to supply chain disruptions (Ivanov & Dolgui, 2020).

Furthermore, AI facilitates the modeling and simulation of complex scenarios that would otherwise remain inaccessible through traditional approaches. The use of intelligent agents to simulate the behavior of supply chain actors allows researchers to evaluate alternative risk management strategies and assess their impact on supply chain resilience (Christopher & Peck, 2004). In addition, natural language processing (NLP) techniques enable the extraction of valuable insights from unstructured data sources—such as financial reports and social media—thereby offering a more holistic view of the supply chain environment (Kamble, Gunasekaran & Gawankar, 2020).

Nevertheless, the integration of AI into SCM research is not without challenges. The complexity of AI algorithms and the requirement for large volumes of high-quality data raise significant concerns related to implementation and data governance (Mikalef, Boura, Lekakos & Krogstie, 2020).

Moreover, ethical issues and the lack of transparency and explainability of AI models—particularly regarding their decision-making processes—remain major obstacles to widespread adoption (Lipton, 2018). Consequently, it is essential to consider not only the potential benefits of AI but also its limitations and broader implications for SCM research.

This article aims to explore the current contributions of AI to SCM research by highlighting its potential to enhance research methodologies, model complex environments, and provide advanced decision-support tools. It also examines the challenges and limitations associated with the use of AI in this field and proposes future research directions to fully exploit its potential. Ultimately, this study seeks to offer a comprehensive overview of the impact of AI on SCM research and to guide both researchers and practitioners in the effective integration of these innovative technologies into their work.

This study focuses on the transformative role of artificial intelligence in supply chain management, with particular emphasis on its contribution to advanced modeling, decision-making, and risk management processes.

The main objective of this research is to analyze how AI techniques enhance supply chain performance and to identify the associated challenges and limitations in their implementation.

This paper is structured as follows: Section 1 presents the evolution of SCM research and the contribution of AI; Section 2 examines AI-enhanced modeling and simulation approaches; Section 3 discusses AI-driven decision-making processes; Section 4 analyzes the main challenges and limitations; and Section 5 outlines future research perspectives and directions.

1. Evolution of SCM Research and the Contribution of AI

Research in supply chain management (SCM) has undergone significant evolution over the past decades. Initially, studies primarily focused on optimizing logistics processes—such as inventory management and transportation planning—using classical quantitative methods, including linear programming and stochastic simulation (Silver, Pyke & Thomas, 2017). Although these approaches proved to be powerful, they were often constrained by their limited ability to cope with the growing complexity of global supply chains, which are characterized by dynamic interorganizational relationships and massive data flows (Christopher, 2016).

Traditional approaches are largely based on simplifying assumptions, such as stable market conditions and linear relationships between variables. These assumptions are frequently inappropriate in contexts where supply chains are exposed to unpredictable disruptions, including geopolitical crises, demand volatility, and environmental constraints (Ivanov & Dolgui, 2020). Consequently, researchers have increasingly sought more flexible and adaptive methodologies to model and analyze complex supply chain systems.

The introduction of artificial intelligence (AI) into SCM research represents a major advancement in researchers' ability to address complex supply chain problems. AI not only enables the automation of data collection and analysis but also facilitates the development of predictive models capable of capturing nonlinear interactions and the complex dynamics inherent in supply chain systems (LeCun, Bengio & Hinton, 2015). For instance, machine learning algorithms—such as random forests and neural networks—have been widely applied to enhance demand forecasting accuracy and inventory optimization (Bertsimas & Kallus, 2020).

AI-based approaches differ fundamentally from traditional methods in their ability to learn directly from data without requiring explicit modeling of relationships between variables (Goodfellow, Bengio & Courville, 2016). In particular, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) enable the analysis of spatial and sequential data, which is essential for understanding material flows and the dynamics of global supply chains (Kuo & Chen, 2020). By contrast, traditional models rely on strong a priori knowledge and restrictive assumptions regarding system structure, thereby limiting their applicability in uncertain and dynamic environments.

The adoption of AI in SCM research has led to a notable increase in publications in leading academic journals, reflecting growing scholarly interest in AI-driven applications within this field. Journals such as *International Journal of Production Economics* and *Journal of Business Logistics* increasingly publish studies that employ AI techniques to address challenges related to distribution network optimization, risk management, and strategic planning (Gunasekaran et al., 2015). This trend demonstrates that AI is no longer viewed solely as an innovative tool but is increasingly recognized as a legitimate research methodology that is reshaping traditional SCM paradigms.

Future perspectives for AI in SCM research are highly promising. AI enables the exploration of research questions that were previously difficult or inaccessible, including large-scale modeling of consumer behavior, adaptive optimization of logistics networks, and the prediction of supply chain disruptions based on unstructured data sources such as social media and economic news (Choi, Wallace & Wang, 2018).

Moreover, AI offers significant opportunities for the development of new research methodologies, such as AI-assisted collaborative research, in which researchers and algorithms work jointly to explore hypotheses and generate novel knowledge (Brynjolfsson & McAfee, 2014).

2. AI-Enhanced Modeling and Simulation in SCM

Machine learning plays a central role in enhancing modeling capabilities in SCM. Unlike traditional models, which rely on predefined equations and static assumptions, machine learning algorithms learn directly from data, enabling greater flexibility in the representation of complex systems. For example, artificial neural networks (ANNs) and random forests are widely employed to predict demand fluctuations by integrating a wide range of contextual variables, such as economic trends, consumer behavior, and weather data (Bertsimas & Kallus, 2020). This data-driven approach helps reduce forecasting errors and improve the accuracy of inventory management decisions (Kuo & Chen, 2020).

Convolutional neural networks (CNNs), originally developed for image processing tasks, have also been successfully applied to modeling product flows in complex logistics environments. CNNs enable the capture of spatial relationships among different nodes within distribution networks, thereby facilitating route optimization and warehouse management (Goodfellow, Bengio & Courville, 2016). In addition, recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) architectures, are commonly used to model time series data for predicting demand variations and supply chain disruptions (Hochreiter & Schmidhuber, 1997).

2.1. Applications of Deep Learning in SCM

Deep learning, a subfield of machine learning, is distinguished by its ability to process large volumes of unstructured data, including images, text, and video. In SCM, deep learning techniques are increasingly used to analyze data collected from sensors, satellite imagery, and textual information derived from social media and news outlets. For instance, natural language processing (NLP) models based on architectures such as BERT or GPT can be employed to analyze online consumer reviews in order to identify early signals of shifts in customer preferences or potential risks affecting the supply chain (Vaswani et al., 2017).

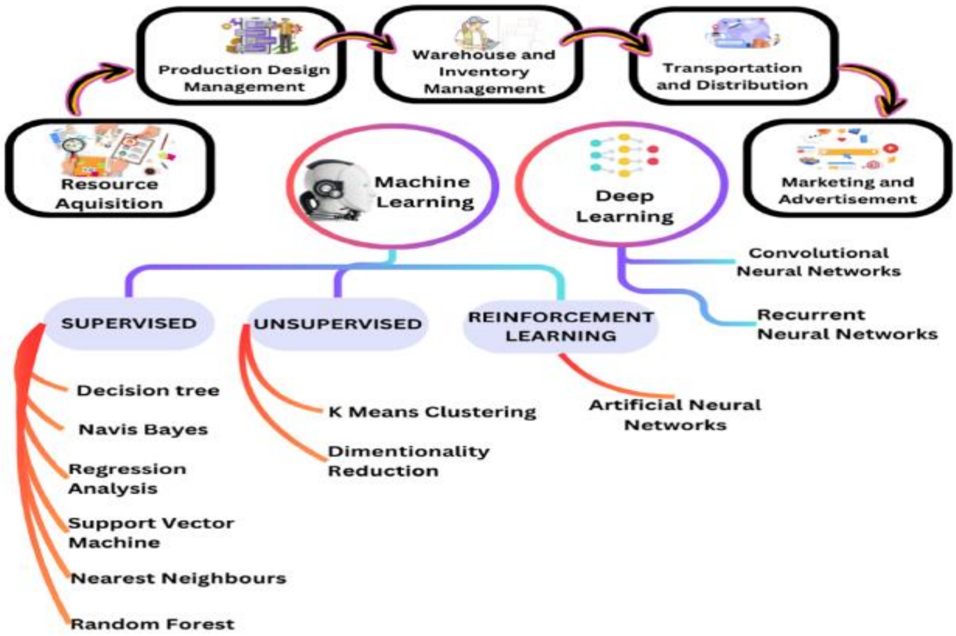

Fig : Ahmed M Khedr and al(2024); Various Machine learning and Deep learning methods applied in SCM.

Computer vision techniques based on convolutional neural networks (CNNs) enable the automated monitoring of inventory conditions in warehouses as well as the inspection of product quality along production lines. These applications not only reduce labor costs but also minimize the risk of human error, while providing accurate, real-time data to support decision-making processes (Kuo & Chen, 2020). In addition, deep learning has been employed to model the effects of complex disruptions—such as natural disasters or economic crises—on global supply chains (Ivanov & Dolgui, 2020).

2.2. Agent-Based Simulation for Risk Management

Agent-based simulation is a modeling approach that relies on autonomous entities, referred to as agents, to represent supply chain actors (e.g., suppliers, distributors, and consumers) and their interactions. AI techniques enhance these simulations by incorporating learning and adaptive behaviors at the agent level. For instance, AI-driven simulations of risk management and resilience strategies enable the evaluation of the effectiveness of different inventory policies and logistics reconfiguration strategies in response to disruptions (Christopher & Peck, 2004).

Agent-based simulations are particularly valuable for modeling complex scenarios involving multiple interconnected variables, such as cascading effects within supply chains disrupted by global health crises. By integrating AI algorithms, these simulations can explore a vast solution space and identify optimal strategies to mitigate negative impacts on supply chain performance (Ivanov & Dolgui, 2020).

For example, agent-based models have been widely used to assess the impact of the COVID-19 pandemic on global supply chains and to test resilience strategies such as supplier diversification and increased safety stock levels (Ivanov, 2020).

2.3. Dynamic and Adaptive Optimization of Logistics Networks

Logistics network optimization is a domain in which AI has delivered substantial improvements, particularly in terms of flexibility and adaptability. Unlike static optimization models, AI-based optimization approaches—such as deep reinforcement learning (DRL)—enable the dynamic adjustment of managerial decisions in response to continuously changing supply chain conditions (Mnih et al., 2015).

For example, deep reinforcement learning (DRL) algorithms can be employed to optimize transportation routes in real time by accounting for constraints such as traffic conditions, fuel costs, and delivery time windows.

Adaptive optimization is particularly critical for resource management in warehouses, where demand variability and capacity constraints require rapid and accurate adjustments to storage and picking strategies. Empirical studies indicate that the application of AI-driven adaptive warehouse management can reduce operational costs while improving order fulfillment efficiency (Bousdekis et al., 2020). These techniques are also applied to multi-echelon inventory management, where replenishment decisions must be coordinated across multiple supply chain tiers to minimize costs and maximize product availability (Kang, Lee & Ryu, 2021).

2.4. Disruption Prediction and Proactive Risk Management

One of the major challenges in SCM lies in predicting and managing disruptions that can have severe consequences for supply chain performance. AI, owing to its ability to process large volumes of real-time data, provides powerful tools for detecting weak signals and anticipating disruptions before they materialize. For instance, machine learning models can analyze social media trends, economic news, and weather data to forecast potential risks such as labor strikes, public health crises, or natural disasters (Choi, Wallace & Wang, 2018).

These predictive capabilities enable supply chain managers to adopt proactive risk mitigation strategies, including inventory repositioning, sourcing from alternative suppliers, and adjusting production policies. Furthermore, real-time simulation techniques combined with machine learning models allow organizations to evaluate alternative disruption response strategies and select the most effective course of action based on the specific conditions of the supply chain (Ivanov & Dolgui, 2020)

3. Artificial Intelligence–Driven Decision-Making in Supply Chain Management

3.1. AI-Based Recommendation Systems and Decision Support

Originally developed and popularized within the field of electronic commerce, recommendation systems have progressively emerged as effective decision-support tools in Supply Chain Management (SCM). In contemporary SCM environments, AI-based recommendation systems are increasingly leveraged to assist decision-makers in critical operational and strategic decisions, including supplier selection, inventory control, and transportation planning.

Specifically, algorithms such as collaborative filtering techniques and artificial neural networks enable the systematic analysis of historical supplier performance data to identify and recommend optimal trading partners. These recommendations are generated based on multidimensional evaluation criteria, including procurement costs, product quality, reliability, and delivery lead times, thereby enhancing supplier selection processes and reducing decision-making uncertainty (Gunasekaran et al., 2015).

Beyond supplier management, AI-driven recommendation systems play a pivotal role in inventory optimization. By exploiting sales data, demand patterns, and consumption trends, machine learning models are capable of recommending optimal inventory levels that simultaneously minimize stockout risks and reduce inventory holding costs (Chai, Liu, & Ngai, 2013). Moreover, AI-based recommendation systems contribute to transportation planning by identifying the most efficient routing alternatives. These systems incorporate real-time and historical variables—such as traffic congestion, fuel costs, and logistical constraints—thus enabling firms to reduce distribution costs and transit times while improving overall supply chain responsiveness (Kamble, Gunasekaran, & Gawankar, 2020).

3.2. Predictive and Prescriptive Decision Analytics

Predictive analytics constitutes a key area in which artificial intelligence delivers substantial value to decision-making processes in SCM. By applying machine learning techniques, predictive models can be developed to generate forward-looking insights into demand evolution, supply chain performance, and potential disruption scenarios. Commonly employed approaches, such as linear regression models and decision trees, are widely used to forecast future demand by integrating multiple explanatory variables, including seasonal effects, marketing campaigns, and macroeconomic fluctuations (Wang et al., 2016).

In addition to demand forecasting, predictive analytics is increasingly utilized in supply chain risk management. By analyzing historical data related to past disruptions—such as delivery delays, labor strikes, geopolitical instability, or natural disasters—machine learning models are able to detect latent patterns and correlations that support the anticipation of future risks and vulnerabilities (Kshetri, 2014). These predictive insights facilitate the development of proactive mitigation strategies. For example, predictive models may recommend increasing safety stock levels or diversifying supplier portfolios across geographically dispersed regions, particularly those exposed to high environmental or geopolitical risks. Such measures significantly enhance supply chain resilience and reduce the likelihood of supply disruptions (Ivanov & Dolgui, 2020).

3.3. Machine Learning Applications in Decision-Making

Machine learning is widely employed to automate and enhance decision-making processes in Supply Chain Management (SCM). In particular, clustering and classification algorithms are used to segment customers based on their purchasing behaviors, thereby enabling the development of more targeted marketing strategies and inventory management policies (Kusiak, 2017). Clustering techniques, such as *k*-means and Gaussian Mixture Models, allow customers to be grouped into homogeneous segments, facilitating offer personalization and improving the prediction of future purchasing behaviors (Sarker et al., 2020).

Supervised learning techniques, including Random Forests and Support Vector Machines (SVMs), are also applied to anomaly detection within supply chains. For instance, these models can be used to identify atypical patterns in financial transactions or inventory movements, which may signal fraudulent activities, logistical errors, or inefficiencies within the distribution network (Kamble et al., 2020). By automating anomaly detection, machine learning–based systems enable managers to respond more rapidly to potential issues and to make informed decisions aimed at correcting operational deviations and improving overall supply chain performance.

3.4. Real-Time Decision-Making Enabled by Artificial Intelligence

One of the major advantages of artificial intelligence in SCM lies in its ability to support real-time decision-making. Technologies such as the Internet of Things (IoT) and cloud computing enable the continuous collection and processing of real-time data from multiple sources, including shipment tracking sensors, warehouse management systems, and traffic monitoring platforms (Wang et al., 2016). When combined with AI algorithms, these data streams provide supply chain managers with a real-time, end-to-end view of the logistics network, thereby facilitating faster and more informed decision-making.

For example, AI can be employed to optimize transportation routes in real time by accounting for traffic conditions, weather forecasts, and delivery constraints. Deep learning algorithms can also be used to predict delivery delays based on both historical and real-time data, allowing logistics plans to be dynamically adjusted and customers to be proactively informed (Kamble et al., 2020). This capability to rapidly respond to changes and disruptions is critical for maintaining supply chain efficiency, agility, and resilience in increasingly complex and volatile operating environments.

3.5. Automation of Decision-Making Processes through Expert Systems

Expert systems are computer-based programs that rely on knowledge-based rules to emulate human decision-making processes within specific domains. In Supply Chain Management (SCM), AI-based expert systems can automate a wide range of routine decision-making processes, thereby allowing managers to focus on more strategic and value-adding activities. For example, expert systems can be employed to automate order management and replenishment decisions by dynamically adjusting inventory levels based on demand forecasts and current stock positions (Sanders, 2016).

Moreover, these systems can be integrated into supply chain management platforms to provide real-time recommendations for complex decisions, such as supplier selection, contract negotiation, and production planning (Heckmann et al., 2015). By leveraging advanced business rules in combination with machine learning models, expert systems contribute to streamlining decision-making processes while improving the consistency, reliability, and overall quality of decisions across the supply chain.

3.6. Limitations and Challenges of AI-Based Decision-Making Systems

Despite the substantial benefits offered by artificial intelligence for decision-making in SCM, several critical challenges remain. One of the most prominent issues concerns the interpretability of AI models, particularly those based on deep learning architectures, which are often regarded as “black boxes” due to their high level of complexity and limited transparency (Lipton, 2018). This lack of interpretability can hinder trust and adoption among managers, who may be reluctant to rely on recommendations generated by systems whose underlying logic they do not fully understand.

In addition, the quality and effectiveness of decisions produced by AI-based systems are highly dependent on the quality of the data used to train the models. Incomplete, inaccurate, or biased data can lead to erroneous predictions and suboptimal decisions, potentially resulting in negative consequences for supply chain performance (Mikalef et al., 2020). Consequently, the implementation of robust data governance frameworks is essential to ensure data integrity, reliability, and ethical use throughout the lifecycle of AI-driven decision-support systems.

4. Challenges and Limitations of AI in Supply Chain Management Research

4.1. System Integration and Compatibility Issues

One of the major challenges in applying artificial intelligence to Supply Chain Management (SCM) research lies in the integration of AI technologies with existing information systems. Modern supply chains rely on complex technological infrastructures, including Enterprise Resource Planning (ERP) systems, Warehouse Management Systems (WMS), and Transportation Management Systems (TMS). Integrating AI algorithms into these legacy and heterogeneous systems requires substantial efforts in software development, system interoperability, and compatibility management (Sanders, 2016).

In addition, AI systems are often required to interact with disparate and heterogeneous data sources, such as IoT sensor data, financial records, and information derived from social media platforms. This integration presents significant technical challenges, as data originating from different sources may vary in terms of format, structure, granularity, and quality. Managing such complexity necessitates the use of advanced tools for data transformation, system interoperability, and coordination among multiple stakeholders across the supply chain (Kusiak, 2017).

4.2. Ethical and Data Privacy Issues

The application of artificial intelligence in SCM research also raises critical ethical concerns, particularly with regard to data privacy and the protection of personal information. Modern supply chains generate and collect vast volumes of data, ranging from consumers' personal information to real-time product tracking data. The use of such data to train AI algorithms raises concerns related to how sensitive information is stored, shared, and utilized throughout the supply chain ecosystem (Mikalef et al., 2020).

Furthermore, AI algorithms may inadvertently reproduce or amplify biases embedded in training data, potentially leading to discriminatory or unfair decision outcomes. For example, a supplier recommendation algorithm trained on historical procurement data may systematically favor suppliers located in economically advantaged regions, thereby marginalizing emerging regions that could otherwise offer competitive alternatives (Floridi et al., 2018). Consequently, it is essential to establish mechanisms for transparency, accountability, and algorithmic fairness to ensure that AI models are deployed in an ethical, responsible, and equitable manner.

4.3. Risks of Over-Reliance on Artificial Intelligence

Another significant challenge concerns the risk of excessive reliance on artificial intelligence in supply chain decision-making. While AI systems can generate data-driven recommendations and forecasts, it is important to acknowledge that such models have inherent limitations and may not fully capture contextual, tacit, or qualitative factors that influence managerial decisions (Jarrahi, 2018).

For instance, an AI-based model may recommend increasing inventory levels in response to a forecasted surge in demand without adequately considering operational constraints, such as limited warehouse capacity, labor availability, or budgetary restrictions. Over-reliance on AI-generated outputs may therefore lead to suboptimal or impractical decisions if human judgment and domain expertise are insufficiently integrated into the decision-making process.

Such excessive reliance on artificial intelligence may also hinder innovation and creativity in supply chain management. When managers rely uncritically on AI-generated recommendations, they may fail to explore alternative solutions or overlook unconventional opportunities that are not captured by existing models. It is therefore essential to combine the analytical capabilities of AI systems with human expertise and managerial judgment in order to support informed, nuanced, and context-aware decision-making.

4.4. Lack of Interpretability and Transparency of AI Models

The interpretability of AI models constitutes a major challenge, particularly in the case of complex algorithms such as deep neural networks. These models are often perceived as "black boxes," as it is difficult to understand how they arrive at specific decisions or predictions. This opacity may limit the adoption of AI in SCM research and practice, as researchers and managers may be reluctant to rely on tools whose internal mechanisms they cannot adequately explain or justify (Lipton, 2018).

Moreover, the lack of model transparency raises important accountability concerns. For instance, if an AI system recommends an inventory management strategy that results in significant financial losses, it may be difficult to determine whether the failure stems from the algorithm itself, the training data, or the manner in which the model was implemented. To address this challenge, there is a growing need to develop Explainable Artificial Intelligence (XAI) techniques that enable AI-driven decisions to be visualized and interpreted in ways that are accessible to non-technical users (Ribeiro, Singh, & Guestrin, 2016).

4.5. Challenges Related to Data Quality and Governance

Data quality is a critical determinant of the success of AI applications in SCM. Inaccurate, incomplete, or outdated data can lead to erroneous predictions and flawed decision-making, thereby undermining overall supply chain performance. For example, incorrect information regarding inventory levels or delivery lead times can distort demand forecasting models, resulting in excessive inventory accumulation or stockouts (Kshetri, 2014).

Furthermore, data governance represents a major challenge, particularly in distributed supply chain environments where data are collected, processed, and stored by multiple independent actors. Ensuring data consistency, integrity, and security across the entire network is essential for maintaining the reliability of AI models. Robust data governance practices must therefore be implemented to regulate data access, monitor data quality, and ensure compliance with regulatory requirements and ethical standards (Mikalef et al., 2020).

4.6. Development and Implementation Costs

Finally, the costs associated with the development and implementation of AI technologies in SCM constitute a significant barrier, particularly for small and medium-sized enterprises. Developing AI models requires specialized expertise and advanced computational infrastructures, which may entail substantial initial investments. In addition, integrating these technologies into existing information systems often requires costly technological adaptations and extensive employee training programs (Sanders, 2016).

It is therefore crucial for organizations to carefully assess the potential return on investment prior to deploying AI solutions at scale. Agile development approaches and pilot projects can be employed to test the feasibility and effectiveness of AI technologies before broader implementation. Moreover, collaborations with universities and research institutions may help reduce research and development costs by facilitating the sharing of resources, expertise, and knowledge (Brynjolfsson & McAfee, 2014).

5. Future Perspectives and Research Directions

5.1. Development of Novel AI-Based Methodologies

One of the most promising research avenues in Supply Chain Management (SCM) concerns the development of novel methodologies based on artificial intelligence to address increasingly complex decision-making problems. For instance, integrating AI techniques with classical optimization methods—such as mathematical programming and evolutionary algorithms—may enable more effective solutions to multi-objective problems by simultaneously accounting for environmental, economic, and social constraints (Deb et al., 2002).

In addition, AI can be leveraged to develop hybrid simulation models that combine agent-based approaches with system dynamics, thereby offering richer representations of complex interactions among supply chain actors and enhancing the understanding of systemic behaviors under uncertainty and disruption scenarios (Ivanov et al., 2019).

5.2. Artificial Intelligence for Sustainable Supply Chains

Sustainability has become a growing priority in Supply Chain Management (SCM) research, and artificial intelligence offers unique opportunities to enhance the environmental performance of supply chains. For instance, the application of AI to transportation routing optimization and inventory management can contribute to reducing greenhouse gas emissions and minimizing waste across logistics networks (Sarkis, 2021).

Future research could further investigate how AI can be integrated with emerging digital technologies, such as the Internet of Things (IoT) and blockchain, to improve product traceability and ensure compliance with environmental and social standards throughout the entire supply chain (Tseng, Wu, & Nguyen, 2018). Such integrative approaches have the potential to support more transparent, accountable, and sustainable supply chain ecosystems.

5.3. AI-Assisted Collaborative Research

Another promising research avenue concerns the development of AI-assisted collaborative research platforms, in which researchers and AI systems work jointly to explore novel ideas and develop innovative solutions (Brynjolfsson & McAfee, 2014). These platforms could leverage Natural Language Processing (NLP) algorithms to systematically analyze existing literature, identify research gaps, and generate new research hypotheses.

In addition, AI systems could be employed to automate experimental design and data collection processes, thereby reducing the time and costs associated with large-scale research projects and enabling more efficient knowledge creation in SCM research (Heckmann et al., 2015).

I. 5.4. Impact of Artificial Intelligence on Employment and Workflow Reconfiguration

The impact of artificial intelligence on employment and work organization within supply chains represents an important area for further investigation. While AI technologies can automate a wide range of routine and repetitive tasks, they also have the potential to reshape job roles and redefine the skill sets required of supply chain professionals. Future research should therefore examine how AI can be leveraged to enhance productivity while simultaneously creating opportunities for workforce training, upskilling, and reskilling (Brynjolfsson & McAfee, 2014).

Moreover, it is essential to explore how AI can be integrated in ways that foster effective human–machine collaboration, in which managers rely on AI systems to support more strategic, complex, and judgment-intensive decision-making processes rather than replacing human expertise altogether (Jarrahi, 2018).

5.5. Exploring the Limits of AI and Advancing Explainable Artificial Intelligence

Finally, continued efforts are required to explore the limitations of artificial intelligence and to advance Explainable Artificial Intelligence (XAI) techniques in order to improve the transparency, interpretability, and trustworthiness of AI-based models. This includes the development of novel tools for visualizing and interpreting algorithmic decisions, as well as the establishment of ethical frameworks to guide the responsible use of AI in both SCM research and practice (Ribeiro, Singh, & Guestrin, 2016).

Such research initiatives are expected to strengthen user trust in AI-driven systems and to promote broader, more responsible adoption of artificial intelligence technologies in supply chain management.

Conclusion

The integration of artificial intelligence (AI) into Supply Chain Management (SCM) research represents a major paradigm shift, offering unprecedented opportunities to enhance research methodologies, decision-making processes, and risk management practices. AI has demonstrated significant potential to transform SCM research by enabling large-scale data analytics, supporting more accurate modeling approaches, and automating complex analytical and operational tasks. In particular, advances in machine learning and deep learning have facilitated the effective addressing of complex challenges such as demand forecasting, logistics network optimization, and the proactive management of supply chain disruptions (LeCun, Bengio, & Hinton, 2015).

Nevertheless, this transformation is accompanied by substantial challenges. The integration of AI into SCM research requires overcoming technical barriers, including system interoperability and data quality issues, as well as addressing ethical concerns related to data privacy, fairness, and responsible use of algorithmic decision-making (Mikalef et al., 2020). Moreover, the limited transparency and interpretability of advanced AI models remain critical obstacles to their widespread adoption among researchers and practitioners, highlighting the urgent need for the development and deployment of Explainable Artificial Intelligence (XAI) techniques (Lipton, 2018).

Future research directions in SCM include the development of novel AI-integrated methodologies, such as hybrid models that combine artificial intelligence with traditional optimization techniques and agent-based simulation approaches (Ivanov & Dolgui, 2020). In addition, AI offers unique opportunities to advance sustainable supply chain management by enhancing product traceability and optimizing logistics flows to reduce environmental impacts, including carbon emissions (Sarkis, 2021). The implications of AI for workforce organization and skill requirements within supply chains also constitute a critical research domain, necessitating further investigation to ensure a smooth transition toward effective human–machine collaboration (Brynjolfsson & McAfee, 2014).

Overall, artificial intelligence has the potential to fundamentally reshape SCM research by providing powerful tools to address the growing complexity of modern supply chains. To fully realize this potential, continued research efforts are required to overcome technical and ethical challenges and to develop governance frameworks that promote the responsible, transparent, and effective adoption of AI in SCM. Close collaboration between researchers and practitioners will be essential to harness the transformative capabilities of AI and to build supply chains that are more resilient, sustainable, and agile in an increasingly uncertain global environment.

Références

Ahmed M Khedr, Sheeja Rani (2024). Enhancing supply chain management with deep learning and machine learning techniques: A review. Journal of Open Innovation, 10 (2024) 100379.

Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. Management Science, 66(3), 1025-1044.

Bousdekis, A., Magoutas, B., Apostolou, D., & Mentzas, G. (2020). A proactive decision making framework for condition-based maintenance. Industrial Management & Data Systems, 120(3), 559-586.

Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W. W. Norton & Company.

Chai, J., Liu, J. N., & Ngai, E. W. (2013). Application of decision-making techniques in supplier selection: A systematic review of literature. Expert Systems with Applications, 40(10), 38723885.

Choi, T. M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. Production and Operations Management, 27(10), 1868-1883.

Christopher, M. (2016). Logistics & supply chain management. Pearson UK. Christopher, M., & Peck, H. (2004). Building the resilient supply chain. The International Journal of Logistics Management, 15(2), 1-14.

CRC Press. Tseng, M. L., Wu, K. J., & Nguyen, T. T. (2018). Information technology in supply chain management: A case study. Procedia Manufacturing, 17, 665-672.

Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182 197.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., ... & Schafer, B. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), 689-707.

Ghouati, S., Rizi, L., Oulfarsi, S., & El Amri, A. (2026). Artificial intelligence and supply chain management: A bibliometric exploration of impacts on operational performance. Business Performance Review, 4(1), 118.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press. Gunasekaran, A., Subramanian, N., & Rahman, S. (2015). Supply chain resilience: Role of complexities and strategies. International Journal of Production Research, 53(22), 6809 6819.

Heckmann, I., Comes, T., & Nickel, S. (2015). A critical review on supply chain risk– Definition, measure and modeling. Omega, 52, 119-132.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780.

Ivanov, D. (2020). Viable supply chain model: Integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic. Annals of Operations Research, 1-21.

Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. International Journal of Production Research, 58(10), 2904-2915.

Ivanov, D., Dolgui, A., Sokolov, B., Ivanova, M., & Rozhkov, M. (2019). Preserving supply chain viability amidst the COVID-19 pandemic: Digital twin and the ripple effect. International Journal of Production Research, 58(18), 5601-5614.

Ivanov, D., & Dolgui, A. (2023). The shortage economy and its implications for supply chain and operations management. *International Journal of Production Research*, 61(1), 1–14.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577-586.

Jubair, H. (2025). *The integration of artificial intelligence in supply chain management: A comprehensive review.* Organize Journal of Economics Management and Finance, 4(1), 80–91.

Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2020). Achieving sustainable performance in a data-driven agriculture supply chain: A review for research and applications. International Journal of Production Economics, 219, 179-194.

Kang, J., Lee, D., & Ryu, K. R. (2021). Multi-echelon inventory management for perishable products using deep reinforcement learning. Computers & Industrial Engineering, 153, 107076.

Kshetri, N. (2014). Big data's impact on privacy, security and consumer welfare. Telecommunications Policy, 38(11), 1134-1145.

Kuo, T. C., & Chen, C. (2020). Application of deep learning in the supply chain management research: A systematic review. Supply Chain Management Review, 20(4), 31-45.

Kusiak, A. (2017). Smart manufacturing. International Journal of Production Research, 55(10), 2582-2594.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444. Lipton, Z. C. (2018). The mythos of model interpretability. ACM Queue, 16(3), 31-57.

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2020). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. British Journal of Management, 31(2), 356-381.

Min, H. (2023). Artificial intelligence in supply chain management: Theory and applications. *International Journal of Logistics Research and Applications*, 26(2), 123–145.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., ... & Hassabis, D. (2015). Human-level control through deep reinforcement learning. Nature, 518(7540), 529-533.

Pearson. Sanders, N. R. (2016). How to use big data to drive your supply chain. California Management Review, 58(3), 26-48. Sarkis, J. (2021). Supply chain sustainability: Learning from the COVID-19 pandemic. International Journal of Operations & Production Management, 41(1), 63-73.

Queiroz, M. M., Fosso Wamba, S., De Bourmont, M., & Telles, R. (2021). Blockchain adoption in operations and supply chain management: Empirical evidence from an emerging economy. *International Journal of Production Research*, 59(20), 6083–6103

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?" Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 1135-1144).

Russell, S., & Norvig, P. (2016). Artificial Intelligence: A Modern Approach (3rd ed.).

Samuels, A. (2025). Examining the integration of artificial intelligence in supply chain management from Industry 4.0 to 6.0: A systematic literature review.

Silver, E. A., Pyke, D. F., & Thomas, D. J. (2017). Inventory and Production Management in Supply Chains (4th ed.).

Teixeira, A. R., Ferreira, J. V., & Ramos, A. L. (2025). Intelligent supply chain management: A systematic literature review on artificial intelligence contributions.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. In Advances in Neural Information Processing Systems (pp. 5998-6008).

Wang, G., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98-110.