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Integration of Machine Learning in the Supply Chain for Decision Making: A Systematic Literature Review

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Abstract:

Purpose: This study presents a systematic literature review that provides a broad and holistic view of how machine learning can be used and integrated to enhance decision-making in various areas of the supply chain, highlighting its combination with other techniques and models.

Design/methodology/approach: A systematic literature review employed three sets of keywords in the Scopus and Web of Science (WoS) databases. Utilizing a predefined filtration process aligned with the PRISMA statement , 70 articles were selected from an initial total of 410, focusing on those that specifically addressed the intersection of machine learning and decision-making in supply chain management.

Findings: Machine learning has proven to be an essential tool in the supply chain, with applications in inventory management, logistics, and transportation, among others. Its integration with other techniques has led to significant advances in decision-making, improving efficiency in complex environments. Combining machine learning methods with traditional techniques has been particularly effective, and integration with emerging technologies has opened up new application possibilities.

Originality/value: Unlike previous studies that focused on specific areas, this study offers a broad perspective on the application of machine learning in the supply chain. Additionally, combining machine learning techniques with other models is highlighted, representing added value for the scientific community and suggesting new avenues for future research.

Keywords: machine learning, decision making, supply chain, inventory management, demand forecasting, supplier selection

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1. Introduction

In an increasingly digital and data-driven world, decision-making has become a strategic and complex process that requires analyzing and interpreting vast amounts of information. Traditionally, decisions were made based on experience, intuition, and available data. However, this dynamic is rapidly changing with the advent of new technologies and digital systems (Rolf, Jackson, Müller, Lang, Reggelin & Ivanov, 2022). Decision support tools, designed to provide relevant, accurate, reliable, and interpretable information, have evolved significantly and now encompass a variety of approaches. These include data-based tools, which apply analytical techniques to evaluate large volumes of data; model-based tools, which use analytical models to weigh and evaluate different decision scenarios; and knowledge-based tools, which employ specialized domain knowledge to assess decision options. Large-scale decision-making (LSDM) and data-driven decision-making (DDDM) approaches have emerged from a rapidly evolving research field (Maghsoodi, Torkayesh, Wood, Herrera-Viedma & Govindan, 2023; Ni, Xiao & Lim, 2020).

In this regard, machine learning emerges as a revolutionary technology redefining how organizations make decisions. This innovation provides decision-makers with real-time information access, allowing for more accurate analysis and, therefore, more informed decisions. Moreover, with the ability to learn from data, machine learning offers a data-driven approach to decision-making, which can complement, and in some cases replace, traditional experience-based methods (Mohamed-Iliasse, Loubna & Abdelaziz, 2022). The supply chain, essential for the operability and efficiency of organizations, means that the integration of machine learning can be key to overcoming challenges and optimizing processes. The adaptability and predictive capacity of machine learning position it as an invaluable tool for anticipating demand fluctuations, managing inventories efficiently, and optimizing distribution routes. These applications improve operational efficiency and translate into competitive advantages in a globalized market (Akbari & Do, 2021). In this context, this article will focus on exploring how machine learning has been used and how it has been integrated into the supply chain to enhance decision-making. Through a thorough analysis of existing literature and a detailed review of practical applications, this study aims to provide a comprehensive view of the opportunities machine learning offers for decision-making in the supply chain and identify potential areas for future research and emerging challenges in this constantly evolving field.

1.1. **Previous Works**

In general, areas such as Big Data Analytics (BDA) and Machine Learning (ML) are becoming increasingly crucial for the field of Supply Chain Management (SCM). Therefore, in the last decade, a plethora of research has been published on BDA and ML in the SCM area, and consequently, many review articles have been published in this field. The analysis of previous reviews is presented in Table 1 below to emphasize their importance and highlight its differentiating approach compared to the present study. The differences with the work intended to be carried out are highlighted for each of them.

At the review level, numerous studies have been conducted on machine learning applications in the supply chain. These studies have explored various areas, from inventory management and demand forecasting to digital transformation and supply chain process management. However, most of these studies have focused on specific areas of the supply chain or specific machine learning techniques. For instance, some studies have examined how machine learning techniques can enhance inventory management or demand forecasting. Others have explored how machine learning can support digital transformation or process management in the supply chain. Some studies have also investigated the general research trends in machine learning applications in the supply chain. However, what sets our work apart from previous works is the focus on how machine learning has been integrated with other models or techniques to support decision-making in the supply chain. Unlike previous studies that have focused on specific areas or techniques, our study aims to provide a broader and more comprehensive view of how machine learning can be used to enhance decision-making across all areas of the supply chain. Moreover, while many previous studies have examined the applications of machine learning in the supply chain in isolation, our study seeks to understand how these techniques can be combined with other models and techniques to provide more effective and efficient solutions. This makes our study highly relevant and significant to the scientific community and can pave the way for future research.

Article	Title	Aim
Albayrak-Ünal, Erkayman & Usanmaz (2023)	Applications of Artificial Intelligence in Inventory Management: A Systematic Review of the Literature	Review artificial intelligence (AI) applications used in inventory management.
Hosseinnia-Shavaki & Ebrahimi-Ghahnavieh, (2022)	Applications of deep learning into supply chain management: a systematic literature review and a framework for future research	Review articles on deep learning applications in supply chain management, analyzing trends, perspectives, and potential research gaps.
Rolf et al. (2022)	A review of reinforcement learning algorithms and applications in supply chain management	Explore the current state of reinforcement learning in supply chain management (SCM) and propose a classification framework.
Mohamed-Iliasse et al. (2022)	Machine Learning in Supply Chain Management: A Systematic Literature Review	Study how machine learning techniques can be integrated into the range of tools available to decision-makers in the supply chain to leverage the growing volume of data generated in the supply chain.
Lee & Mangalaraj (2022)	Big Data Analytics in Supply Chain Management: A Systematic Literature Review and Research Directions	Conduct a systematic review of existing studies on big data analysis in the supply chain, examining theoretical foundations, research models, techniques, and algorithms from interdisciplinary perspectives.
Tavana, Shaabani, Vanani & Gangadhari (2022)	A Review of Digital Transformation on Supply Chain Process Management Using Text Mining	Using text mining, explain existing knowledge about digital transformation in supply chain process management.
Moradi & Dass,(2022)	Applications of artificial intelligence in B2B marketing: Challenges and future directions	Examine AI methods and their applications in B2B marketing across the four stages of the customer lifecycle: reach, acquisition, conversion, and retention.
Akbari & Do (2021)	A systematic review of machine learning in logistics and supply chain management: current trends and future directions	Provide a systematic view of research trends in ML in both logistics and the supply chain.
Filali, Ben-Lahmer & Filali (2021)	Exploring applications of Machine Learning for supply chain management	Provide a summary of new research in the field of machine learning in the supply chain, particularly in demand forecasting, through systematic analysis.
Riahi, Saikouk, Gunasekaran & Badraoui (2021)	Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions	Analyze what the general research trends are for AI applications in supply chains.
Grander, da Silva & Santibañez-Gonzalez (2021)	Big data as a value generator in decision support systems: a literature review	Analyze how decision support systems manage Big Data to extract value.
Rai, Tiwari, Ivanov & Dolgui (2021)	Machine learning in manufacturing and Industry 4.0 applications	Report on the latest efforts in the fundamental theoretical and experimental aspects of machine learning and its applications in manufacturing and production systems
Breitenbach, Haileselassie, Schuerger, Werner & Buettner (2021)	A Systematic Literature Review of Machine Learning Tools for Supporting Supply Chain Management in the Manufacturing Environment	Review the literature on machine learning tools in supply chain management from a manufacturing perspective and build a comprehensive, task-oriented overview based on the supply chain management operations reference model
Ni et al. (2020)	A systematic review of the research trends of machine learning in supply chain management	Provide a comprehensive view of ML applications in SCM.

Table 1. Literature reviews and their aims

2. Methodology

Systematic literature reviews focus on identifying, interpreting, evaluating, and classifying all articles related to pre-established research questions. Unlike a conventional literature review, which primarily focuses on the descriptive findings of a specific field of knowledge, a systematic literature review provides a more comprehensive and valuable overview of research disciplines (Wee & Banister, 2016). The filtering and screening process is depicted in Figure 1.

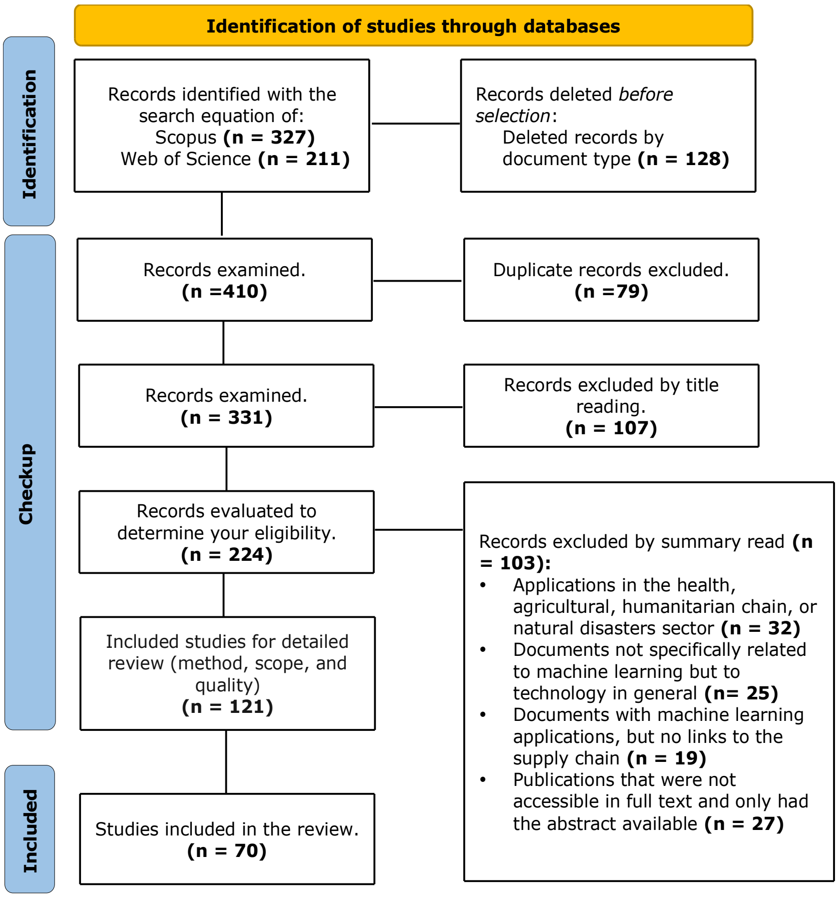

Figure 1. The process of selecting relevant papers (Page, McKenzie, Bossuyt, Boutron, Hoffmann, Mulrow et al., 2021)

This study combines three sets of keywords to gather relevant sources from the Scopus and Web of Science (WoS) databases. The first set contains "Machine Learning" and "Deep Learning" to encompass studies focusing on machine learning and deep learning techniques in various contexts. Is chosen to encompass a broad spectrum of studies focusing on both general machine learning techniques and their more specialized subset, deep learning. This inclusion ensures that the review captures all relevant advancements and applications in these areas, which are pivotal in the context of decision-making processes within the supply chain.

The second set contains "decision making", "decision support", "DSS", "Decision Theory", "decision support system" to include studies that address decision-making and decision support systems, this set is crucial to explore how machine learning influences decision-making processes, both from a theoretical perspective and in practical applications.. The third set includes "supply chain" and "SCM" to capture studies focusing on the supply chain and supply chain management. The inclusion of these terms ensures that the review is firmly anchored in the context of supply chain, aligning with the core focus of the research.

Finally, the AND and OR operators were used to combine these keyword sets to cover studies exploring the intersection of machine learning and decision-making in the context of supply chain management. Thus, the search equation used was: ("Machine Learning" OR "Deep Learning") AND ("decision making" OR "decision support"

OR "DSS" OR "Decision Theory" OR "decision support system*") AND ("supply chain" OR "SCM"). This approach ensures a comprehensive and targeted review, effectively aligning with the study's objectives to explore the integration of machine learning in supply chain decision-making processes.

In the next step, the Scopus and Web of Science databases were selected to gather relevant articles using the search query from the previous step. Initially, Scopus and WoS yielded 327 and 211 results for the query, respectively. Then, a filter was applied in each database, by document type, considering only articles and conference papers, without any filter based on the year of publication, resulting in 217 articles in Scopus and 193 in Web of Science for a total of 410. Subsequently, duplicate items were removed, leaving 331 results. Then, a title reading filter was applied to account for the main theme, filtering out 224 articles. In the next step, to further reduce the database size, the abstracts of the retained articles were analyzed to construct the final database. The primary objective of this step was to eliminate studies whose applications were related to the health sector, agriculture, humanitarian chain, or natural disasters, documents not specifically related to machine learning but to technology in general, documents with machine learning applications but without links to the supply chain, and publications where only the abstract was available and not the full text. After a careful review of the abstracts, 121 studies were gathered for detailed review. Upon examining the full text of the 121 documents from various perspectives (method, scope, and quality), 70 articles were selected for the final database of this research.

This set of articles was subjected to a detailed bibliometric analysis, using R software and the Bibliometrix library in the BiblioShiny environment, as described in the corresponding section. This bibliometric analysis provided a quantitative view of trends and patterns in the existing literature. Subsequently, a qualitative content analysis of the selected articles was carried out, which is detailed in sections 4 and 5 of the article. Section 4, 'The Role of Machine Learning in Supply Chain Decision Making', analyzes how machine learning has been used for decision making in various areas of the supply chain, exploring in depth the integration and application of these techniques. Section 5, 'How is machine learning integrated with other models or tools?', examines how machine learning integrates with other models or tools, identifying three key perspectives. This qualitative analysis not only presents the applications of machine learning, but also delves into the 'how' it is used and integrated to improve decision making.

Bibliometric analysis together with qualitative analysis make up a mixed methodological approach that provides a holistic and detailed vision of both the general structure and the specific content of the selected literature, thus reflecting the rigor and depth necessary for a comprehensive understanding of the topic.

3. Bibliometric Analysis

The bibliometric analysis was carried out using R software and the Bibliometrix library in the BiblioShiny environment, applied to the final database composed of 70 selected articles. This analysis delved into several key aspects of the existing literature, allowing us to gain a detailed perspective of the field of study.

In section 3.1 'Studied areas of the supply chain', the different areas of the supply chain studied in the literature were analyzed, providing an overview of the predominant topics and applications in the field of machine learning. Section 3.2 'Annual Scientific Production' presented an analysis of annual scientific production, highlighting trends and growth of interest in the topic over time. In section 3.3 'Keyword co-occurrence graph', keyword co-occurrence was explored, allowing thematic relationships and emerging research areas to be identified in the machine learning and supply chain literature.

Finally, section 3.4 'Thematic Map' provided a detailed thematic map, illustrating the structure and key domains of the field of study, which helped to understand how different themes and concepts are interconnected within the existing literature. This comprehensive approach to bibliometric analysis allowed for a comprehensive and multidimensional understanding of the current state of knowledge in the area of machine learning applied to supply chain decision making.

3.1. Studied Areas of the Supply Chain

This section evidences the applications of machine learning within the supply chain, based on the 70 articles selected for this review. Figure 2 illustrates the frequency with which different areas of the supply chain are addressed in current literature, reflecting both the predominant research focus and those emerging niches with potential for future studies. Through this section, we seek to establish a bridge between the quantitative view of bibliometric analysis and the qualitative and applied discussion that characterizes Section 4. Each area identified here serves as a precursor to a more detailed analysis, providing a complete understanding of how the Machine learning is being applied to strengthen decision making within the supply chain.

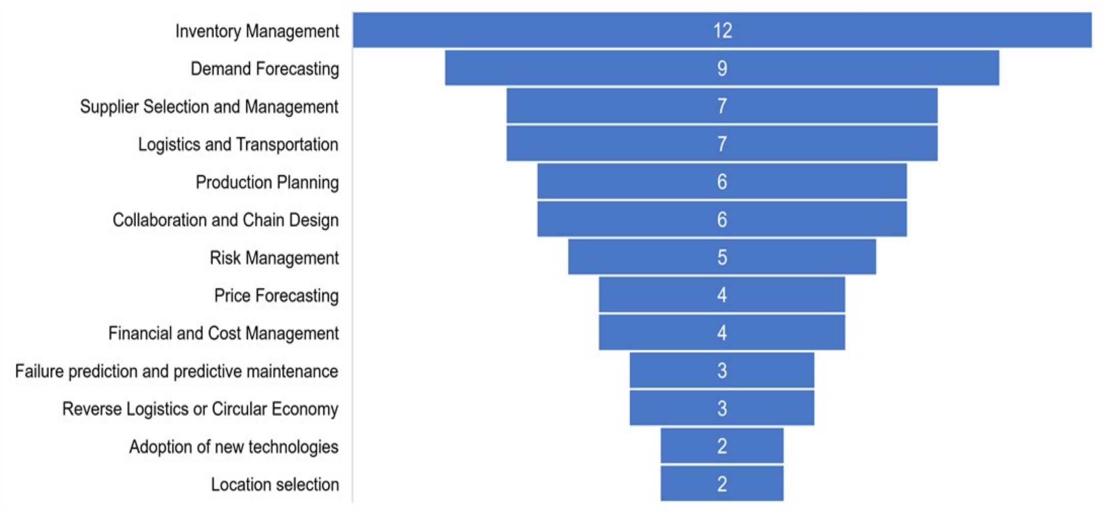

Figure 2. Studied areas of the supply chain

For example, inventory management emerges as the most explored area, with 12 articles focusing on how machine learning can contribute to more accurate predictions and optimizations. This emphasis is reflected in the innovative proposals of authors such as Wang, Long, Ong, Zhang and Yuan (2023) and Wu, de Carvalho-Servia and Mowbray (2023), who use reinforcement learning techniques to improve real-time decision making related to inventory. These and other in-depth studies are discussed in detail in Section 4.5.

Demand forecasting is also identified as a significant field, demonstrating the value of machine learning in anticipating market needs and planning accordingly. Section 4.4 of the article delves into specific methods and their practical applications, such as the hybrid models of learning algorithms adopted by Hamdan, Aziguli, Zhang and Sumarliah (2023) to predict the arrival of electronic orders in real time, highlighting the synergy between ML techniques and fuzzy approaches.

In supplier selection and management, as well as logistics and transportation, the areas highlighted in the graph are discussed further in sections 4.1 and 4.11, respectively. These segments detail how machine learning methods, such as the dynamic decision support systems proposed by Alavi, Tavana and Mina (2021), are redefining the landscape of sustainable supplier selection by integrating techniques such as the Best-Worst Method (BWM) and the Fuzzy Inference System (FIS).

The integration of machine learning within reverse logistics and the circular economy, summarized in Section 4.9, reflects the evolving nature of the supply chain towards sustainability and resource efficiency, with real-world applications such as the system proposed by Liu (2023) for green supply chain management. Furthermore, the financial and cost management aspects of the supply chain, discussed in Section 4.10, reveal the critical role of machine learning in strategic decision making, as seen in the application of LSTM for supply rate forecasting. change by Weerasingha, Bandara and Edirisinghe (2023).

In the context of machine learning applications within supply chains, in the business arena Makeev (2023) reveal significant industry adoption, with companies like Amazon optimizing inventory levels through predictive models and industry giants. logistics such as UPS improving equipment reliability with predictive maintenance algorithms. For example, Amazon's use of machine learning is said to have improved inventory cost reductions by 20% and customer satisfaction by 15%. Walmart's implementation of optimized delivery routes through machine learning models has led to a 10% reduction in transportation costs and a 5% increase in delivery efficiency.

Similarly, Unilever stands out for its use of machine learning in supply chain management, which has resulted in a 15% reduction in transportation costs and a 20% increase in process efficiency(Bharadwaj, 2022). Its platform analyzes sales, inventory and logistics data to identify improvements, evidencing the synergy between operational efficiency and environmental sustainability.

Unleashed Software and John Galt (n.d.) demonstrate the effectiveness of machine learning in predicting product demand. Both companies use advanced predictive models (linear regression and neural networks, respectively) to analyze sales and inventory trends, achieving 95% accuracy in their predictions. The models were principally used in agroindustrial sector such as Zespri, a New Zealand's Kiwifruit cooperative, and Fonterra, a New Zealand's dairy industry bussiness in wich ML optimise milk production and delivery systems. Transportation companies such as Maersk Line is also an user of ML, their Logistics Hub dashboard powered by AI enables its clients to have total visibility of their end-to-end supply chain.

Gramener (2022) and Pluto7 (n.d.) apply machine learning to detect patterns and trends in the supply chain, making it easier to identify opportunities for improvement. These models analyze a variety of data, from sales to consumer behavior, highlighting machine learning's ability to reveal operational efficiencies. Acordin to the article, AI is currently being tested or employed in Pfizer for GPS data analysis and optimization of supply chain a critical factor given the temperature requirements of vaccines. Other companies in automotive an aircraft sectors such as Bosch, Boeing, Audi AG emplois AI to ensure sustainability, zero defects, and promote operational efficency.

Inveritasoft and RevUnit illustrate the application of machine learning in equipment breakdown prediction and delivery route optimization. Inveritasoft uses logistic regression to predict failures with 90% accuracy, while Revunit uses neural networks to design more efficient routes, reducing transportation costs by 10% (RevUnit, n.d.)

These examples reflect the concepts addressed in the selected articles. In the section on 'Demand Forecasting' (Section 4.4), where Hamdan et al. (2023) discuss hybrid learning algorithms, the parallels with Amazon's approach to predicting product demand are evident. Similarly, Walmart's route optimizations are reflected in our 'Logistics and Transportation' analysis (Section 4.11), which shows the broader relevance of machine learning models to operational efficiencies.

While these examples from industry leaders offer tangible demonstrations of the impact of machine learning, they also underscore the potential for future research to bridge the gap between academic exploration and practical implementation. Integrating these insights into our discussion not only exemplifies existing applications but also highlights opportunities for academic contributions to influence real-world supply chain practices.

Therefore, while these industry examples are not part of the 70 articles selected for review, they provide complementary evidence of the practical applications of machine learning, offering a broader perspective that enriches our academic analysis.

3.2. Annual Scientific Production

Continuing with the bibliometric analysis, this section presents the behaviour of scientific production, allowing us to examine how academic interest in machine learning applications in the supply chain, reflected in the 70 selected articles, has evolved over time. As shown in Figure 3, scientific production on the topic has shown notable growth starting in 2018, peaking in 2022. This increase coincides with several key factors, including the maturity of machine learning technologies, their greater accessibility and the proliferation of big data in various industries. Additionally, the push given by digital transformation in sectors such as manufacturing, logistics and e-commerce has stimulated research that seeks to leverage machine learning to gain competitive advantages and improve operational efficiency. These trends are reflected in the increasing number of publications, indicating growing interest and recognition of the strategic importance of machine learning in supply chain management.

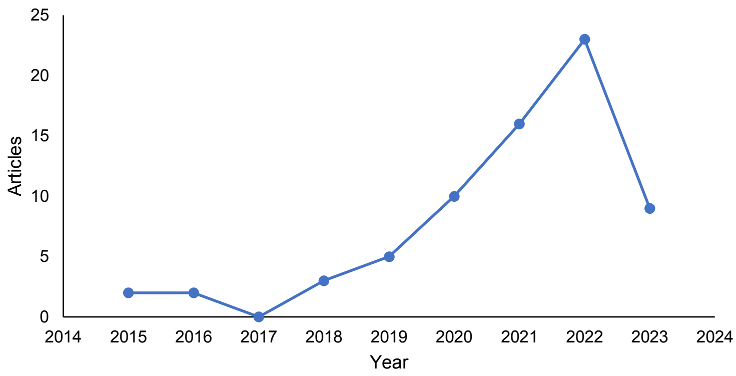

Figure 3. Annual Scientific Production

3.3. Keyword Co-occurrence Graph

Furthermore, the keyword co-occurrence analysis depicted in Figure 4 allows us to identify four main thematic groups in the study of machine learning in the supply chain.

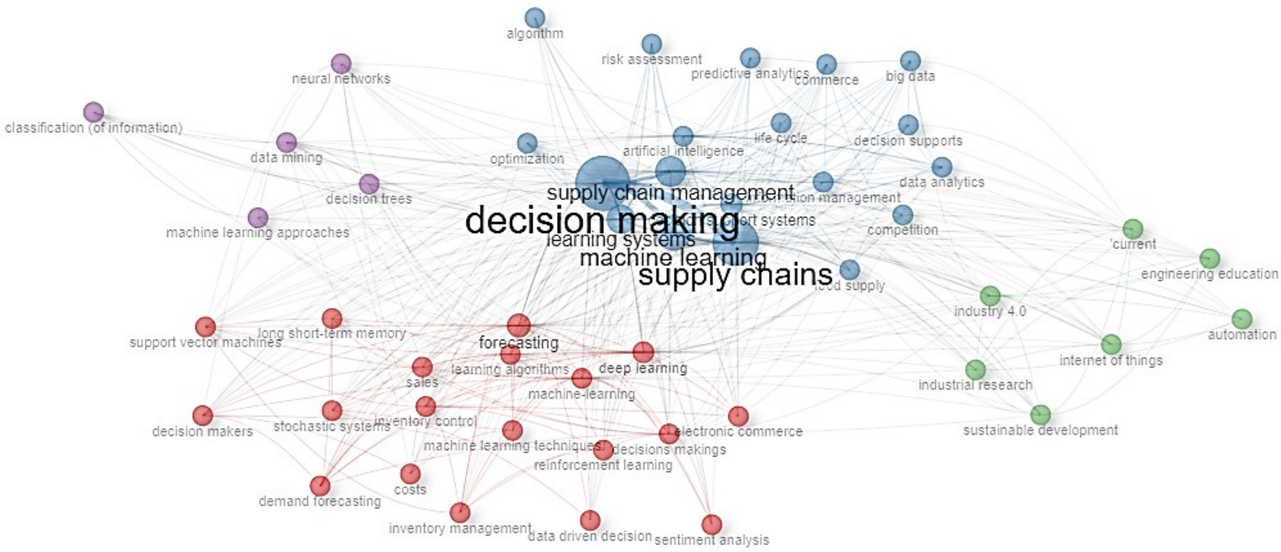

Figure 4. Keyword co-occurrence graph

Emerging Technologies (green cluster): Research works that has analyzed how emerging technologies are impacting the supply chain and how engineering education must adapt to address these changes and ensure a sustainable approach in the industry.

Predictive Analysis and Decision Making (blue cluster): Associated to topics such as predictive analysis, optimization, risk assessment, and machine learning. The keywords suggest a focus on how machine learning and related technologies can support decision-making in areas like commerce, information management, and life cycle assessment.

Data-based Forecasting and Inventory Management (red cluster): Cluster associated with research that has focused on the application of data-driven approaches to forecast demand, manage inventory, and improve sales decisions in the supply chain context. The keywords suggest research on how e-commerce and data-driven approaches, like machine learning, can enhance the efficiency and effectiveness of supply chain management.

Machine Learning Techniques (purple cluster): Focuses on specific machine learning techniques, such as neural networks, decision trees, and data mining, applied to data classification and analysis in the supply chain. This keyword group suggests a focus on researching advanced machine learning methods to extract valuable information from supply chain data and improve decision-making.

3.4. Thematic Map

The Thematic Map, shown in Figure 5 is a graph that identifies groupings of themes and their interconnections based on their co-occurrence in the dataset. This graph is subdivided into four quadrants, reflecting the different characteristics of the themes or keywords in terms of their impact and development.

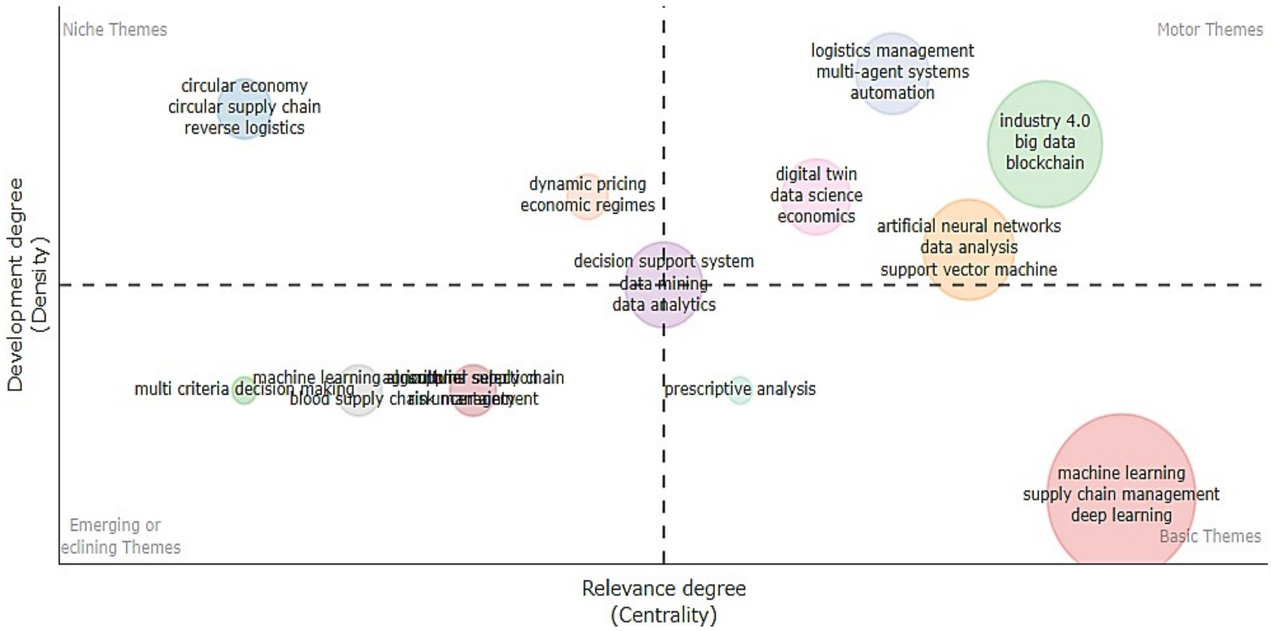

Figure 5. Thematic Map

Areas of specialized or emerging study, such as circular economy in the supply chain and reverse logistics, are grouped as Niche Themes, meaning that although frequent, they have limited connections with other themes. Due to their potential for innovation, these areas represent opportunities for pioneering research.

On the other hand, we find the Driving Themes, such as logistics management, multi-agent systems, industry 4.0, big data, blockchain, digital twins, neural networks, and support vector machines. These themes are vital and well-established, driving innovation and development in the field. Continuous research in these areas is essential to maintain and enhance existing knowledge, offering opportunities for interdisciplinary collaborations.

Emerging or Declining Themes, such as uncertainty, multi-criteria decisions, and Machine Learning, although less frequent and with limited connections, mark evolving trends in the field. If these themes are emerging, they offer opportunities to intellectually lead and develop solutions to novel problems. However, if they are declining, they should be evaluated to determine their current and future relevance.

Finally, Basic Themes such as prescriptive analysis, Machine Learning, Deep Learning, and supply chain management represent fundamental concepts in the field. Despite their less frequent appearance, they are well connected with other themes, reflecting their importance and the need for constant research to improve the understanding of these fundamental concepts, develop new methodologies, and seek opportunities to connect these themes with other related fields or areas.

4. The Role of Machine Learning in Supply Chain Decision Making

In the current era of digitalization and rapid technological evolution, machine learning has established itself as a powerful and transformative tool in various fields, and the supply chain is no exception. This section will provide a detailed analysis of how machine learning has been used for decision-making in various areas of the supply chain.

Instead of merely listing applications, this section will explore the 'how', that is, how machine learning has been used and integrated for decision-making.

4.1. Supplier Management and Selection

Supplier management and selection focus on identifying and evaluating potential suppliers. It goes beyond simple procurement of goods, considering factors such as quality, reliability, delivery capability, and sustainability. Proper management allows companies to establish long-term relationships, negotiate better terms, and ensure a steady flow of materials and services (Harikrishnakumar, Dand, Nannapaneni & Krishnan, 2019). In this regard, Ali, Nipu and Khan (2023) proposed a supplier selection framework based on the Random Forest (RF) algorithm, using a wide range of potential criteria selected through the PRISMA technique. This approach represents a significant evolution from supplier selection techniques based on single or limited criteria, providing a more comprehensive and robust assessment. In a different approach, Alavi et al.(2021) proposed a dynamic decision support system for sustainable supplier selection, integrating the Best-Worst Method (BWM) and the Fuzzy Inference System (FIS). In this system, machine learning is used to maintain and synthesize the criteria scores for suppliers after each selection engagement, allowing the system to learn and improve over time as more data is collected. This approach highlights the value of machine learning not only in the initial supplier selection but also in ongoing management and performance assessment. In the study by Islam, Amin and Wardley (2021), researchers integrated the Holt's Linear Trend, ARIMA, and Relational Regressor Chain (RRC) forecasting techniques to predict future demands. The resulting forecasts were used to feed a Stochastic Mixed Integer Linear Programming (SMILP) model, which served to select suppliers and plan order allocations.

In the works of de Cavalcante, Frazzon, Forcellini and Ivanov (2019) and Zhang, Li, Wu and Meng (2016) they adopt more specific approaches, focusing respectively on supplier resilience and supplier portfolio selection. In the study by Cavalcante et al. (2019) they use a simulation model that generates a database, which is used as input for a machine learning model (ML), composed of the K-Nearest Neighbors algorithm, which classifies suppliers based on their past performance (time and order quantity) and Logistic Regression (LR) that generates a probability that each supplier will deliver an order within the expected timeframe. Between both algorithms, they select the least risky supplier, and finally, these results are used as input for a test simulation experiment. On the other hand, Zhang et al. (2016) use a classification neural network (RankNet) to select supplier portfolios, and a training engine is developed to train and update the classification neural network. In this way, the proposed model can intelligently learn from historical experiences, meaning that the selection model becomes increasingly smarter with the accumulation of order data.

The study by Harikrishnakumar et al. (2019) uses supervised machine learning algorithms to classify suppliers into four categories: excellent, good, satisfactory, and unsatisfactory. Providing a more efficient and effective way of supplier evaluation and reducing the bias involved in this process, while in the study by Cheng, Peng, Zhou, Gu and Liu (2017) appropriate suppliers are selected using the fuzzy multi-objective Data Envelopment Analysis (DEA) model, then the expert database is built containing appropriate and inappropriate suppliers. Thus, the learner can be trained by the expert database using the proposed Adaboost algorithm.

4.2. Production Planning

Optimization and efficiency in production systems represent a central challenge in the field of industrial engineering, and in the last couple of years, machine learning has emerged as an invaluable technique to address these challenges. In the context of production planning and operation, there are studies such as that of Nakao and Nishi (2022), which use RFM (Recency, Frequency, Monetary) analysis and K-Means clustering to construct customer buying behavior and thus optimize production decisions based on their preferences. This allows companies to maintain efficiency while meeting individual market demands. In the study by Gahm, Uzunoglu, Wahl, Ganschinietz and Tuma (2022) neural networks are used to anticipate and approximate batch feasibility in hierarchical production planning, based on the consideration of interdependencies between top-level decisions and base-level decisions, thus improving the efficiency and effectiveness of the decision-making process. Meanwhile, Chen, Zhou and Zhang (2021) sought to improve production performance by creating an algorithm integrating machine learning with Model Predictive Control (MPC) to enhance decision-making and maximize overall net gain.

In this algorithm, historical data from the decision-making process is collected as participants make their individual decisions with a certain degree of bias. This data is then analyzed using machine learning to estimate the values of unknown parameters by solving a regression problem.

On the other hand, Dohale, Gunasekaran, Akarte and Verma (2021) and González-Rodríguez, Gonzalez-Cava and Méndez-Pérez (2020) present different but equally innovative approaches. Dohale et al. (2021) propose a three-stage Delphi-MCDM-Bayesian Network framework, where MCDM stands for multicriteria decision making, to identify the most suitable production systems for a company. In the first stage, Process Choice Criteria (PCC) are identified through an exhaustive literature review, which is then validated with experts using the Delphi method. In the second stage, the Analytical Hierarchy Process-based Voting Method (VAHP) is adopted to determine the relative importance of each criterion for a company. The obtained relative weights are then used as input for the Bayesian Network (BN) in the third stage. The BN model quantifies the probability of selecting production systems. Meanwhile, González Rodríguez et al. (2020) propose an approach that combines regression trees with a fuzzy inference system to improve task scheduling. In this study, regression trees are used in the initial modeling step to map the relationships between the inputs and outputs of the training data, as these are defined by nodes and leaves that, based on simple yes or no conditions, establish a correlation between an input and an output. As a result, it is possible to translate the nodes and leaves of a regression tree into a membership function structure to relate fuzzy inputs and outputs through if-then statements. In this way, if-then rules are automatically generated from the conditions in the regression tree. These rules link the input membership functions with the outputs and represent the fuzzy logic of the system.

Finally, Liu, Hwang, Yund, Neidig, Hartford, Boyle et al. (2020) use the Random Forest algorithm to predict the completion times of work orders. These predictions provide users with a more reliable understanding of when open work orders will be delivered and what the estimated delivery times will be for future work orders currently being planned. Additionally, the Principal Component Analysis (PCA) method is applied to identify the most influential levels of categorical variables.

4.3. Price Forecasting

Price forecasting involves predicting changes in the prices of products or services in the market. This is crucial for strategic decision-making, such as pricing, production planning, and inventory management. The advancement of machine learning has revolutionized numerous disciplines, and price prediction and management have been no exception. In this field, Sirisut and Sansrimahachai (2023) applied a deep learning-based approach to forecast the prices of plastic resin in the petrochemical industry. This study stands out for the incorporation of Global Vectors for Word Representation (GloVe) to transform textual news information into numerical data, which is then incorporated into Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) for predictions.

On the other hand, Lee, Abdollahian, Schreider and Taheri (2023) used several machine learning models to predict product demand in the supply chain. The results of these models are used as input in the price optimization model, which is a constraint programming problem based on a weekly time frame and a product category level aggregation. This price optimization model is capable of maximizing profits from many price combinations. Meanwhile, Bodendorf, Xie, Merkl and Franke (2022) proposed a multiperspective cost estimation system that incorporates statistical learning techniques, deep learning, and decision-making. Unlike previous studies, this work included multi-agent theory and post-hoc explainability to facilitate negotiations between manufacturers and suppliers and improve understanding of the model's results. Lastly, Hogenboom, Ketter, van Dalen, Kaymak, Collins and Gupta(2015) presented an approach for real-time tactical price decision-making in complex supply chain markets. This study differs from the previous ones by its use of Radial Basis Function Networks (RBFN) to estimate the parameters of the bid price distribution based on real-time available information and the use of clustering techniques to identify economic regimes.

4.4. Demand Forecasting

Demand forecasting involves predicting the quantity of products or services that customers will require in the future. This is essential, considering it influences areas such as production planning, inventory management, and strategic decision-making. Machine learning has been used to analyze historical data and relevant variables to predict future demand. In studies like the one by Hamdan et al. (2023) a hybrid learning algorithm is used that combines the benefits of Adaptive Neuro Fuzzy Inference System (ANFIS) and neural networks to predict real-time electronic order arrivals. This illustrates the complementarity between ML techniques and fuzzy approaches, demonstrating their effectiveness in logistical decision-making. Similarly, Terrada, El-Khaili and Ouajji (2022) employ a forecast model based on Long Short-Term Memory (LSTM) to predict the demand quantities of a specific product based on historical data. This approach is useful for informing decision-making in critical areas such as production planning, inventory management, and delivery scheduling. These predictions feed decisions in multiple areas of SCM, illustrating the potential of LSTM in supply chain optimization. Another interesting model is presented by Zhuang, Yu and Chen (2022) where internal and external data are integrated to predict intermittent demand. By combining two optimization techniques based on transfer learning. First, the classification model (TrAdaboost) is used to predict whether there will be demand. If it is predicted that the demand will not be zero, then the regression model (LightGBM) is used to predict the amount of that demand. These results are combined to produce a final demand prediction that can inform decision-making in later stages of the supply chain process, such as inventory planning.

Birim, Kazancoglu, Mangla, Kahraman and Kazancoglu (2022) integrates several ML and deep learning techniques to predict demand based on advertising expenses. This study illustrates the flexibility of these algorithms to adapt to various influencing factors in demand prediction. Similarly, Gonçalves, Cortez, Carvalho and Frazão (2021) propose a two-stage forecasting framework that combines the ARIMAX model with different ML models to predict manufacturer demand. In the first stage, a multivariate dataset of input time series sequences is constructed for each inventory component. In the second stage, the optimized machine learning model is used to model the relationship between the selected inputs and the target variable, which is the manufacturer's demand. For their part, Pereira and Frazzon (2021) use the K-means algorithm and neural networks to generate demand forecasts based on historical sales of each product from each channel. This demand forecast information is used in simulation-based optimization (SBO) to make decisions about which facility would most effectively meet the identified demands, optimizing supply chain operations and allowing more effective coordination between supply and demand and a reduction in operating costs. The implementation of deep learning (DL) in demand prediction is also reflected in the study by Abosuliman and Almagrabi (2021), who propose a Logistics Management Framework Using Deep Learning (eLMF-DL) that integrates a hybrid CNN-LSTM network to implement Computer-Human Interaction (HCI) assisted by artificial vision in the logistics management sector. The eLMF-DL model combines production maximization and demand forecasting to make optimal decisions about the allocation of logistic service power. This study exemplifies the potential synergy between DL and other AI techniques in improving logistical efficiency.

Sousa, Ribeiro, Relvas and Barbosa-Povoa (2019) explore the impact of the bullwhip effect in the oil and gas industry using artificial neural networks to predict demand. This approach allows simulating the effects of demand fluctuations and evaluating the impact on the supply chain, highlighting the value of ML in managing demand volatility. Finally, Brahami, Zahra, Mohammed, Semaoune and Matta (2022) integrates ML techniques with knowledge management (KM) processes, maximizing efficiency in demand forecasting. This study demonstrates the potential synergy between ML and KM, facilitating informed decision-making in SCM.

4.5. Inventory Management

Inventory management involves controlling and monitoring a company's inventory levels. This includes determining optimal inventory levels, replenishment planning, and optimizing costs associated with storage and inventory obsolescence. In this area, machine learning has been used from different perspectives. In the studies by Wang et al. (2023) and Wu et al. (2023) two distinct but complementary approaches are presented for the use of reinforcement learning (RL) in inventory management. While Wang et al. (2023) focuses on lot sizing for perishable materials in an uncertain environment, Wu et al. (2023) introduces a risk management approach in its objective function to balance risky decisions. Both studies highlight the importance of prediction in defining the state of the reinforcement learning model and the need for real-time sequential decision-making for inventory management. Likewise, their approaches differ in the integration of other models or techniques. While Wang et al., (2023) integrate ARIMA and LSTM techniques for delivery time and demand predictions in the RL algorithm, Wu et al.

(2023) integrate a recurrent neural network (RNN) to parameterize the RL policy and use a derivative-free optimization algorithm to explore the control and state space.

On the other hand, Wang, Peng and Yang (2022) and Badakhshan and Ball (2022) address the issue of inventories with lost sales and waiting times. Wang et al. (2022) proposes a solution framework based on Double Deep Q-Networks (DDQN), formulating the inventory management problem as a Markov Decision Process, where the current inventory level state only depends on its previous state. In contrast, Badakhshan and Ball (2022) integrate machine learning and simulation to identify inventory and cash replenishment policies that minimize the impact of disruptions on supply chain performance. The simulation model generates data considering interruptions in the physical and financial flows of the supply chain, which are introduced into a decision tree algorithm to identify actions that reduce the cash conversion cycle. Finally, a digital twin of the supply chain is created that integrates the simulation model and the decision tree algorithm.

Another relevant sub-area is multi-criteria decision-making, as demonstrated by the work of, Paula-Vidal, Caiado, Scavarda, Ivson and Garza-Reyes (2022), which presents a two-stage framework for decision support in inventory management. In the first stage, a hybrid MCDM method is applied that combines fuzzy logic with the Analytic Hierarchy Process (AHP) and the VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method to classify and select SKUs based on their importance and criticality. Once the most critical SKUs are revealed, a second stage is introduced to forecast the demand for these SKUs through an ML model, which combines a genetic algorithm and an artificial neural network (GA-ANN).

Furthermore, the integration of reinforcement learning with deep learning algorithms for supply chain order management is addressed by Huang and Tan (2021) whose model allows determining when and how much to order to minimize total inventory costs, considering factors such as storage costs, transportation costs, and uncertain product demand. In contrast, Andaur, Ruz and Goycoolea (2021) and Meisheri, Sultana, Baranwal, Baniwal, Nath, Verma et al. (2022) explore the issues of stockouts and multi-product, multi-period inventory management, respectively. Andaur et al. (2021) develop two AA-based systems to automatically detect such events, integrating Principal Component Analysis (PCA), RFID, and stochastic prediction models. In contrast, Meisheri et al. (2022), emphasizes uncertain demand and cross-restrictions between products.

Similarly, Shakya, Lee and Ng (2022) and Punia, Singh and Madaan (2020) address stochastic demand and supply problems, with reinforcement learning and data-based approaches, respectively. Shakya et al. (2022) model a linear supply chain problem with stochastic delivery time and demand within the Markov Decision Processes (MDP) framework and compare the efficiency of traditional reinforcement learning (i.e., Q-learning) and rule-based learning (i.e., the (R, S) policy) with their Deep Q Network (DQN) model. Punia et al. (2020) approach is based on the fact that, instead of making assumptions about demand distribution, which can often be incorrect, the machine learning model uses historical demand data and independent features to predict future demand. These predictions are then used as input in inventory optimization models to determine the optimal amount of products to order.

In contrast, Leung, Mo, Ho, Wu and Huang (2020) propose a specific predictive methodology for the arrival rate of electronic orders, integrating the features of time series data into an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the electronic order arrival rate and Priore, Ponte, Rosillo and de la Fuente (2019) offer a decision tree-based solution to adjust the replenishment policy to environmental changes. For this, they establish the inventory replenishment model according to the company's state and the supply chain over time, using a simulation model to generate an example dataset. Through this dataset, the inductive learning algorithm can acquire knowledge and encapsulate it in a decision tree for future decision-making.

4.6. Failure Prediction and Predictive Maintenance

Failure prediction and predictive maintenance refer to the ability to predict and prevent failures in the equipment and machinery used in the supply chain. This involves continuous monitoring of equipment performance data. In this sense, the use of machine learning algorithms to identify patterns and early warning signals of potential failures has been notable. In an effort to optimize reverse supply chain operations, Gayialis, Kechagias, Konstantakopoulos and Papadopoulos (2022) proposed a system that meets the needs of predictive maintenance, using machine learning in combination with the Internet of Things (IoT), cloud computing, and collaborative business process models. Real-time data collection through smart sensors, combined with the high computing power of cloud technology, allows for pattern identification to assess equipment status. In parallel, the implementation of collaborative business process models improves inventory management, purchase orders, and scheduling of maintenance workshop visits. Following a similar line, Shahbazi and Byun (2021) also leverage IoT for environmental data collection but apply big data techniques to handle this massive and unstructured data. Through the implementation of a hybrid prediction model based on Random Forest, they manage to detect failures in the manufacturing system. On the other hand, Mahato and Narayan (2020) focus their study on predicting failures in order fulfillment, by developing a pipeline with gradient-boosted decision trees. Unlike previous studies, their approach provides a level of explainability that benefits decision-makers, helping them understand why the model makes the predictions it does, thus establishing trust in the model's results to prevent future failures.

4.7. Collaboration and Supply Chain Design

Integration and coordination between suppliers, manufacturers, distributors, and customers are essential for an efficient supply chain. Effective collaboration allows for information sharing, reduced response times, and quick adaptation to market changes. Therefore, activities such as information exchange, activity synchronization, and optimization of material and product flows throughout the chain require special attention. In this regard, studies like those of Ali, Ghazal, Ahmed, Abbas, Khan, Alzoubi et al. (2022) and Nizamis, Vergori, Ioannidis and Tzovaras (2018) use machine learning to enhance collaboration and efficiency in the supply chain, focusing on the customer-supplier interaction. Ali et al. (2022) model reveals the interrelationships between performance assessment and customer feedback by integrating the Support Vector Machine (SVM) algorithm and the K-Nearest Neighbors (k-NN) algorithm with a simulation model. Raw data obtained through IoT sensors are processed and categorized, eliminating outliers and missing values. The SVM and k-NN algorithms are applied at the prediction layer, and this data is merged and stored in the cloud once the required learning accuracy is achieved. This information is used to adjust and improve supply chain collaboration strategies. A point to highlight is the role customer feedback plays in shaping supply chain collaboration strategies. Although decision-making is driven by machine learning, it is human interaction through customer feedback that ultimately informs strategic decisions.

On the other hand, Nizamis et al. (2018), integrate a semantic framework with a set of deep learning tools for automated decision-making in agent-based markets. Collaboration between the two components occurs through REST communication in the point-to-point connection, and the deep learning toolkit queries the information stored in the ontology warehouse using the query engine services to receive the necessary dataset for analysis. The output data generated by the machine learning model is sent back to the semantic framework to enhance the efficiency of the semantic matcher in supporting automated decision-making within the collaborative ecosystem.

In contrast, Belhadi, Kamble, Fosso-Wamba and Queiroz (2022), Gumte, Pantula, Miriyala and Mitra (2021) and Xiao, Zhi and Keskin (2022) adopt approaches focused on supply chain optimization and resilience. Belhadi et al. (2022) research proposes an integrated multi-criteria decision-making (MCDM) technique driven by machine learning algorithms to identify patterns in AI Techniques for developing different strategies to develop Supply Chain Resilience (SCRes). In the first phase, a Fuzzy Wavelet Neural Network (FWNN) is used; this network calculates the appropriate weights for the SCRes strategies. In the second phase, the Solution Average Distance methodology (EDAS) is used to determine the ranking of Artificial Intelligence (AI) techniques according to the weights of the SCRes strategies obtained in the previous phase. On the other hand, Xiao et al. (2022) use a data-driven metaheuristic (DDMH) that uses machine learning models to extract valuable information from a supply chain network for smarter decision-making. The DDMH framework is based on three performance drivers: a data-based initial solution heuristic that uses machine learning to improve the quality of initial solutions. A reduced search space, which uses machine learning to reduce this search space, decreasing the number of candidate solutions to evaluate. And a data-based efficient fitness function that uses learning to approximate the target value of a candidate solution efficiently and accurately. This study highlights the practical application of machine learning in a real-life problem, offering insight into its effectiveness in real-world environments.

For their part, Gumte et al. (2021) address market condition uncertainty through a data-based robust optimization methodology (DDRO). This methodology uses a Neuro Fuzzy C-means (NFCM) clustering algorithm with density-based boundary point detection and Delaunay triangulations to eliminate unnecessary sampling regions as much as possible. The boundary points obtained are joined using Delaunay triangulation to create the outer envelope of each group, within which Sobol sampling is used for the generation of uncertain parameter realizations. The study shows that machine learning can be integrated with optimization techniques to improve decision-making in supply chain planning models by allowing more precise and efficient handling of uncertainty.

Finally, Alves and Mateus (2020) use the Proximal Policy Optimization (PPO2) algorithm to efficiently operate the entire supply chain and minimize operating costs. The problem was modeled as a Markov Decision Process (MDP), defining states, actions, rewards, and the transition model. Once the supply chain operation simulation environment was implemented, the PPO2 algorithm was used to adjust the hyperparameters and train the agent over thousands of episodes. The model was then evaluated at each step.

4.8. Risk Management

Every link in the supply chain is exposed to potential risks, from production interruptions to demand fluctuations. Effective risk management identifies these factors, assesses their impact, and establishes measures to mitigate them. Based on this premise, Akhtar, Ghouri, Khan, Amin-ul-Haq, Awan, Zahoor et al. (2022) employed the Support Vector Machine (SVM) algorithm in a decision-making model, designed to help companies prevent such interruptions. This ML application demonstrates its potential to identify and differentiate between fake and real news, a significant contribution to decision-making in the information age. In contrast, Zhu, Zhou, Xie, Wang and Nguyen (2019) proposed an improvement in the accuracy of SME credit risk prediction using a hybrid approach that combines the Random Subspace (RS) method and MultiBoosting. This study highlights the relevance of data analysis in decision-making related to supply chain financing.

Lu (2021) introduced a more strategic and knowledge-focused approach. Using machine learning based on the knowledge spiral theory and the SECI theory, they created a dynamic early risk warning management system. A genetic algorithm is used to adjust the initial weights of a backpropagation neural network (BPNN), allowing for network optimization. The neural network is then used for decision-making. Through this process, an optimal fitness function is obtained, and if the network error of the genetic algorithm meets a certain parameter, the algorithm stops running, and the optimal solution is passed to the neural network for training.

Similarly, Wang, Swartz, Corbett and Huang (2020) used Principal Component Analysis (PCA) and Dynamic Principal Component Analysis (DPCA) to model normal operating conditions and detect abnormal operations in the supply chain, providing valuable insight for risk management. On the other hand, Zhang, Li and Peng (2020) provided a different perspective by focusing on food safety risks in fresh product logistics companies. Here, the support vector machine (SVM) algorithm based on historical monitoring data allowed for the identification and mitigation of risks in the cold chain for strawberries. This application of ML in risk management demonstrates how these techniques can be used to improve food safety and operational efficiency, achieving sustainable development.

4.9. Reverse Logistics or Circular Economy

Instead of following a linear "produce-consume-discard" model, reverse logistics promotes the reuse and recycling of products. This not only reduces environmental impact but can also generate new business opportunities. In this sense, Liu (2023) proposes a system for green supply chain management for small and medium-sized enterprises. His approach focuses on minimizing carbon emissions and considers consumer sensitivity to prices and green products. He uses machine learning models to predict consumer response to price variations and the supply of eco-friendly products. On the other hand, Shahidzadeh and Shokouhyar (2022) developed a multi-industry model to improve product return decisions in reverse logistics. Their approach is based on social network analysis and deep learning methods, using data extracted from social networks and manufacturer documents to make recommendations on production, reuse, recycling, remanufacturing, refurbishment, and disposal of returned products. This approach is notable for its emphasis on the circular economy and the integration of social networks as a valuable data source.

Finally, Shahidzadeh, Shokouhyar, Javadi and Shokoohyar (2022) seek to integrate social behavior with industrial practices, using a sentiment analysis framework to make efficient reverse logistics decisions. Their framework is based on evaluating positive and negative customer comments, aiming to reduce waste and increase the productivity and sustainability of the supply chain. This approach shows how machine learning can contribute to decentralized and highly efficient decision-making, and how customer-provided information can be a valuable input in the decision-making process.

4.10. Financial and Cost Management

Financial and cost management in the supply chain involves controlling and optimizing costs associated with the acquisition, production, storage, and distribution of products. Beyond simple accounting, this area analyzes how supply chain-related costs affect a company's profitability. This includes evaluating investments, financing, and cost-reduction strategies. From this perspective, Weerasingha et al. (2023) use Long Short-Term Memory Neural Networks (LSTM) to forecast exchange rates. This approach allows for both time series data analysis and categorical data, leading to accurate predictions that help decide the best dates for invoicing in international transactions. This study underscores how ML can be fundamental in optimizing business decisions, in this case in the manufacturing sector. In a similar approach but applied to a different problem, Zhou, Sun, Fu, Fan, Jian, Hu et al. (2020) developed a solution for detecting financial fraud in the Supply Chain using Convolutional Neural Networks (CNN). The CNNs, implemented in the Apache Spark and Hadoop big data infrastructure, facilitate the parallel processing of large data volumes, reducing processing time, allowing more effective classification and detection of fraudulent transactions. This use of ML reflects its ability to increase accuracy and reduce losses, especially in areas where data is voluminous and pattern detection is critical.

In a third study, Bodendorf, Merkl and Franke (2022) explore the application of Artificial Neural Networks (ANN) to estimate costs in purchasing decisions, using a case study from the automotive industry. They also identified that ML algorithms outperform ANNs in terms of accuracy. The research results provide indications for choosing the ML approach that promises the best result for cost estimates and cost structure information to support decision-making in buyer-supplier relationships. Finally, Kumar, Shrivastav and Mukherjee (2022) integrate the Relief algorithm with Data Envelopment Analysis (DEA) and created a new model called Feature Selection Data Envelopment Analysis (FSDEA) to identify and encode indicators that can serve as early signals of potential bank failure.

4.11. Logistics and Transportation

Logistics and transportation refer to the planning, coordination, and execution of activities related to the movement of products and materials along the supply chain. This includes route management, load optimization, shipment tracking, and warehouse and distribution center management. In this regard, Zhan, Zhang, Yuan, Chen, Zhang, Fathollahi-Fard et al. (2023) and Oguntola, Ülkü, Saif and Engau (2023) highlight the importance of informed and quantitative decision-making. Both studies address sustainability in logistics and transportation, but from different angles. While Zhan et al. (2023) focus on the evaluation of low-carbon transport system development, Oguntola et al. (2023) focus on the optimal design of a multimodal logistics network, considering factors such as shipment consolidation. In both cases, machine learning models play a significant role in generating accurate and objective predictions to guide decision-making. However, they differ in approach, Zhan et al. (2023) use a combination of CRITIC and DEMATEL, where they use the CRITIC weight matrix to obtain the weight ratio, reducing the subjectivity of the DEMATEL method. The weighting results are then corrected using an artificial neural network. Whereas Oguntola et al. (2023) use a combination of machine learning techniques (Attention CNN-LSTM and Attention ConvLSTM) and a Mixed Integer Linear Program (MILP), where historical data from the stochastic parameter (demand) feeds the machine learning models, and these predictions are then used to formulate a deterministic supply chain model optimized to meet this forecasted demand.

On the other hand, Almeida, Munis, Camargo, da Silva, Sasso-Júnior and Simões (2022) and Aloui, Hamani and Delahoche (2021) adopt a more operational efficiency-oriented approach, albeit with different applications. Almeida et al. (2022) use various machine learning algorithms to predict the volume of wood to be transported, aiming to minimize waste and optimize resource utilization. Aloui et al. (2021), on the other hand, address the need for logistics companies to find high-performance strategies to enhance their sustainability. They consider the problem of sustainable goods transport planning by formulating and solving a collaborative and integrated two-level inventory, location, and route problem (2E-CILRP). They use a machine learning-based hybrid heuristic that combines K-means clustering and genetic algorithms. The machine learning model takes inputs from the formulated model and generates outputs that minimize logistics costs, CO2 emissions, and the accident rate.

These hybrid strategies are reinforced with the integration of other techniques, such as simulation and optimization, used in the works of Gutierrez-Franco, Mejia-Argueta and Rabelo (2021) and Ren, Choi, Le and Lin (2020) illustrating how these integrations enhance decision-making in urban distribution and cross-border e-commerce. Gutierrez-Franco et al. (2021) present a framework that integrates machine learning techniques, simulation, optimization, and stochastic techniques. The system leverages self-adjusting learning procedures to meet stakeholder objectives in mutually beneficial situations. The simulation model is an agent-based simulation that evaluates the dynamic and learning process of the solution, allowing for the creation of early warning systems, and making the best use of resources. For their part, Ren et al. (2020) propose a deep learning methodology for optimal decision-making in third-party logistics forwarding service (3PFL), which they call S2SCL (Seq2Seq based on CNN-LSTM). This methodology intelligently integrates inventory optimization and the demand forecasting process, modeling the system dynamics and dependency relationships in the variable demand for logistics services. Finally, Ouadi, Malhene, Benhadou and Medromi (2020) use clustering algorithms and predictive models to improve efficiency in the distribution of goods in urban logistics planning. This study exemplifies how machine learning techniques can be used for urban zoning and demand behavior prediction.

4.12. Adoption of New Technologies

The adoption and adaptation to new technologies, such as artificial intelligence (AI) and blockchain, are crucial for survival and success in today's dynamic business world. Adopting these technologies can provide organizations with competitive advantages, but also presents challenges, including evaluating and understanding the factors that can influence their successful adoption. In this context, both Kamble, Gunasekaran, Kumar, Belhadi and Foropon (2021) and Dohale, Akarte, Gunasekaran and Verma (2022) have used machine learning techniques to develop decision support systems aimed at predicting and understanding these factors.

Kamble et al. (2021) focused their research on predicting the likelihood of an organization successfully adopting Blockchain, combining Bayesian Networks (BN) with the Structural Equation Model (SEM). SEM was used to validate the factors defining the latent variables related to blockchain adoption and to test the statistical relevance of the model. On the other hand, BN was used to develop and validate a predictive model using the scores of the latent variables derived from the SEM model. This integration of methods offered a more complete and accurate representation of the relationships between variables, highlighting the complementarity of these modeling approaches in analyzing technology adoption. For their part, Dohale et al. (2022) developed a decision support system to predict and understand the critical success factors (CSF) influencing the improvement of production resilience through AI adoption. This study integrated a voting analytical hierarchy process (VAHP) and BN. First, the CSFs for AI adoption was determined, then VAHP was used to calculate the relative weights of these CSFs to prioritize and determine the most significant ones. Finally, BN was adopted to predict and understand the influential CSFs.

4.13. Location Selection

Location selection in the supply chain involves the strategic choice of facility locations, such as factories, warehouses, and distribution centers. This involves considering factors such as proximity to suppliers and customers, resource availability, transportation costs, and logistics infrastructure. Considering this, Han, Jia, Chen, Gupta, Kumar and Lin (2022) proposed a machine learning model for location selection focused on estimating the sales potential of a prospective site, overcoming the limitations of historical data and the subjective criteria of conventional models. They used an attribute selection algorithm to identify the critical factors for a site's profitability, then used an improved gray comprehensive evaluation method to determine the similarity between the candidate site and existing stores. Finally, they employed a kernel regression model to predict the sales potential of the prospective site. On the other hand, Khalid and Herbert-Hansen (2018) explored the application of unsupervised machine learning for international location selection. Using the k-means clustering technique, used to classify 94 countries using 24 indicators grouped into five categories, this study provided a quantitative and flexible strategy for preselecting potential locations. Despite its advantages, this study recognizes limitations, including the generality of the selected indicators and the dependency on the clustering algorithm used.

5. How is Machine Learning Integrated with Other Models or Tools?

In the review process, it was possible to identify three key perspectives in which machine learning is integrated with other models or techniques to support decision-making in the supply chain. These perspectives provide us with a useful framework to understand how machine learning is used in different contexts and how it can be effectively integrated with other approaches to improve decision-making.

The first perspective refers to the context in which the results of machine learning algorithms are used to generate predictions that are then used as inputs for other models or decision-making techniques. The second perspective is the situation in which data generated by other models or techniques are used as inputs for machine learning algorithms, which are then used to refine or improve decisions. The third perspective is when machine learning is used in conjunction with other models or techniques to support decision-making, often iteratively, to improve the efficiency and effectiveness of decision-making. Below are the cases related to each perspective.

Supply chain topics	Perspective 1. The results of the machine learning feed other models or techniques
Inventory management	• **ARIMA and Long Short-Term Memory Neural Networks** (LSTM) perform the delivery time and demand predictions using the **RL4LS Reinforcement Learning Algorithm** (Wang et al., 2023) • **Random Forest and Deep neural networks** predict future demand that an **Inventory optimization model uses** (Punia et al., 2020)
Demand forecast	• **Algorithm K-means and Artificial neural networsk (ANN)** generate the demand forecast than then is used by the **simulation based optimization (SBO) model** (Pereira & Frazzon, 2021)
Management and Selection of suppliers	• **Holt's Linear Trend, ARIMA and relation regressor chain (RRC)** predict the future demands used by the **Stocastic mix linear integer programming (SMILP**) (Islam et al., 2021)
Logistics and Transport	• **Atención CNN-LSTM and Attention ConvLSTM** perform the demand predictions which are then used by the **Mixed Integer Linear Program (MILP)** (Oguntola et al., 2023) • **Random Forest, Neural Networks (ANN), Support Vector Machine (SVM)** generate the predictions that are then used by the **Simulation-Optimization Model** (Gutierrez-Franco et al., 2021)
Production planning	• **Gradient descent machine learning** analizes the historical data of the decision making process that uses the **Model prediction control (MPC)** (Chen et al., 2021)
Collaboration and supply chain design	• **Support vector machines (SVM) and K-nearest neighbour algorithm (k-NN)** generate the predictions that are used in the **Simulation model** in turn the model generates data that is used by the machine learning algorithms (Ali et al., 2022) • **Fuzzy wavelets neural network (FWNN)** calculates the weigths of the strategies that uses the **Evaluation based on Distance from Average Solution (EDAS)** (Belhadi et al., 2022) • **Proximal Policy optimization (PPO2)** adjust the hiperparameters and train the **Simulation environment** (Alves & Mateus, 2020)
Price forecast	• **Global vectors for Word representation (GloVe)** transform the textual information in numerical data that uses the **neural networks of type ANN, and RNN** (Sirisut & Sansrimahachai, 2023) • **Multivariant linear regression (MLR), K-Nearest neighbours, Decision trees, and Random Forest** performs the demand forecast that the demand forecast that the **Price Optimization Model** uses (Lee et al., 2023).

Perspective 1. When machine learning results feed into other models or techniques

A notable pattern is the recurrent use of certain machine learning algorithms, such as Neural Networks (specifically LSTM), Random Forest, and ARIMA. These algorithms are used in various areas, from inventory management to price forecasting. This may be due to their ability to handle large datasets and their effectiveness in predicting complex and non-linear patterns. The integration of these algorithms with other models and techniques, such as Mixed Integer Linear Programming, the Reinforcement Learning Algorithm, and Optimization Models, demonstrates how machine learning can complement and enhance existing techniques. Machine learning algorithms provide accurate predictions that are then used to feed these models, resulting in more informed and efficient decisions.

Additionally, there is a trend towards using machine learning techniques in combination with simulation. This is evident in areas such as collaboration and chain design, where machine learning algorithms generate predictions that are used in simulation models. This combination allows for a deeper exploration of possible solutions and strategies, which can lead to more effective decisions. Similarly, in areas such as logistics and transportation, machine learning algorithms are used to generate predictions that feed simulation-optimization models. This indicates a trend towards the integration of prediction, simulation, and optimization to improve decision-making. These findings demonstrate significant potential for exploring the integration of machine learning algorithms with more advanced optimization techniques. Furthermore, as new machine learning algorithms are developed, these could be integrated into the supply chain to further enhance decision-making.

The analysis of the results of the literature review for the second perspective reveals an intriguing and valuable trend in using the outputs of other models or techniques to feed machine learning algorithms in the supply chain. This trend underscores the ability of machine learning to leverage and enhance existing techniques, resulting in more informed and effective decision-making. Regarding the models and techniques that feed machine learning algorithms, a variety of approaches are observed, from simulation models to sentiment analysis techniques. This suggests that machine learning can leverage a wide range of techniques and models, allowing for effective integration and synergy.

Furthermore, it is interesting to observe the variety of machine learning algorithms that benefit from the outputs of these models and techniques. From decision trees to neural networks, these machine learning algorithms are leveraging the outputs of other models and techniques to improve their accuracy and effectiveness. Despite the diversity of models, techniques, and algorithms used, certain patterns can be identified. For example, in inventory management and demand forecasting, simulation models and hybrid MCDM methods are commonly used to generate data that feeds machine learning algorithms. This suggests effective synergy between simulation, multi-criteria decision-making, and machine learning.

Additionally, in areas such as logistics and transportation, there is a trend towards using multi-criteria analysis techniques, such as CRITIC and DEMATEL, to obtain the weight proportion of the variables that feed machine learning algorithms. This indicates a trend towards the integration of multi-criteria decision-making and machine learning to improve decision-making. Despite these trends, there are also opportunities to explore other combinations of models, techniques, and machine learning algorithms. For example, less-used techniques, such as principal component analysis (PCA), could be explored in combination with popular machine learning algorithms, such as Random Forest. Furthermore, less-used machine learning algorithms, such as Support Vector Machines (SVM), could be explored in combination with sentiment analysis techniques.

In this perspective, it is observed that neural networks, in their various variants (RNN, LSTM, CNN), frequently appear in multiple areas, from inventory management to logistics and demand forecasting. Their ability to handle large volumes of data and adapt to complex patterns makes them an essential tool. Likewise, it is evident that neural networks and genetic algorithms are often used in conjunction with simulation models, sentiment analysis techniques, and optimization methods to improve the quality of initial solutions, reduce the search space, and model system dynamics.

Supply chain topics	Perspective 2. The results of models or other techniques feed the machine learning
Inventory management	• **Simulation model** generates the data that is entered into a **Decision Tree** (Badakhshan & Ball, 2022) • **Hybrid MCDM method that combines fuzzy logic with AHP and VIKOR** classifies and selects SKUs that are fed into a **Hybrid Model of Genetic Algorithm and GA-ANN Neural Network** (de Paula-Vidal et al., 2022) • **Principal Component Analysis (PCA)** determines the predictor variables and the class variable using the **Random Forest, Logistic Regression, Decision Tree, Naive Bayes, Support Vector Machines and Neural Networks algorithms** (Andaur et al., 2021) • **Simulation model** generates the data set used by **Decision Trees** (Priore et al., 2019) • **Markov Decision Process** formulates the inventory management problem using the double-depth Q-Network (Wang et al., 2022)
Demand Forecast	• **ARIMAX model** generates time series using **Dynamic Linear Regression (DLR), Random Forest (RF), Automated Machine Learning (automl) and Elman Recurrent Neural Network (ERNN) models** (Gonçalves et al., 2021) • **Knowledge Management (KM)** generates information that feeds the **K-Nearest Neighbors (KNN), Bayesian Networks and Adaboostm1 models** (Brahami et al., 2022)
Management and selection of suppliers	• **PRISMA** selects the criteria to be used by **Random Forest (RF)** (Ali et al., 2023) • **Simulation model** generates the database using the **K-Nearest Neighbors Algorithm and Logistic Regression** (Cavalcante et al., 2019) • **Data Envelopment Analysis (DEA)** selects the providers that are stored in the database to train the **Adaboost Algorithm** (Cheng et al., 2017)
Logistics and Transport	• **CRITIC and DEMATEL** obtain the weight ratio of the variables using the **Backpropagation Neural Network (BP)** (Zhan et al., 2023) • **Genetic algorithms** feed the **K-Means model** (Aloui et al., 2021)
Production Planning	• **Regression Trees** generate the if-then rules used by the **Fuzzy Inference System** (González-Rodríguez et al., 2020) • **RFM model (Recency, Frequency, Monetary)** generates the customer characteristics that feed the **K-Means algorithm** (Nakao & Nishi, 2022) • **Delphi-MCDM** determine the relative importance of each criterion used as input to the **Bayesian Network** (Dohale et al., 2021)
Collaboration and chain production	• **Semantic framework** generates the data set that is used by **Deep Learning,** outputs are sent back to the semantic framework (Nizamis et al., 2018)
Price Forecast	• **Global Vectors for the Representation of Words GloVe** transform textual information into numerical data using the **ANN, RNN Neural Networks** (Sirisut & Sansrimahachai, 2023)
Failure prediction and predictive maintenance	• **Internet of Things (IoT) and cloud computing** collect the data using **Forecast Models** (Gayialis et al., 2022) • **Internet of Things (IoT) and Big Data** collect the data using the **Random Forest model** (Shahbazi & Byun, 2021)
Risk management	• **Natural language processing techniques (NLP)** collect and synthesize information using the **Support Vector Machine (SVM)** (Akhtar et al., 2022)
Cost and financial management	• **Vector Autoregressive Model (VAR), Time Series Analysis, Fundamental and Technical Analysis** generate the information using the **Long-Short Term Memory Neural Network (LSTM)** (Weerasingha et al., 2023)
Inverse logistics or circular Economy	• **Sentiment analysis techniques** extract data from social networks using the **Convolutional Neural Networks (CNN) and Long-Short Term Memory (LSTM) model** (Shahidzadeh & Shokouhyar, 2022)
New technologies adoption	• **Structural Equation Model (SEM)** validates the factors that define the variables used by the **Bayesian Network (BN) model** (Kamble et al., 2021) • **Voting Analytical Hierarchy Process (VAHP)** calculates the relative weights of criteria that are then used in **BN Bayesian Networks** (Dohale et al., 2022)

Perspective 2. When results from other models or techniques feed machine learning

Supply chain topics	Perspective 3. Machine learning is used in conjunction with other models or techniques to support decision-making.
Inventory management	• **Traditional reinforcement learning (Q-learning), Deep Network Q (DQN) model** integrates with **Markov Decision Processes (MDP)** to model stochastic lead time and demand (Shakya et al., 2022) • **Adaptive Neuro-Fuzzy Inference System (ANFIS)** integrates with time series analysis to predict order arrival rate (Leung et al., 2020) • **Recurrent neural network (RNN)** parameterizes the policy of a **Distributive Reinforcement Learning (RL) Framework and optimization models** explore the control space and state (Wu et al., 2023)
Demand forecast	• **Adaptive Neurofuzzy Inference System (ANFIS)** and **Neural Networks** predict order arrivals (Hamdan et al., 2023) • **Tradaboost** predicts whether or not there will be demand and **LightGBM** predicts the amount of demand (Zhuang et al., 2022) • **Long Short-Term Memory (LSTM) Neural Networks** predict demands that are then used in decisions in multiple areas of SCM (Terrada et al., 2022) • **Support Vector Regression (SVR), Neural Networks (NN), Long Short Term Memory (LSTM), Random Forest Regression (RFR) and Decision Tree Regression (DTR)** predict demand (Birim et al., 2022) • **CNN-LSTM-Human-Computer Interaction (HCI) hybrid network assisted by artificial vision** for assignment in the logistics sector (Abosuliman & Almagrabi, 2021) • A **statistical model** simulates the effects of demand fluctuations and **artificial neural networks (ANN)** perform the demand forecast. (Sousa et al., 2019)
Management and Selection of suppliers	• **Classification neural network (ranknet)** integrated with a training engine to select supplier portfolios (Zhang et al., 2016) • **Support Vector Machines (SVM), Naive Bayes Algorithm (NBA), Classification and Regression Trees, (CART), and Logistic Regression (LR)** support supplier classification (Harikrishnakumar et al., 2019) • **The Machine Learning model** maintains and synthesizes the criteria scores generated by the **Best-Worst Fuzzy Method (BWM) and the Fuzzy Inference System (FIS)** (Alavi et al., 2021)
Logistics and Transport	• **CatBoost Regressor, Decision Tree Regressor, and K Neighbors Regressor** predict the product quantities to be transported (Almeida et al., 2022) • **Linear regression (LR), Bayesian regression (BR), artificial neural networks (ANN) and support vector machines (SVM)** improve efficiency in merchandise distribution (Ouadi et al., 2020) • **The S2SCL (Seq2Seq based CNN-LSTM) model** integrates with Inventory Optimization to **model system dynamics** (Ren et al., 2020)
Production planning	• **Neural networks** predict batch viability in hierarchical production planning (Gahm et al., 2022) • **Random Forest (RF)** predicts work order completion times and **PCA Principal Component** Analysis identifies the most influential levels of categorical variables (Liu et al., 2020).
Collaboration and supply chain design	• **Machine learning** improves the quality of initial solutions and reduces this search space and reduces the search space of **metaheuristic algorithms** (Xiao et al., 2022) • **Neuro Fuzzy C-means (NFCM)** contributes to the identification of the exact regions of uncertainty in the **Data Driven Robust Optimization Methodology (DDRO)** (Gumte et al., 2021)
Risk management	• **Random subspace (RS) method and MultiBoosting predict credit risk in SMEs** (Zhu et al., 2019) • **Principal Component Analysis (PCA) and Dynamic Principal Component Analysis (DPCA) model the operating conditions** (Wang et al., 2020) • **Genetic Algorithm** Adjusts the weights of the **Backpropagation Neural Network (BPNN)** (Lu, 2021)

Supply chain topics	Perspective 3. Machine learning is used in conjunction with other models or techniques to support decision-making.
Price Forecast	• **Deep Neural Decision Tree (DNDT)** that integrates **multi-agent theory and post-hoc explainability** to improve understanding of model results (Bodendorf, Xie et al., 2022) • **Radial Basis Function Networks (RBFNs)** estimate the parameters of the price distribution, it is integrated with estimating the parameters of the price distribution (Hogenboom et al., 2015)
Failure prediction and predictive maintenance	• **Internet of Things (IoT) and cloud computing** collect data using **Forecast Models** (Gayialis et al., 2022) • **Internet of Things (IoT) and Big Data** collect the data using **Random Forest model** (Shahbazi & Byun, 2021)
Cost and financial management	• **Convolutional Neural Networks (CNN)** are implemented on the big data infrastructure of **Apache Spark and Hadoop** (Zhou et al., 2020) • **Artificial Neural Networks (ANN)** estimate costs in purchasing decisions (Bodendorf, Merkl et al., 2022)
Inverse logistics or circular Economy	• **Convolutional Neural Network (CNN)** integrates with social network analysis to evaluate customer feedback (Shahidzadeh et al., 2022)

Perspective 3. When machine learning is used in conjunction with other models or techniques to support decision-making

It is noteworthy how ML is combined with traditional techniques, such as time series analysis, Markov Decision Processes, and principal component analysis. This fusion of the "new" with the "traditional" allows leveraging the best of both worlds, providing precision and comprehensibility. This combination of models allows capturing a broader range of patterns and relationships in the data, resulting in more accurate predictions and greater flexibility. By integrating different techniques, companies can adapt their models to different scenarios and needs, from inventory management to reverse logistics.

In areas such as inventory management and demand forecasting, there is a trend to combine models that operate at different levels of abstraction. For example, the use of RNNs to parameterize reinforcement learning policies shows how one can operate from a micro-level (individual predictions) to a macro level (general policies). It is interesting to observe the variety of techniques used in supplier management and selection, from neural networks to support vector machines and logistic regression. This suggests that supplier selection is a highly complex area that requires multiple approaches.

Although the literature shows a wide range of combinations, there is still room to explore new integrations. Techniques such as deep learning could be combined with simulation models to improve production planning. Reverse logistics, essential for the circular economy, shows less diversity of techniques compared to other areas, representing an opportunity to investigate how ML can transform this area.

6. Further Research Opportunities

In general, the integration of machine learning with other models or techniques in the supply chain has proven to be an effective strategy to improve efficiency and reduce costs. This integration allows for better inventory management, more accurate demand forecasting, better supplier selection and management, among other benefits. However, it is important to emphasize that the effectiveness of this integration largely depends on the quality of the data used. Machine learning models require large amounts of high-quality data to function effectively. Therefore, it is crucial to ensure that the data used is accurate, complete, and relevant.

Furthermore, although the integration of machine learning with other models or techniques has proven to be effective, there is still room for exploration and innovation. The exploration of advanced techniques, such as Support Vector Machines (SVM), Graph Neural Networks, and Deep Reinforcement Learning (DRL), promises to revolutionize different aspects of the supply chain, opening doors to more accurate and efficient solutions (Brahami et al., 2022). The post-COVID-19 era has highlighted the need to strengthen our systems (Dohale et al., 2022). It is imperative to research how the adoption of artificial intelligence can strengthen the productive resilience of manufacturing companies in a post-pandemic scenario. In parallel, it is essential to understand the adoption patterns of these techniques over time, and for this, longitudinal studies are presented as an invaluable tool. Likewise, with the evolution of information systems, data customization becomes a pillar, making it imperative to adapt input data to obtain insights that align with their specific supply chain environment (Belhadi et al., 2022). In addition, considering the interrelationships between different AI techniques can enhance strategies in this area. Data-driven robust optimization (DDRO) is emerging as a promising technique, capable of handling more complex models and offering solutions to combinatorial optimization problems (Gumte et al., 2021).

On the other hand, collaboration and cooperation between different tools and frameworks are essential. It's not just about improving existing techniques, but integrating them with already established systems and processes, seeking synergy that enhances results (Nizamis et al., 2018). In this sense, multi-agent approaches can be crucial for optimizing decision-making, especially in systems where collaboration between multiple agents is essential (Wang et al., 2022). Likewise, vertical, and horizontal integration stands out as an imperative need. Supply chain decisions cannot be isolated from the strategic and tactical decisions of the organization (Wu et al., 2023). In addition, we face the challenge of incorporating additional uncertainties, such as supply disruptions or quality problems, into different models and algorithms.

The expansion and scalability of the proposed models, continuous optimization, and cooperation with the industrial community are aspects that cannot be overlooked. Real-time monitoring, risk assessment, and error detection and correction are areas that require immediate attention (Mahato & Narayan, 2020). Finally, it is essential that future research focuses on specific case studies to ensure practical and applicable solutions in the real world.

7. Conclusion

Machine learning has indeed become a transformative tool in various sectors, especially in the supply chain. Its ability to process vast amounts of data and predict outcomes based on patterns has revolutionized how businesses operate and make decisions. The integration of machine learning with other technologies, such as IoT, cloud computing, and big data, has opened up new avenues for innovation. For instance, in the supply chain, machine learning can predict when a part is likely to fail, allowing for timely replacements and reducing downtime. In inventory management, it can forecast demand, ensuring that businesses have the right amount of stock at the right time. In logistics and transportation, machine learning can optimize routes, reducing fuel consumption and improving delivery times.

However, as you rightly pointed out, there isn't a one-size-fits-all approach to integrating machine learning. The specific challenges and contexts of each supply chain will dictate the techniques and models that are most appropriate. For instance, a supply chain that deals with perishable goods might prioritize real-time data processing and predictive analytics to reduce wastage, while a manufacturing supply chain might focus on predictive maintenance to reduce machine downtime. Future research should indeed focus on understanding the nuances of how different techniques and models can be adapted for various situations. As machine learning models become more sophisticated, there's also a growing need for them to be more explainable. Stakeholders will want to understand how a model arrived at a particular decision, especially if it has significant financial implications. In conclusion, while there are challenges to overcome, the potential of machine learning in the supply chain is vast. As the technology continues to evolve, we can expect even more sophisticated applications that further enhance the efficiency and effectiveness of supply chains across various industries.

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