Journal of Open Innovation: Technology, Market, and Complexity 10 (2024) 100379

Contents lists available at ScienceDirect

Journal of Open Innovation: Technology, Market, and Complexity

journal homepage: www.sciencedirect.com/journal/journal-of-open-innovation-technology-market-and-complexity

Enhancing supply chain management with deep learning and machine learning techniques: A review

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ARTICLE INFO

Keywords:
Multi-criteria decision-making
Deep learning
Supply chain management
Machine learning
Supplier selection

ABSTRACT

Supply chain management (SCM) is crucial in establishing long-term partnerships that are pivotal for achieving sustained business success. Effective SCM demands rigorous criteria and decision-making processes, which significantly impact the overall outcomes. Recent studies highlight cloud-based market analysis as a valuable tool for assessing supply chain dynamics, offering insights into the benefits and challenges of SCM. The integration of deep learning (DL) and machine learning (ML) approaches in SCM presents transformative potential, enabling more efficient management of the supply chain. This paper identifies the contributions of DL and ML techniques in various aspects of SCM, including supplier selection, production, inventory control, transportation, demand and sales estimation, and others. The extensive review presented in this work delivers an in-depth examination of the integration of DL and ML with SCM, highlighting strategies for enhancing operational efficiency, addressing current limitations, and identifying future research opportunities. A comprehensive literature table consolidates existing research on enhancing SCM with ML and DL techniques, offering a precise overview of objectives, findings, and areas for improvement, and providing rapid insights into the evolving landscape of SCM.

1. Introduction

Supply Chain Management (SCM) is the strategic coordination of business functions within an organization, designed to optimize procurement procedures, enhance overall performance, and improve customer satisfaction. SCM is pivotal to the success of any business operation, and even minor errors or inaccuracies in data can lead to significant issues for end-users (Radivojevic et al., 2022; Tirkolaee et al., 2021). For instance, displaying incorrect inventory levels online or showing items as stock-outs during in-store purchases or at checkout can severely impact customer satisfaction. Such errors not only frustrate customers but also create a negative impression, potentially leading to lost business and adverse reviews on social media. Therefore, maintaining accuracy and near real-time data in supply chain processes is crucial to ensure a positive customer experience and uphold the reputation of the business (Mitrovic et al., 2021). A critical component of SCM is supplier selection, where purchasing managers identify and choose the most suitable suppliers for sourcing raw materials. Selecting the right suppliers can significantly enhance operational performance, reduce procurement costs, and foster positive, long-term relationships, ultimately leading to increased customer satisfaction. Another key element of SCM is production, which involves identifying the range of products to offer in response to market demand and company capabilities (Yun et al., 2020; Kazemargi et al., 2022). Inventory control plays a vital role in managing inventory levels to balance supply and demand, thereby reducing holding costs and preventing stock-outs. In a globalized market, effective SCM ensures the seamless flow of goods, minimizes costs, boosts efficiency, and supports the company's financial health. Conversely, poor supplier selection can result in financial issues and negatively impact overall company performance, underscoring the importance of meticulous supplier selection within the broader SCM framework.

The term '*logistics*' broadly refers to the physical distribution of goods. Historically, logistics for strategic and managerial goals were considered dormant until the 1950s, a period marked by a military-oriented approach to logistics. The modern conceptualization of logistics and supply chain management (SCM) was advanced by experts such as (Ballou, 2007) and (Saleheen and Habib, 2022). SCM is designed to manage the supply chain through a unified strategy, aligning strategic decisions among all parties involved. It plays a crucial role in

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https://doi.org/10.1016/j.joitmc.2024.100379
Received 30 July 2024; Received in revised form 7 September 2024; Accepted 9 September 2024
Available online 17 September 2024

comprehensive management, addressing various management aspects. Numerous researchers have explored the adoption of SCM across different domains, highlighting its significance and diverse applications (Kotsiopoulos et al., 2021; Wang et al., 2018; Weng et al., 2020).

1.1. SCM evolution and the need for optimizing supply chains

Today, supply chains are increasingly complex and require greater accuracy to address the different challenges associated with supply chains. The need to optimize supply chains is increasing. Innovation is a key aspect that companies should share with both suppliers and customers. In recent years, the concept of open innovation has emerged as a prominent approach in the field of innovation management. This paradigm advocates for a new approach suggesting that companies should integrate both external and internal ideas, as well as utilize diverse pathways to market, to advance their technology (Kazemargi et al., 2022; Shcherbakov and Silkina, 2021; Teodorescu and Korchagina, 2021). Applying the concept of open innovation, firms actively collaborate with various external actors, such as customers, competitors, academics, and companies in unrelated industries, to encourage innovation. The underlying premise of open innovation is that not all the necessary knowledge for innovation resides within a company's own boundaries; thus, it is essential for companies to seek and acquire knowledge from external sources. According to a recent Gartner survey of supply chain leaders, Artificial Intelligence (AI) is expected to significantly influence the supply chain industry by 2025. Further adoption of Machine learning (ML) and Deep Learning (DL) approaches is essential to manage the increasing complexity of supply chains. ML/DL applications in SCM Market was valued at USD 1.5 billion in 2023 and is projected to grow at a compound annual growth rate (CAGR) of over 29% from 2024 to 2032. (Lin et al., 2022) explored various applications of machine learning (ML) and deep learning (DL) in supply chain management, highlighting their distinct advantages and disadvantages. In supplier selection, ML and DL enhance decision-making accuracy by analyzing large datasets to identify the best suppliers based on multiple criteria. However, this approach requires high-quality data and substantial computational resources. For production optimization, ML and DL streamline manufacturing processes, predict maintenance needs, and minimize downtime, leading to greater efficiency and cost savings. The primary challenge here is the complexity of integrating ML models into existing production systems. In inventory control, ML and DL improve demand forecasting, optimize stock levels, and reduce holding costs, but challenges such as managing data variability, ensuring real-time data processing, and addressing computational expenses persist. Across these applications, common issues include maintaining data quality, integrating diverse data sources, scaling ML/DL models, and ensuring model interpretability, all of which are essential for the effective implementation of advanced SCM solutions.

SCMevolutionarytimeline: Fig. 1 illustrates the evolutionary timeline of Supply Chain Measurement (SCM) since 1950. The idea of SCM is created from military logistics in the year 1950. During the years 1970–1980, the logistics concept is developed and logistics is incorporated into SCM. In the 1980s and 1990s, SCM began to be incorporated into the manufacturing industry. The period from 1990 to 2000 marked a revolutionary phase for SCM, with the introduction of the Balanced Scorecard (BSC) model by BSC (2019) (Chavez, 2019) and the evolution of the SCOR model by the Supply Chain Council in 1996 (Saleheen and Habib, 2022). SCM concepts are also extended to the service industry. Since 2020, many scholars have focused on Supply Chain Performance Measurement (SCPM), emphasizing attributes and the performance measurement index for both qualitative and quantitative aspects. Research from 2000 to 2010 has analyzed the limitations of the BSC and SCOR models, highlighting the need for updated approaches to SCPM. During 2010 and 2024, researchers have made various contributions to the field, with numerous articles addressing different aspects of SCM. In agile manufacturing, scholars have emphasized the importance of agility for achieving organizational competitiveness, identifying five key competencies: agile supply chains, intelligent automation, employee empowerment, technology integration, and transparent customization. These competencies are crucial for generating positive outcomes. (Dohale et al., 2022) reviewed 52 years of manufacturing strategy literature (1969–2021), analyzing numerous articles and manuscripts related to supply chain performance measurement. Existing reviews highlight significant gaps in SCM research and demand further investigations (Xu et al., 2024; Rolf et al., 2023; Barzizza et al., 2023).

GlobalSupplyChainPressureIndex(GSCPI): GSCPI is a measure of the intensity of disruptions to global supply chains. It was developed by the Federal Reserve Bank of New York and combines data from a variety of sources, including transportation costs, manufacturing indicators, and inventory levels. Fig. 2 describes the GSCPI results for years ranging from October 2016 to April 2024. It is a crucial tool for monitoring the health of the global economy, as supply chain issues significantly impact economic growth, inflation, and employment. Its importance has increased in recent years due to the severe disruptions caused by the COVID-19 pandemic. Disruptions and strains in supply chains can ripple across industries and economies, making the GSCPI an essential economic indicator. Higher index values indicate greater strains on global supply chains compared to historical norms. By leveraging ML and DL, businesses can better manage supply chains, enhance operational efficiency, and maintain stability even during global disruptions.

RevenueLossDuetoInefficientSCM: Fig. 3 shows the various factors identified as the biggest risks to SCM. It highlights the significant impact of various factors on revenue losses within SCM. Supply chain disruptions often lead to increased production costs. Recent studies reveal that such disruptions can result in a 3–5% increase in expenses and a 7% decrease in sales (Jasrotia et al., 2024; Li et al., 2024; Xu et al., 2024). Businesses may need to procure materials from alternative suppliers at higher costs, expedite shipping, or temporarily suspend production. These increased expenses can diminish profit margins. Additionally, delays in product delivery can lead to lost sales and revenue, as dissatisfied customers might turn to competitors, adversely affecting future

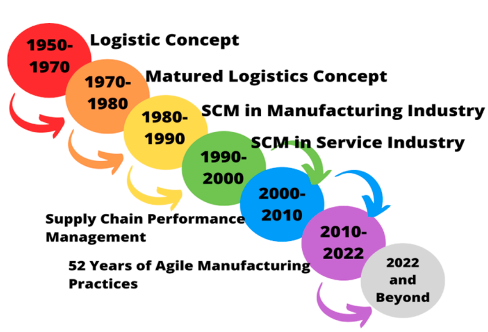

Fig. 1. Evolutionary Timeline of SCM.

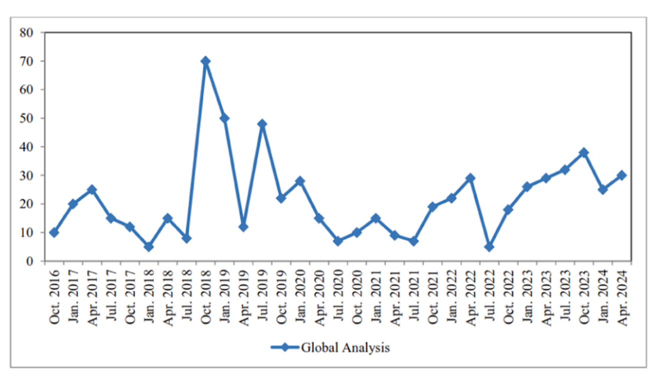

Fig. 2. Global SCM Analysis (Global Supply Chain Pressure Index).

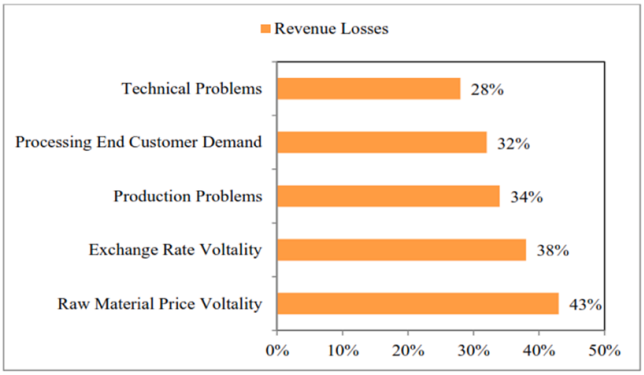

Fig. 3. Revenue Losses in Inefficient SCM.

sales. Raw material price volatility emerges as the most critical factor, causing substantial revenue loss and highlighting the importance of effective supplier management and risk mitigation strategies. Technical problems, although causing less revenue loss at 28%, still highlight the need for robust operational and maintenance practices to ensure uninterrupted production. Exchange rate volatility, contributing to 38% of revenue loss, emphasizes the importance of financial risk management and hedging strategies in global supply chains. Production problems, accounting for 34% of revenue loss, reveal the necessity of efficient production planning, quality control, and supply chain resilience strategies. To minimize revenue losses, enhance operational efficiency, and maintain profitability amidst external and internal challenges, SCM practitioners should focus on effective supplier management, robust operational and maintenance practices, financial risk management and hedging strategies, and efficient production planning and quality control. To manage the growing complexity of supply chains and mitigate revenue losses due to inefficiencies, further studies on the adoption of ML and DL approaches are crucial. These technologies can enhance SCM operations such as operational efficiency, optimize inventory management, and improve demand forecasting, thereby reducing costs and enhancing the SCM functionalities.

PhasesofSCMmanagement: Fig. 4 gives the different phases of SCM. The first stage of SCM is the planning stage. In this stage, the companies forecast demand, set goals, develop strategies, and create budgets. The planning stage involves analyzing market trends, customer preferences, and historical data to determine the future demand for products or services. Through planning, businesses compute the quantity of goods to purchase from suppliers. The second step of SCM is sourcing. It is an important step in SCM for identifying suppliers, discussing contracts, managing relationships, and ensuring quality control. Companies find reliable suppliers to provide the necessary raw materials. The favorable terms and conditions help secure cost-effective deals for handling the quality standards. The third step in SCM is the manufacturing phase. It aimed on transforming the raw materials into finished products through the production process. The activities comprised the assembly lines, quality control verification, inventory management, and packaging. Manufacturing guarantees that goods are produced in a timely manner with minimum waste and resource consumption. Delivery is the fourth phase of supply chain management. This phase included the transportation and delivery of products or services to customers. Delivery performed activities like order fulfillment, inventory organization, and logistics. The companies considered different factors like transportation costs, delivery speed, and customer preferences. The fifth phase of SCM returns. A return is the process of handling the product returns from the customers. Returns occur because of various causes like product faults, customer disappointment, or variations in customer requirements. The phase comprised activities like product inspection, disposal, return authorizations, and processing of refunds or replacements. Return handling is an effective process for companies to minimize costs and maintain customer loyalty.

MajorSCMchallenges: The major SCM challenges are presented in Fig. 5.

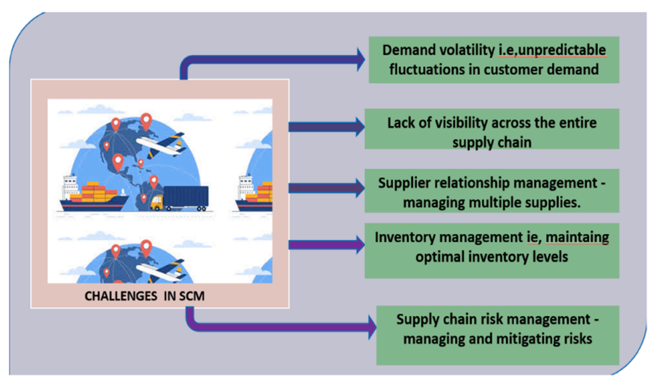

Fig. 5. Major SCM challenges.

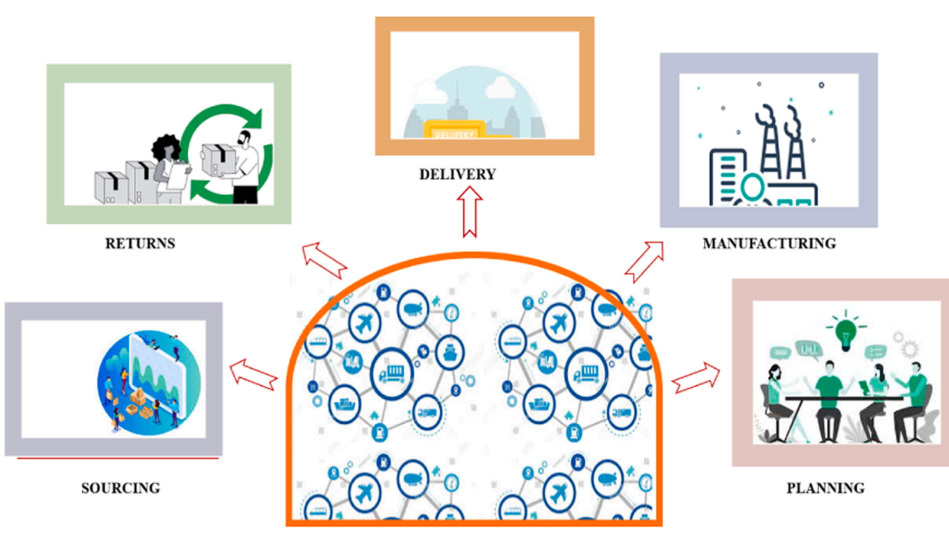

Fig. 4. Different phases of SCM.

- *Demand volatility:* The major challenge in supply chain management is demand volatility. It denotes unpredictable variations in customer demand for products or services. It failed to accurately forecast the demand and plan its production and inventory levels.
- *Lack of visibility:* Lack of visibility across the supply chain is another challenge. Many companies do not track the movement of goods and materials from suppliers to customers. It leads to delays, inefficiencies, and increased costs.
- *Supplier relationship management:* The strong relationship maintenance with suppliers is essential one for a smooth supply chain. The multiple supplier's management is a demanding one when they are located in diverse regions or countries. Companies experience issues like poor communication, quality control problems, or supplier capacity constraints.
- *Inventory management:* Effective inventory management is an essential one to balance supply and demand. Optimal inventory level maintenance is a challenging one for dealing with different products or seasonal demand fluctuations. Companies strike the balance between inventories to address customer demand with minimum holding costs.
- *Supply chain risk management:* Supply chains are susceptible to different risks like natural disasters, economic downturns, or transportation disruptions. Risk Management and mitigation is a critical challenge for supply chain managers.

1.2. Research contributions using DL/ML over different SCM challenges

Fig. 6 illustrates the research contributions using DL/ML over different SCM challenges, This analysis provides a clear overview of various SCM challenges that have been addressed using ML/DL algorithms, highlighting the specific aspects of SCM where these technologies have delivered the most significant impact. The evaluation results highlight that forecasting has garnered the most research attention compared to other SCM applications. According to the chart, financial management and quality management received 9% and 16% of research focus, respectively. Product clarification and inventory management both attracted 9% of the research attention, while traceability, data security, and cost management each accounted for 5%. Supply chain mapping received the least attention at 2%. In contrast, forecasting is the most researched area, with a substantial 40% of the focus.

1.3. SCM cloud market analysis

Supply market analysis is an emerging concept aimed at understanding the market characteristics for specific goods or services. This analysis is crucial for developing effective procurement strategies and informing significant procurement decisions. It provides insights into market dynamics, competitiveness, trends, price fluctuations, and the capabilities of key suppliers. The market report highlights the growing importance of cloud-based solutions in transportation management, emphasizing their cost-effectiveness and expanding utilization. Cloud providers are expanding their machine learning-powered supply chain offerings to meet the increasing demand for advanced analytics and optimization tools.

Fig. 7 illustrates the SCM cloud market analysis for the ten years from 2013 to 2024. The global cloud SCM market grew from USD 7.23 billion in 2013 to USD 21.88 billion in 2024. This reflects the improvements in cloud-based supply chain management. (Taherdoost and Brard, 2019) focused on identifying trends through SCM cloud market data analysis, revealing regional differences and customer behavior to inform future cloud computing services. The study aimed to uncover new information and address regional variations in service requirements. Additionally, (Chatzithanasis et al., 2021) introduced a cloud brokering model with a profit-maximization economic model, suggesting various pricing policies to enhance business viability and profitability. (Balco et al., 2017; Zhu et al., 2021) analyzed trends and regional differences in customer behavior to determine cloud computing service needs.

The results indicate a CAGR of 0.66% over this period, reflecting a steady increase in cloud SCM adoption. Starting with modest values in 2013, the market peaks in 2024, signaling the growing integration of cloud technologies in SCM. This upward trend highlights the shift towards leveraging cloud solutions to enhance efficiency, streamline procedures, and reduce costs across the supply chain. The peak in 2024 underscores the realization of efforts to harness cloud computing's scalability, accessibility, and data integration capabilities, facilitating real-time data sharing, improved collaboration, and predictive analytics. This analysis emphasizes the importance of incorporating cloud market insights into SCM to achieve operational excellence, strategic agility, and sustainable competitive advantage in a dynamic business environment. The steady increase in cloud market value from 2013 to 2024 reflects the ongoing enhancements in SCM processes and the benefits of adopting cloud-based solutions.

1.4. Problem statement and contribution

There is a significant demand to explore the diverse applications of ML and DL techniques across various aspects of supply chains, as most existing studies have concentrated on only one or a few specific SCM areas (Radivojevic et al., 2022; Mitrovic et al., 2021; Tirkolaee et al., 2021; Wilson et al., 2020; Toorajipour et al., 2021). This creates a gap in understanding the effective integration and optimization of ML and DL-based techniques to address various SCM challenges to improve overall performance. For instance, ML has been used to design automated SCM frameworks, resilient supplier selection, predict financial risks in supply chains, and determine appropriate replenishment policies. Additionally, ML and DL have been applied to predict supply chain

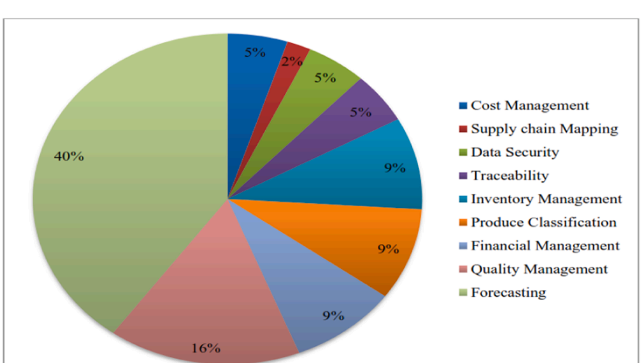

Fig. 6. Research contributions using DL/ML over different SCM challenges.

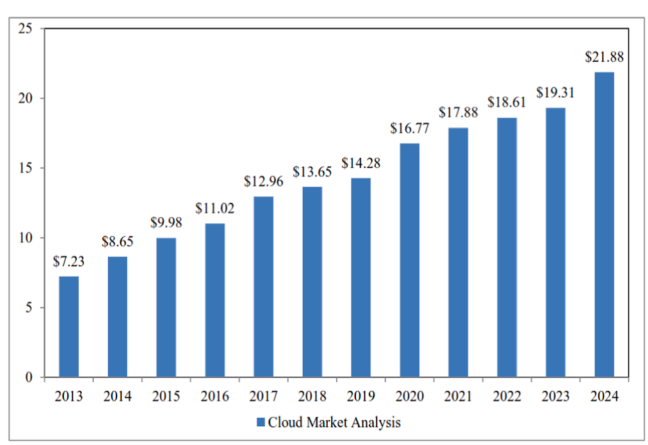

Fig. 7. SCM cloud market analysis.

risks, segment suppliers based on environmental factors using hybrid approaches, and address many other SCM challenges. Existing studies often limit their scope to particular aspects such as supplier selection, inventory management, or demand forecasting. However, comprehensive studies that examine ML/DL applications across various aspects of SCM are limited. This indicates the pressing need for an up-to-date study that investigates the broader applicability of these advanced techniques, aiming to uncover their potential to improve the efficiency, resilience, and effectiveness of the entire supply chain (Teodorescu and Korchagina, 2021). This paper explores the application of ML and DL across different supply chains without focusing on a specific industry. This review offers a detailed analysis of integrating DL and ML into SCM, focusing on strategies to enhance operational efficiency, overcome current limitations, and identify future research opportunities, offering valuable insights into the evolving landscape of SCM. Table 1 highlights the focus and distinctions between existing studies and our present work. A comparative overview of different existing papers, detailing their publication years, specific areas of focus, and the range of years examined are included in the table. It also highlights how these studies differ from our present study. This comparison illustrates that our work addresses this gap by offering a more comprehensive view and advancing the field with new insights through thorough analysis.

Table 1
Focus of Existing Studies in Literature and Comparison with Our Work.

Ref. (Year)	Focus	Years Analyzed	Comparison with our Work (Gap in study)
(Zhu et al., 2021)	Descriptions and applications of ML, DL, and machine vision methods in food processing	1991 – 2020	Focused on food processing and not considered additional industries
(Xu et al., 2024)	SCM under cap-and-trade regulation	2008 – 2024	Focussed on bibliometric analysis and content analysis under SCM-CAT.
(Rolf et al., 2023)	Reinforcement learning (RL) algorithms and applications in SCM	2000–2022	Focussed mainly on RL and industrial applications of SCM
(Barzizza et al., 2023)	Big Data Analytics and Machine Learning in Supply Chain 4.0	2009 – 2022	Surveyed only the ML based approaches employed in SCM
(Bertolini et al., 2021)	Potentialities and criticalities of ML algorithms in operation management	2000 – 2020	Focused only on AI/DL methods applied on industrial operation management
(Zhou et al., 2020)	Applications of DL in food industry	2009 – 2019	Considered Food Industry only
(AlSahaf et al., 2019)	Applications of evolutionary ML in supply chain and manufacturing of dairy, wine, and seafood industries	1992 – 2018	Evolutionary ML aspects in SCM of specific industries are only discussed. Deeper aspects regarding DL in SCM not discussed
(Nti et al., 2022)	Applications and advancements of AI in engineering and manufacturing	2006 – 2020	Focused on manufacturing challenges and reviewed AI-based solutions. Not all operational challenges of the supply chain are discussed.
(Kotsiopoulos et al., 2021)	Applications of ML and DL in industry 4.0	1985 – 2020	Review included limited information on supply chains in the smart manufacturing industries
(Wang et al., 2018)	DL methods and their application in smart manufacturing	1986 – 2018	Focussed only on smart manufacturing
Proposed Work	**Detailed review on the application of ML and DL techniques in addressing various SCM challenges**	**2013 – 2024**	**Comprehensive analysis on enhancing SCM using ML and DL techniques**

This review explores several research questions to evaluate the recent advancements in SCM using ML and DL methods. The primary questions explored include:

- *RQ*1: What types of SCM issues are addressed by ML and DL algorithms?
- *RQ*2: Which ML and DL methods are employed in SCM?

This study aims to identify the most effective ML and DL algorithms for various SCM challenges and explore the applicability of these techniques to enhance SCM functionalities. Additionally, it examines the challenges and limitations of applying ML/DL methods in SCM and investigates how these technologies can improve the resilience and efficiency of supply chain operations. Finally, it highlights future research opportunities for ML/DL applications in SCM, providing insights for continued innovation and improvement in this critical area of research. To address these questions, we reviewed and categorized selected papers, focusing mainly on research papers from the last decade (2013–2024) to analyze the growth and development of the SCM over this period. This review process involved a detailed examination of the SCM issues studied, the ML/DL techniques used, and the results of statistical analyses comparing these methods.

The contributions of this work can be summarized as below:

- Provides a comprehensive review of the application of ML and DL techniques across various aspects of SCM, highlighting their impact and effectiveness.
- Identifies and analyzes the most commonly used ML and DL algorithms in SCM, detailing their applications and performance in addressing different supply chain challenges.
- Examines the key challenges and limitations associated with implementing ML and DL methods in SCM, including issues such as computational cost, time complexity, data variability, data quality, integration of diverse data sources, scalability, and model interpretability, which are critical for improving the overall efficiency, accuracy, and reliability of SCM.
- Analyzing the integration of traditional methods with advanced ML and DL techniques to enhance the accuracy and efficiency of various SCM operations, leading to a more comprehensive evaluation and robust decision-making in SCM.
- Highlights potential areas for future research in ML and DL applications within SCM, offering guidance for further investigation and development of this evolving field.
- Comprehensive evaluation of literature results by using a broad range of performance metrics, such as computational cost (Cost), time complexity (T), efficiency (E), computational complexity (C), accuracy (A), F1-Score (F-Score), precision (P), recall (R), area under the curve (AUC), sensitivity analysis (S), precision-recall curve (PRC), and Matthews correlation coefficient (MCC). This analysis highlights the strengths and weaknesses of different models, guiding the selection of the most suitable techniques for various SCM applications.

1.5. Paper selection criteria

The papers with contributions containing DL and ML methods for SCM are selected to conduct the systematic review. A specific set of inclusion and exclusion criteria are used to identify and examine papers related to SCM and from different SCM fields such as logistics, marketing, supply chain, and production. The primary search strings are used to ensure that papers adopt different taxonomies. The first criterion targets the period of the literature which was initially set between 2008 and

2024. This period is considered because of the substantial papers and the number of new trends as well as applications contributing to this topic in this period. The second criterion was relevance and quality. Only peer-reviewed journal and conference papers are considered for the review, meaning book reviews, chapters, case reports, discussions, and news articles are not included. Furthermore, each paper has been examined by the two authors to guarantee that the paper has the required quality. The set of selection criteria is: (i) The article is written in English, (ii) It employs DL and ML techniques as the main tool/perspective/focus for SCM. The criteria to exclude are irrelevant papers with different applications and contributions and those that do not belong to the mentioned time span.

1.6. Paper organization

The remainder of this paper is organized as follows: Section 2 discusses the details of how ML and DL techniques are utilized for optimizing SCM operations. Section 3 covers supplier selection techniques within SCM. Section 4 discusses production management in SCM. Section 5 details transportation and distribution aspects of SCM and Section 6 presents the inventory control aspects. Section 7 focuses on sales and demand estimation. Section 8 delivers the review discussion and summary analysis, evaluating the performance results of various DL and ML methods applied in SCM, identifying the research gaps and providing directions for future research. Finally, Section 9 summarizes the findings and concludes the work.

2. Optimizing supply chains with ML and DL techniques

ML and DL approaches have significantly transformed various domains by enhancing the ability to handle large volumes of data and derive valuable insights. SCM involves many complex decision-making processes and information barriers. ML and DL algorithms constitute a significant asset for addressing these challenges. These methodologies offer improved forecasting, route optimization, and inventory management, ultimately reducing costs and enhancing operational effectiveness. Essentially, ML and DL approaches help SCM systems to become more predictive and adaptive to varying market conditions.

Fig. 8 gives an overview of various ML and DL methods applied in optimizing different SCM operations. ML approaches such as supervised learning, unsupervised learning, and reinforcement learning (RL) techniques are applied across several SCM aspects.

For example,

- Demand and Sales Estimation: ML algorithms, including regression analysis and time series forecasting, predict future sales based on historical data. This alignment helps companies synchronize production schedules and inventory levels with market demand, minimizing stock-outs and managing excess inventory.
- Transportation and Distribution: ML techniques such as clustering and optimization algorithms are utilized to plan efficient routes, reduce delivery times, and lower transportation costs. Reinforcement learning further enhances production scheduling by adapting to new scenarios based on past experiences, improving manufacturing efficiency.

DL, a subset of ML, employs neural networks with multiple layers to analyze complex data patterns and make advanced predictions. The adoption of DL techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) in SCM can contribute to overall advancement and operational sustainability.

For example,

- Demand Forecasting and Anomaly Detection: CNNs analyze visual data for quality control in manufacturing, while RNNs process time-series data to improve demand forecasting and detect anomalies.
- Supply Chain Optimization: DL approaches like RNNs improve decision-making processes related to route optimization, resource allocation, and logistics planning.
- Production and Quality control: DL techniques such as CNNs are used for quality inspection and defect detection in manufacturing

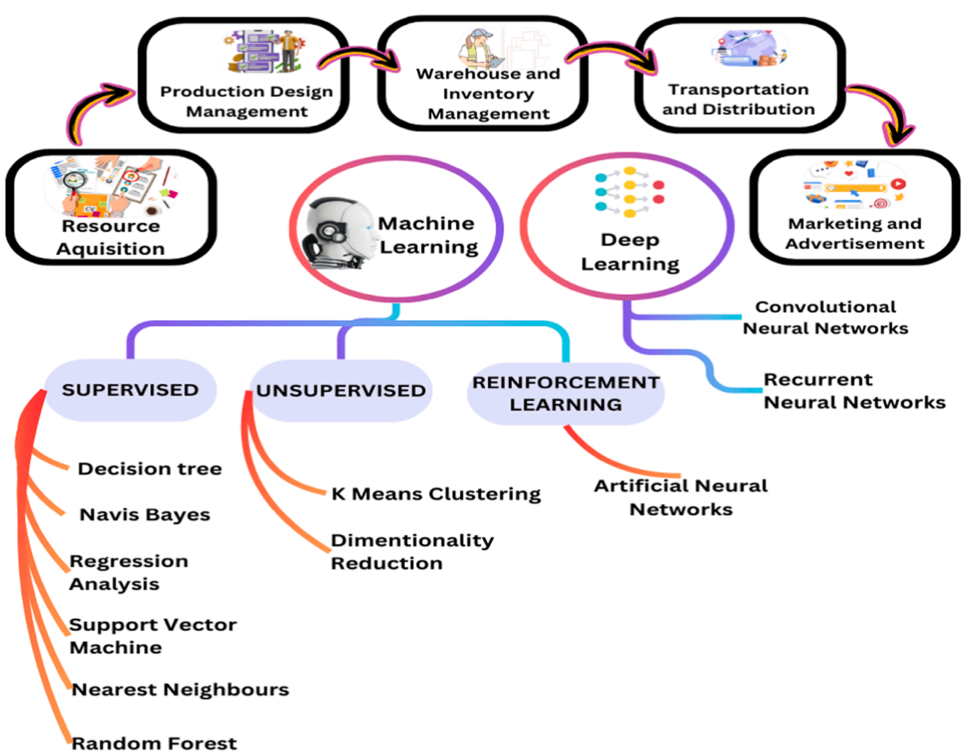

Fig. 8. Various ML and DL methods applied in SCM.

processes. These algorithms analyze visual data to identify defects and ensure product quality.

The capability of DL to handle unstructured data and uncover intricate patterns provides higher prediction accuracy and adaptability compared to traditional ML methods. By integrating ML and DL, SCM systems achieve greater efficiency, adaptability, and effectiveness, leading to a more resilient and optimized supply chain.

Fig. 9 illustrates the key steps involved in managing supply chains using ML and DL.

- Data preprocessing includes cleaning as well as transforming raw information to guarantee quality and stability, which can be challenging due to the diversity of data sources.
- Model assembly integrates multiple models to enhance prediction accuracy and robustness, presenting challenges in combining models effectively without overfitting.
- Prediction analysis involves interpreting model outputs to inform supply chain decisions, requiring careful evaluation of model performance metrics and ensuring the interpretability of complex models while aligning predictions with business objectives.
- Model exploitation includes selecting and training suitable ML or DL models, with challenges in choosing the right model, tuning hyperparameters, and managing computational costs.

These steps necessitate meticulous handling of data variability, computational resources, and strategic alignment with supply chain goals to address the inherent challenges.

Table 2 discusses the advantages and disadvantages of the commonly employed ML methods, providing SCM researchers and practitioners with a clear understanding of these algorithms. Neural Networks (NNs) are powerful tools for identifying complex nonlinear input or output relationships, making them valuable for application in SCM to warn against potential competitors (Zhu et al., 2021; Kotsiopoulos et al., 2021). NNs come in various forms, including Backpropagation (BP) Neural Networks, Radial Basis Function (RBF) Networks, and Convolutional Neural Networks (CNNs). Each variation has applications in SCM; for instance, CNNs, crucial for DL, are often used to analyze interactions between customers and salespersons through audio and video communication, as well as for lead-time planning and customization. However, a key limitation of NNs is their lack of transparency in decision-making, which makes them challenging to interpret (Wang et al., 2018). Decision Trees (DTs) are commonly used for classification and regression tasks. While they are easy to understand and have low bias, they are prone to overfitting. Random Forests (RF) address this issue by combining multiple DTs trained on different data subsets and averaging their predictions, improving accuracy and robustness (Ali et al., 2023; Islam et al., 2021). Both DTs and RFs are beneficial in SCM for evaluating different decisions and their probabilities, aiding in lead scoring and resource allocation. Bayesian Networks, based on Bayes' Theorem, are effective for small-scale datasets and can be used in SCM to assess the reliability of stakeholders, potentially predicting contract violations and

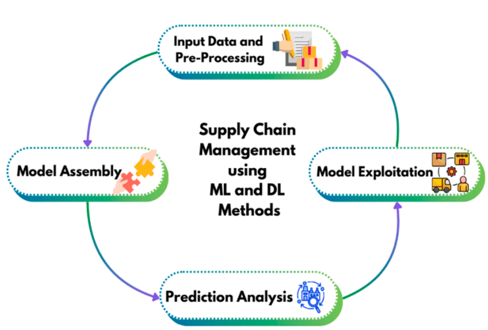

Fig. 9. Supply Chain Management process using ML and DL Methods.

Table 2
Advantages and disadvantages of commonly Used ML methods.

ML Method	Advantages	Disadvantages
Neural Network (NN)	Nonlinear adjustment, Simple learning rules, Strong robustness, Independent learning, Spreading error backward, Good parallelism	Inability to judge, Unsuitable for a small dataset, Sensitive to initial values
Bayesian Network (BN)	Good for small datasets, Applicable to multi-classification, Easy implementation, Works with continuous and discrete data	Uncertainty condition leads to less accuracy, Poor performance classification
Support Vector Machine (SVM)	Suitable for nonlinear classification, Applicable to classification and regression problems, Easy to understand, Minor errors in generalization	Sensitive to functions and parameters, Performance declines with large datasets, Long training time
Logistic regression (LR)	Easy to operate, Small storage resources	Weak fitness and precision
K-Nearest neighbor (KNN)	Easy for classification and regression (especially nonlinear classification), Immune to outliers, Low complexity	Require to preset K, Incapable to solve large unbalanced data sets
Decision Tree (DT)	Easy calculation and handling of missing value attributes, Evaluates different attribute characteristics, Strong interpretability	Problem of overfitting, Unstable tree size control, Local optimal solution
Random forest (RF)	High accuracy of training results, Robust to missing or abnormal values, Relative bagging can converge to a small generalization error	Over-fit for large data noise, Sensitive to the features with different values

providing early warnings to other stakeholders. Support Vector Machine (SVM) offers a solution to some of the limitations of NNs. They feature a simple structure and aim for a global optimum rather than a local one, providing strong generalization and mathematical interpretability. SVMs are particularly well-suited for high-dimensional data, which can enhance cross-selling and up-selling opportunities in SCM. However, SVMs depend heavily on kernel functions, which require prior knowledge of the dataset. Logistic Regression (LR) uses a nonlinear model to fit data, offering improved prediction capabilities for continuous variables. It is widely used in sales forecasting within SCM, although it relies heavily on the choice of the fitting model and may have limitations in model fit. K-Nearest Neighbors (KNN) is a clustering method that assigns data points to K clusters. Unlike K-means, KNN is a supervised learning technique and is less sensitive to noise. However, KNN struggles with large datasets and requires complete, regular data. Both K-means and KNN are applied in SCM for customer segmentation, such as identifying frequent buyers and analyzing their purchase amounts (Weng et al., 2020; Balco et al., 2017).

DL algorithms are increasingly being applied to tackle various challenges in SCM (Tang and Ge, 2022; Chien et al., 2020). For instance, RNNs and Long Short-Term Memory (LSTM) networks significantly enhance demand forecasting accuracy by analyzing historical sales data to uncover complex patterns and trends (Weng et al., 2020; Wang et al., 2018). CNNs and other DL methods also play a crucial role in optimizing inventory management by predicting stock needs, thereby reducing both overstock and stock-outs and improving inventory turnover. DL techniques such as CNNs are used for quality inspection and defect detection in manufacturing processes. DL models assess and mitigate risks by predicting potential disruptions and evaluating their impacts. They analyze various risk factors and provide insights for contingency planning. DL algorithms evaluate supplier performance and suitability by analyzing historical data, transaction records, and other relevant metrics to identify the best suppliers (Ali et al., 2023; Radivojevic et al., 2022; Taherdoost and Brard, 2019). DL helps in analyzing customer behavior and feedback to enhance customer service and engagement. Techniques like sentiment analysis and recommendation systems are used to improve customer satisfaction (AlSahaf et al., 2019; Nti et al., 2022). DL algorithms assist in financial forecasting, credit risk evaluation, and fraud detection by analyzing financial data and identifying patterns that could indicate potential issues (Zhou et al., 2020; Abdelsalam, 2020).

2.1. Analyzing the application of ML techniques in SCM

Machine learning (ML) is a subset of artificial intelligence (AI) that identifies patterns and insights from data. In SCM, ML enhances business operations by leveraging data-driven insights to improve decision-making and operational efficiency. By applying ML techniques, businesses can significantly boost profitability through improved customer experiences and reduced costs. ML plays a crucial role in SCM by optimizing processes such as demand forecasting. It achieves more accurate demand predictions by analyzing historical data and external factors, which helps to mitigate out-of-stock and overstock situations. Additionally, ML improves inventory management by recommending optimal stocking levels and replenishment strategies, thereby lowering costs and enhancing service levels. However, challenges persist, including integrating data from diverse sources, the complexity of deploying and maintaining ML models, and the interpretability of ML outputs. Adapting models to dynamic supply chain environments also remains a challenge. Despite these hurdles, the ongoing evolution and adoption of ML techniques promise to further streamline SCM operations, enhance resilience, and drive competitive advantage in the marketplace.

(Ali et al., 2023) proposed an integrated framework combining supervised ML with a Random Forest (RF) classifier and an RF-based feature selection method to identify critical criteria and performance measures. The RF classifier demonstrated improved accuracy and F-score by eliminating non-critical criteria. Notably, transportation cost, a critical criterion, received less focus in existing studies. Managers can utilize this integrated approach to select suppliers based on specific requirements. However, other ML classifiers, such as SVM, were not employed in the study for critical evaluations. Additionally, the integrated framework did not target any specific industry.

(Abdulla et al., 2023) introduced an integrated method combining ML with the MARCOS technique for supplier assessment. This approach used aspect significance techniques based on interpretable tree-based ML models to calculate weights for supplier selection criteria. The method was validated through a real-time case study in the oil and gas sector, showing its effectiveness in supplier evaluation. However, the method is less applicable to scenarios with limited or poor-quality data.

(Abdulla et al., 2019) developed an integrated approach combining ML with AHP to select the most suitable suppliers. While the Decision Tree (DT) classifier identifies key criteria more effectively than AHP, it results in a refined subset of selection criteria. This approach was validated through a case study involving two oil and gas companies in Libya.

Fig. 10 illustrates the steps involved in integrating ML classification with the AHP. The process begins by defining the problem and identifying the relevant criteria and alternatives within the decision context.

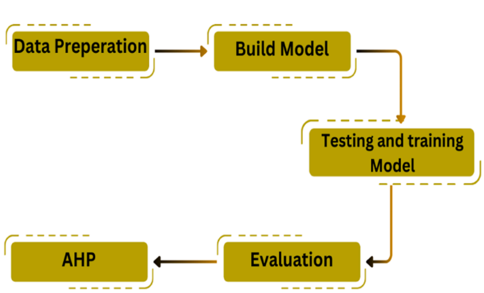

Fig. 10. Different steps of ML Classification with AHP.

AHP is then used to structure these criteria hierarchically and determine their relative importance through pairwise comparisons, often based on expert judgments or historical data. Next, ML algorithms, such as DT or SVM, are applied to model and classify the data according to these criteria, using the priorities established by AHP to guide the classification. This integration combines the qualitative decision-making framework of AHP with the quantitative predictive power of ML, resulting in a comprehensive approach that supports informed, data-driven decision-making across various applications, including supplier selection and risk assessment in supply chain management.

(Zhao et al., 2021) developed an ML method to assess the trustworthiness of specialists using historical data. Their approach involves assigning weights during the evaluation process. The SVM classifier categorizes past evaluations of specialists and evaluates the credibility of their estimates. By calculating these weights and organizing the results, the method ranks suppliers accordingly. This technique improves the credibility of supplier selection outcomes and enables effective categorization of previous assessments using SVM. Although the weights assigned to specialists are adjustable based on evaluation credibility, the study did not determine optimal kernel parameters for enhancing the SVM classifier model or for better integration of expert evaluation results.

(Islam et al., 2021) proposed a novel two-stage solution approach that integrates prediction with optimization methods. The approach uses the New Relational Regressor Chain technique to enhance forecasting accuracy for future demand. In the first stage, demand is predicted, and in the second stage, this forecast is used to conduct integrated demand forecasting, supplier selection, and order distribution planning. The method was applied to the Canadian food supply network to calculate order distribution to each supplier. However, the approach did not utilize comprehensive models for the forecasted factors.

(Radivojevic et al., 2022) explored the application of machine learning and artificial intelligence in supply chain management. While these technologies offer significant optimization opportunities, the study did not address the use of a combined model for selecting criteria and suppliers in the supply chain.

(Tirkolaee et al., 2021) examined the applications of ML in SCM. Their conceptual framework demonstrated how ML techniques can be used for supplier selection, separation, and forecasting supply chain risks. The framework estimates demand, sales, stock discrepancy (SD), and customer experience (CE). However, implementing efficient solutions for SCM issues remains costly and challenging due to the complex and ill-structured nature of these problems.

(Mitrovic et al., 2021) explored the use of classification models to group one hundred suppliers using ML techniques. The study considered independent attributes such as delivery quality, price, location, reputation, and professionalism to evaluate supplier efficiency. The Multilayer Perceptron (MLP) algorithm was employed to address the supplier selection problem in the supply chain. However, the MLP model did not identify the best suppliers. It rather categorized them into efficient or inefficient groups.

(Wilson et al., 2020) examined the role of ML and Data science in supplier evaluation. While the issue of identifying the best suppliers has been longstanding, modern techniques offer numerous solutions. However, the study noted that different classifiers and datasets have not been fully utilized to compute the best suppliers in the industry.

(Kandel et al., 2023) discussed various DL architecture like VGG16Net, VGG19Net, GoogLeNet, ResNet-50, and AlexNet to predict different traffic patterns. The performance metrics like accuracy, sensitivity, and specificity were discussed with ResNet-50 and AlexNet. Descriptive statistics and statistical models like ANOVA and the Wilcoxon Signed Rank Test attained better results.

The SCM was handheld by other techniques such as the following: (El-kenawy et al., 2024) introduced the Greylag Goose Optimization (GGO) algorithm. GGO is a swarm-based algorithm inspired by Greylag

Goose. Geese were excellent flyers during seasonal migrations. GGO algorithm flies in groups and covers thousand of kilometers in a single flight. In (Benyamin et al., 2024), Abdollahzadeh et al. (2024) introduced Puma Optimizer (PO). The designed optimization was employed in each phase of exploration and exploitation. A new type of intelligent mechanism was employed for phase change. PO algorithm carried out phase change operation to balance both phases. Each phase was adjusted to the nature of the problem. (Towfek et al., 2024) introduced binary Particle Swarm Optimization and Whale Optimization Algorithms for feature selection and the predictive modeling of Linear Regression. The remarkable ability of AI and ML methods increased relevant forecasts with possible decisions to improve education effectiveness.

2.2. Analyzing the application of DL Techniques in SCM

DL holds immense promise in transforming SCM by leveraging its advanced capabilities to handle complex and unstructured data, thereby enhancing decision-making processes and optimizing various operational facets (Toorajipour et al., 2021; Raj et al., 2022). Its significance lies in its capacity to process large volumes of information sourced from diverse channels, including IoT sensors and supply chain transactions, to extract actionable insights. DL shows excellence in tasks such as predictive maintenance, anomaly detection, and real-time demand forecasting, enabling SCM operations to achieve higher efficiency and responsiveness. Despite these advantages, DL faces significant challenges such as the demand for substantial computational resources, and extensive data requirements for training and interpretability of models, which can complicate implementation and scalability within SCM environments.

DL techniques have already made a substantial impact on SCM, particularly in areas like supplier selection, production, and inventory control. The integration of DL has led to improvements in operational efficiency and supply chain optimization through predictive analytics and enhanced decision-making capabilities (Lin et al., 2022). For instance, applications like deep Q-learning have been instrumental in optimizing supplier selection processes, resulting in more effective supplier evaluations and selections (Seuring et al., 2022). However, the adoption of DL technologies in SCM comes with its set of challenges. These include the complexity of integrating new technologies into existing SCM systems, the high computational demands, and the ongoing need for data quality and model training to ensure accuracy. Key parameters considered in DL applications for SCM typically include historical data analysis, real-time analytics capabilities, and performance metrics evaluation. Despite the initial setup costs and maintenance requirements, DL has consistently demonstrated its ability to significantly enhance efficiency and decision accuracy in SCM operations.

(Toorajipour et al., 2021) reviewed the applicability of AI in enhancing SCM operations. (Raj et al., 2022) explored SCM strategies during and after the COVID-19 pandemic, discussing mitigation strategies and practical lessons learned. (Lin et al., 2022) introduced a dynamic method for selecting supply chain members using Conditional Generative Adversarial Networks (CGANs). This method reduces the information dimension and simplifies the classification process. It analyzes and predicts purchasing and inventory links within the supply chain, enhancing the operational efficiency of the vehicle scheduling module. While the approach minimizes complexity, it does not reduce computational costs. (Seuring et al., 2022) revisited the current state of hypothesis development in Sustainable SCM (SSCM). Their research addressed each construct of the initial framework, which includes drivers and barriers related to stakeholder management. However, the study noted that the accuracy level of the framework was not improved. The research emphasized that hot topics such as the circular economy, digital transformation, and base-of-the-pyramid supply chains still require careful scrutiny and theoretical development in SSCM. (Jasrotia et al., 2024) designed a PLS-basis of the structural equation modeling method. Information gathered as of individuals as of producing industry at India. BT adoption assisted comprehension of sustainable supply chain uses. But, the error rate is not reduced. (Li et al., 2024) discussed an enterprise digital transformation. Enterprise digital transformation increases the company stage of SCM. Heterogeneity analysis is pronounced at models through elevated levels of marketization as well as superior industry rivalry intensity. However, complexity is not minimized by enterprise digital transformation. (Xu et al., 2024) introduced SCM-CAT depend on bibliometric as well as content study. The bibliometric study examines the present status with an assessment path comprising yearly output and so on. (Sun et al., 2024) introduced the technology-driven logistics and SCM on different features of social values. The designed methodology classified technologies, and ESG considerations. DL-based optimization techniques enhance the accuracy of capacity planning and demand forecasting, ensuring the effective delivery of goods and services. By leveraging DL concepts, SCM can be optimized to maintain the proper flow of items in and out of a warehouse. This approach helps prevent issues such as overstocking, inadequate stocking, and unexpected stock-outs (Bertolini et al., 2021). The demand for raw materials often deviates from initial forecasts, necessitating multiple revisions of the plans during production and manufacturing. Accurate material demand forecasting is crucial for minimizing purchasing and production costs within supply chains. (Tang and Ge, 2022) introduced a forecasting model that leverages both sales demand and historical material demand time series data to predict material requirements for consumer products. Additionally, (Chien et al., 2020) developed an innovative framework employing deep reinforcement learning (DRL) to identify the most suitable demand forecasting model from a range of options. This framework considers the specific demand patterns of items distributed by electronics distributors to enhance forecasting accuracy.

3. Supplier selection in SCM

Supplier selection is the process of choosing prospective vendors or suppliers with whom an organization will do business (Cristea and Cristea, 2017; Pereira et al., 2023). Ensuring supplier quality contributes to a more agile supply chain. The primary goal of supplier selection is to establish a mutually beneficial business-to-business relationship with reliable suppliers that offer good value. This selection process is crucial as it lays the foundation for long-term partnerships that can significantly influence the success or failure of a business. Business priorities and policies play a vital role in determining the criteria used for assessment (Yazdani et al., 2021; Behera and Beura, 2023; Saha et al., 2024). Supplier ranking depends on purchasing executives who evaluate different categories of assessment criteria. The definition and weighting of these criteria are key steps in the supplier selection process. After evaluating potential suppliers against these criteria, the next stage involves selecting the most qualified suppliers. The supplier selection process is a strategic activity within supply chain management and typically involves six steps:

- Recognize business priorities and plans.
- Compute criteria used in the selection.
- Determine criteria importance.
- Recognize possible suppliers.
- Rank suppliers based on particular criteria.
- Choose one or more suppliers depending on ranking.

Fig. 11 illustrates the different steps involved in supplier selection to ensure optimal sourcing decisions in SCM. The process begins with identifying sourcing needs and defining criteria that suppliers must meet, such as quality standards, pricing, delivery capabilities, and ethical considerations. Potential suppliers are then identified through market research, supplier databases, or recommendations. A thorough evaluation follows, where suppliers are assessed against predefined

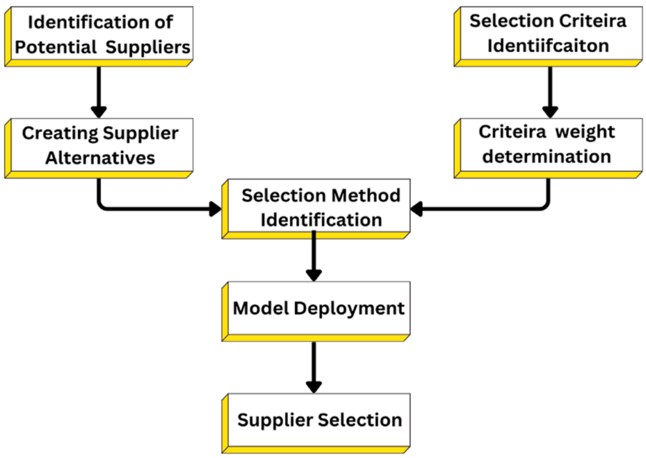

Fig. 11. Different steps in supplier selection.

criteria using tools like supplier scorecards, performance metrics, and sometimes advanced analytics or machine learning algorithms for predictive performance assessment. After evaluation, negotiations are conducted to finalize terms and conditions, including pricing, delivery schedules, and service level agreements. Finally, selected suppliers are onboarded, and a continuous monitoring process is established to ensure ongoing performance meets expectations and to identify opportunities for improvement or adjustment. This structured approach to supplier selection aims to mitigate risks, optimize costs, and enhance overall supply chain effectiveness and resilience.

The study conducted by (Taherdoost and Brard, 2019) discusses the different supplier selection methods designed to identify, evaluate, and contract with suppliers. Their findings indicate that the supplier selection process is crucial for any organization as it utilizes significant financial resources and impacts success. Its primary goals are to minimize purchase risk, reduce costs for the purchaser, and foster a close, long-term relationship between buyers and suppliers. Some researchers have introduced hybrid models that combine multiple selection techniques to improve outcomes. Understanding these supplier selection methods is essential for companies seeking to enhance their success and competitiveness. The multiple criteria decision-making analysis was carried out by (Cristea and Cristea, 2017) for supplier selection in the flexible packaging industry. The potential supplier performance is computed against multiple criteria, suitable criteria in supplier selection, and decision-maker preferences consideration with existing constraints. The variants are ranked based on their suitability for supplier selection. CRITIC-GRA-3 N method was designed by (Pereira et al., 2023) to choose and rank suppliers for dealerships. The designed method was employed for choosing and ordering the suppliers/distributors of automotive parts efficiently. (Yazdani et al., 2021) developed a sustainable supplier evaluation framework using various criteria and the interval-valued fuzzy neutrosophic (IVFN) model. This framework employed the CRiteria Importance Through Inter-criteria Correlation (CRITIC) method and the combined compromised solution (CoCoSo) for evaluating and selecting suppliers in Iran. (Behera and Beura, 2023) addressed the planning and management of physical commodities transportation from raw materials to finished products within the scope of SCM. As market challenges grow, the demand for collaboration across all supply chain components has increased, making task allocation a critical aspect for decision science experts. (Saha et al., 2024) discussed the merits of PHF sets, generalized Dombi operators, and the MCDM method known as measurement of alternatives and ranking according to compromise solution (MARCOS) for building consensus in decision-making scenarios. This model showed a high degree of adaptability and flexibility in addressing complexities in healthcare supplier selection problems. Additionally, (Shidpour et al., 2023) proposed a multi-phase methodology to integrate Corporate Social Responsibility (CSR) into the Supplier Selection and Order Allocation Problem (SSOAP). They designed a multi-objective model based on senior managers' criteria, using linguistic terms and fuzzy numbers to address uncertainty issues. The Best Worst Method (BWM) was utilized to compute the weights of the criteria. Table 3 discusses different supplier selection techniques along with their advantages and limitations.

3.1. Criteria for supplier selection

Selecting potential suppliers is a strategic decision for any company, involving various criteria that influence supplier outcomes. Authors in the literature offer different rationales for supplier selection, each presenting multiple criteria for evaluation using specific ML/DL methods. Table 4 details the criteria and sub-criteria for effective supplier selection in SCM. There are five primary criteria identified: Quality of Service (QoS), price, location, reputation, and professionalism. Each of these criteria includes five sub-criteria to ensure efficient SCM, as illustrated in the table.

4. Production management in SCM

In SCM, production plays a crucial role in ensuring profitability, high productivity, sustainability, efficiency, and competitiveness. Leveraging ML and DL methods considerably improves these aspects. By utilizing predictive analytics, ML algorithms can forecast demand more accurately, aligning production schedules to meet market needs, thereby increasing profitability and reducing wastage. DL techniques, through advanced pattern recognition, can optimize production processes, improving productivity by identifying bottlenecks and streamlining operations. Sustainability is achieved through ML-driven resource optimization, minimizing energy consumption and material waste. Efficiency gains are realized by automating routine tasks and maintenance predictions, reducing downtime and operational costs. Furthermore, these technologies provide a competitive advantage by enabling faster adaptation to market changes, superior product quality, and more responsive supply chains. Thus, ML and DL integrate seamlessly into SCM to create a robust, forward-thinking production environment that balances profitability with sustainability and operational excellence.

(Guchhait and Sarkar, 2024) introduced a service-driven digital global SCM framework. Their innovative investment approach uses radio frequency identification technology to distribute product information through retailers, optimizing global SCM for maximum profit. However, the time complexity remains unaddressed. (Li and Zhao, 2024) discussed digital transformation's impact on reducing transaction expenses, highlighting heterogeneity in vertical relationship structures such as enterprise-scale differences. Despite these advancements, recall during digital transformation has not improved. (Burgess and Sunmola, 2023) conducted a systematic literature review of seventy-eight papers to identify supply chain quality management practices. However, their study lacks sensitivity analysis. (Duan et al., 2024) applied the Technology Acceptance Model and Diffusion of Innovation Theory to integrate blockchain technology into SCM, addressing implementation challenges but not reducing complexity. (Chen and Hammad, 2023) conducted a systematic literature review to synthesize modeling techniques in SCM, focusing on construction supply chains. Although the structural dimensions answer the formulated research questions, the modeling methods do not reduce computational complexity. (Abualigah et al., 2023) discussed diverse metaheuristics algorithms for sustainable SCM (SSCM). Their designed algorithm addresses SSCM challenges, considering issue difficulty and information quality, and presents recommendations for future research. However, the efficiency level is not improved by the metaheuristic algorithm. (Mahmoud et al., 2024) proposed a conceptual framework for an RL model, studying dynamicity, complexity, and uncertainty in CSCM. While the framework recommends areas needing further research, it does not reduce complexity.

Table 3
Summary of Supplier Selection Techniques employed in SCM.

Ref. No.	Approach	Contribution	Findings	Merits	Demerits
(Cristea and Cristea, 2017)	Multiple criteria decision making analysis	To perform the supplier selection in flexible packaging industry	The variants are ranked depending on suitability for supplier selection.	The potential supplier performance is computed against multiple criteria with decision maker preferences	Error rate is not reduced
(Pereira et al., 2023)	CRITIC-GRA-3 N method	To choose and rank supplier for dealership object	The designed method selected and ordered suppliers/ distributors of automotive parts in efficient manner	Supplier selection is carried out in efficient way	The complexity level is not reduced
(Yazdani et al., 2021)	Sustainable supplier evaluation structure	To compute different criteria and interval valued fuzzy neutrosophic (IVFN) model	The designed structure performed evaluation and selection of suppliers in Iran	The structure improved selection efficiency	The time complexity is not reduced
(Behera and Beura, 2023)	Planning and management of physical transportation	To address the business market difficulties	Task allocation satisfies the different criteria	The management used with raw materials falls under SCM	Accuracy is not at required level
(Saha et al., 2024)	Measurement of alternatives and ranking according to compromise solution (MARCOS)	To address the healthcare supplier selection problems	The designed model presented for consensus-building in decision-making scenario	MARCOS increased higher degree of adaptability and flexibility in handling complexities	Computational cost is not reduced
(Shidpour et al., 2023)	Multi-phase methodology	To address integrating Corporate Social Responsibility (CSR) in Supplier Selection and Order Allocation Problem (SSOAP)	BWM based weight computation	The designed methodology addressed uncertainty issues	The computational cost was not reduced

Table 4
Criteria and sub-criteria in supplier selection.

Criteria	Sub-criteria	Aspects	Advantages	Disadvantages
Quality of delivery	Quality of goods Delivery time Accuracy Flexibility Assortment Packaging and securing of goods	Efficiency	Streamlined processes improve productivity Cost savings through optimized operations	Increased complexity may lead to bottlenecks Supply chain disruptions can impact efficiency
Price	Unit price of goods Terms of payment Tax Discounts	Customer Satisfaction	Enhanced customer experience Better fulfillment of customer demands Improved product availability	Coordination challenges across stakeholders Potential for information leakage
Location	Geographical distance Traffic infrastructure Road speed Type of transport Transport conditions and administration	Visibility	Increased visibility into operations Improved risk management strategies	Dependency on external factors can be risky Difficulty in integrating new technologies
Reputation	Reliability Organization Automation Financial stability Environmental and social responsibility	Innovation	Innovation in product development Competitive advantage through innovation	Requires significant investment Potential for supplier conflicts
Professionalism	Servicing Providing additional services Application of information and communication technologies Responding to disturbance conditions Compliance with business confidentiality agreements	Sustainability	Environmental sustainability Regulatory compliance	Need for continuous monitoring and compliance Environmental risks and regulations

(Aslam et al., 2024) introduced a fuzzy control approach with MRRG to ensure stability during positive matrix recognition. Despite providing valuable insights for managing SCM dynamically, the fuzzy control approach does not improve stability.

In SCM, the production phase is crucial for transforming raw materials into finished products, ensuring efficient and effective production of goods (Drljavca and Sesar, 2023). This phase integrates key elements and best practices to streamline production processes, reducing stock-carrying costs and preventing stock-outs. Recent advancements in SCM have focused on integrating digital technologies and advanced methodologies to enhance efficiency, sustainability, and competitiveness (Wang et al., 2018; Chien et al., 2020; Lim and Chen, 2024). Service-driven digital SCM frameworks aim to optimize profits by managing international tax and environmental factors, although time complexity remains a challenge. Digital transformation initiatives have improved supply-demand matching and minimized transaction costs, yet issues with recall improvement persist. Systematic literature reviews have identified numerous supply chain quality management practices but often lack sensitivity analysis (Burgess and Sunmola, 2023; Kotsiopoulos et al., 2021). Blockchain integration in SCM addresses standardization and regulation, but complexity challenges remain (Matenga and Mpofu, 2022). Modeling techniques for construction supply chains highlight computational complexity issues. Metaheuristics offer valuable tools for sustainable SCM, enhancing sustainability but not necessarily efficiency. Reinforcement learning models are being explored for dynamic and uncertain SCM environments, yet complexity reduction is still needed (Kayal and Chanda, 2016; Tian et al., 2024; Mohamadi et al., 2024; Suemitsu et al., 2024). Fuzzy control approaches aim to ensure stability in SCM systems but require further improvements in stability metrics (Aslam et al., 2024). Overall, these advancements underscore the critical role of digital technologies and advanced methodologies in addressing SCM challenges, while also highlighting areas for future enhancement.

Table 5 gives the summary of production management techniques in SCM along with their merits and demerits.

5. Transportation and distribution in SCM

Transportation and distribution are critical components of SCM that ensure the effective movement of goods from suppliers to consumers. Advanced technologies such as ML and DL have revolutionized these processes by optimizing route planning, enhancing load management, and improving delivery schedules. However, these technologies face significant challenges, including high computational costs, data variability, and the complexity of integrating real-time data. Performance metrics such as delivery time, transportation cost, on-time delivery

Table 5
Summary of production management techniques employed in SCM.

Ref. No.	Approach	Contribution	Findings	Merits	Demerits
(Guchhait and Sarkar, 2024)	Service-driven digital global SCM	To perform product information distribution through retailers	An investment approach used radio frequency recognition technology for product distribution	The profit level is identified through global SCM	The time complexity is not minimized
(Li and Zhao, 2024)	Digital transformation	To minimize the transaction expenses	Digital transformation determined the heterogeneity at vertical relationship structures	The difference in enterprise scale is reduced	The recall is not improved during digital transformation
(Burgess and Sunmola, 2023)	Systematic methodology	To study the seventy-eight papers for SCM	To recognize the accurate method for supply chain management practices	The designed methodology performed supply chain quality management practices	The sensitivity analysis is not carried out
(Duan et al., 2024)	Technology Acceptance Model and Diffusion of Innovation Theory	To design the blockchain technology model	The designed method addressed the challenges with blockchain expertise implementation in SCM	The security problems are addressed through blockchain concepts	The complexity level is not minimized by Technology Acceptance Model
(Chen and Hammad, 2023)	Modeling techniques	To perform efficient supply chain management	The designed technique computes the structural dimensions	The designed technique addressed formulated research questions	The computational complexity is not reduced by modeling method
(Abualigah et al., 2023)	Metaheuristics algorithm	To address the challenges of SSCM	To emphasize metaheuristics for sustainable SCM	The designed algorithm reduced difficulty and improved information quality	The efficiency level is not improved by metaheuristics algorithm
(Mahmoud et al., 2024)	Conceptual framework of RL model	To study dynamicity and uncertainty in CSCM	Recommends studies with little or no attention	The designed framework minimized complexity	The complexity level is not reduced
(Aslam et al., 2024)	Fuzzy control approach with the MRRG	To guarantee constancy	Perform positive matrix recognition	Provide valuable insight for SCM handling	The stability level is not improved by fuzzy control approach

rates, and fuel efficiency are crucial for assessing the effectiveness of transportation and distribution systems. Additionally, sustainability metrics like carbon footprint and energy consumption are becoming increasingly important. Despite advancements, issues like infrastructure limitations, regulatory compliance, and fluctuating demand patterns continue to pose challenges, necessitating ongoing innovation and adaptation in SCM transportation and distribution strategies.

(Drljavca and Sesar, 2023) discussed transportation issues in supply chains leading to market imbalance and negative consequences such as black market emergence and crime during extreme conflicts and wars. They highlighted the role of transportation in developing a circular economy and waste management through recycling and reuse. However, the sensitivity analysis is not improved. (Jang and Lee, 2024) introduced multi-stage stochastic programming (SP) and the Weighted Scenario Sample Average Approximation (WSSAA) for the hydrogen supply chain, which, despite its efficiency, still struggles with high time complexity. (Fu et al., 2023) explored the Partial Least Squares Structural Equation Modeling (PLS-SEM), linking supply chain relationships and organizational culture to low-carbon practices in green SCM, but the efficiency level has not improved. (Matenga and Mpofu, 2022) discussed the integration of industrial DevOps and blockchain-based systems in SCM, yet did not address the computational cost reductions needed. (Niu et al., 2024) proposed a new supply chain network design involving location choices for production plants and allocation centers, but found that accuracy improvements were still needed. (Deng et al., 2023) introduced a distributionally robust optimization (DRO) approach. Pipeline-transported replenishment strategy is used to identify challenges as well as pipeline working status. The replenishment policies are computed with the differentiated service level requirements, which handled service level requirements well but did not minimize storage costs. (Sirina and Zubkov, 2021) discussed the transport and logistics method for transport services administration. The typology of optimum management is discussed with association flows in the sector of freight traffic as well as optimization. Transport and logistics methods are essential for preparation as well as running transport services. However, the f-measure is not increased by the designed method. (Peng et al., 2022) discussed the big data technology for integrated transportation preparation as well as retailing optimization of supply chain networks. The uncertainty theory handles uncertainty in big data elements and classifies metrics to address incorporated optimization issues. However, the method faces complex challenges. (Zulqarnain et al., 2024) introduced a fuzzy set and integrated approach with ambiguous data. Einstein aggregation operators (AOs) are considered: IVq-ROFSEWA and IVq-ROFSEWG. However, the accuracy level is not improved by the fuzzy set and integrated approach. (Mohd Anwer, 2022) discussed quantitative methodology for gathering and analyzing the primary data. The designed methodology incorporated 212 participants from developed firms in the Middle East area. The conceptual model test performs a hypothesis-testing deductive approach. But, time complexity is not reduced by this quantitative methodology. (Wang et al., 2022) presented an in-depth study of transportation capability deficiency problems concerning Australian logistics service providers. The relationship among driver shortages is discussed with logistic capability and logistics performance. Structural equation modeling (SEM) analyzes the measurement models. However, it did not address time consumption effectively. (Li et al., 2023) introduced the descriptive statistical study, bibliometric analysis as well as a literature review. The bibliometric study comprised a collaboration network, emerging trends, and co-citation study. (Fartaj et al., 2020) examined the critical transportation disturbance factors of SC of automotive tasks manufacturing companies as well as computed interrelationships through BWM and RSR analysis techniques. (Chen et al., 2023) introduced an analytical approach and related mathematical procedure. The traffic congestion and so on are estimated the household truck loads as well as motor vehicle miles for domestic manufacture capability. However, the precision level is not improved by the analytical framework. (Tsolaki et al., 2023) located current transport, supply chain, and logistics depend on arrival time and so on. Transportation classified the associated works consistent with ML methodologies to provide development during the time of their amalgamation as well as their association. However, the accuracy level is not improved.

From the above discussion, it is evident that transportation and distribution control plays a vital role in moving goods efficiently to end-users. These processes involve managing the movement of goods from one location to another to fulfill supply chain requirements and effectively deliver customer orders. Advanced technologies and methodologies continue to enhance these processes, but ongoing challenges necessitate continuous innovation to maintain efficiency and competitiveness. Table 6 gives the summary of employed techniques for transportation and distribution challenges in SCM.

Table 6
Summary of transportation and distribution techniques employed in SCM.

Ref	Approach	Contribution	Findings	Merits	Demerits
(Drljavca and Sesar, 2023)	Disturbance at unfolding	To perform unfolding of supply chain	Compute negative consequences	Development of circular economy and waste management	Sensitivity analysis not improved
(Jang and Lee, 2024)	Multi-stage stochastic programming (SP)	To derive hydrogen supply chain	Perform efficient resolution for multistage SP	Perform weighted scenario sample average approximation	Time complexity not reduced
(Fu et al., 2023)	Partial least squares structural equation modeling	To compute supply chain relationship	Straightly associated through low-carbon practices	Low-carbon practices stage of green SCM	Efficiency level is not improved.
(Matenga and Mpofu, 2022)	Industrial DevOps	To perform IS and CM process	Perform transportation to different areas	Efficient SCM	Computational cost was not minimized
(Niu et al., 2024)	New supply chain network design	To include position choices for owned producing plants	Comprises allocation centers and choice of third-party manufacturers	Perform efficient distribution	Accuracy not improved
(Deng et al., 2023)	Distributionally robust optimization (DRO) approach	To identify challenges as well as working status	Addressed service level requirements	Fixed Iteration count	Storage cost not minimized
(Sirina and Zubkov, 2021)	Transport and logistics method	To perform transport services administration	Determine association flows at sector	Running transport services	F-measure not improved
(Peng et al., 2022)	Big data technology	To retail optimization of supply chain network	Handles uncertainty in big data details	Classify metrics to address optimization issue	Complexity level not reduced
(Zulqarnain et al., 2024)	Fuzzy set and integrated approach	To perform Einstein aggregation with operators	Perform transportation with minimum cost	Efficient management of supply chains	Accuracy level not improved
(Mohd Anwer, 2022)	Quantitative methodology	To perform performs hypothesis- testing deductive	Incorporated participants in developed firms	Gather and analyzes the primary data	Complexity not reduced
(Wang et al., 2022)	In-depth study	To address transportation capability deficiency problem	Analyzes the measurement models	Increased logistic capability and logistics performance	Time consumption not reduced
(Li et al., 2023)	Descriptive statistical study	To perform bibliometric analysis	Efficient collaboration network	Studies emerging trend and co-citation study	Computational cost not reduced
(Fartaj et al., 2020)	Transportation disturbance factors	To compute interrelationship through BWM and RSR analysis	Performed automotive tasks	Efficient SCM	Error rate not reduced
(Chen et al., 2023)	Analytical approach	To perform related mathematical procedure	Evaluate domestic manufacture capability	Reduced traffic congestion and estimated the household truck loads	Precision level not improved
(Tsolaki et al., 2023)	ML methodologies	Assessing transportation infrastructure impacts from supply chain	Classified associated works	Reduce arrival time	Accuracy level not improved

6. Inventory control in SCM

Inventory control in SCM is essential for maintaining optimal stock levels, reducing costs, and meeting customer demands. Advanced applications such as machine learning (ML) and deep learning (DL) significantly enhance inventory control by accurately forecasting demand, automating restocking processes, and identifying inventory trends. These technologies help minimize overstock and stockouts, reduce holding costs, and improve service levels. However, challenges remain, including ensuring data accuracy, integrating conventional systems, and managing demand variability. Key performance metrics for inventory control include inventory turnover rates, order fulfillment rates, carrying costs, and stockout rates, as well as lead time and service level agreements (SLAs) for efficiency assessment. Despite advancements, addressing issues such as supplier reliability, demand forecasting accuracy, and cost control is crucial for effective inventory management in SCM (Yan et al., 2022; Cai et al., 2013; Tian et al., 2024).

(Yan et al., 2022) discussed the complete appraisal of development as well as the relevance of the RL method in logistics as well as SCM. RL methodology was discussed and performed classification of preceding research studies. Existing research is evaluated and current demands are explained. But, time consumption is not reduced. (Cai et al., 2013) introduced a new incentive scheme for supply chain management. WMC contract between producer and distributor as well as WDS contract among producer as well as 3PL provider is explained. However, the complexity level is not reduced by the new incentive scheme. (Tian et al., 2024) introduced a replenishment model termed IACPPO. The designed model combined A2C algorithm with the PPO method. IACPPO extracts information as of ecological state series through memory logic. A2C with PPO method trains the network to attain a replenishment strategy. But, the time complexity is not reduced by IACPPO. (Nya and Abouaissa, 2023) discussed the model-free control to mention SCM problem. However, time complexity is not reduced by model-free control. (Mohamadi et al., 2024) designed an Advantage Actor-Critic (A2C) algorithm to handle continuous action space in inventory allocation. An empirical data from a real-world blood supply chain in Tabriz is employed for numerical experiments. However, the accuracy level is not improved by the A2C algorithm.

The review of existing methods suggests that inventory control in SCM is critical for maintaining optimal stock levels, reducing costs, and meeting customer demands. Table 7 shows the summary of inventory control techniques employed in SCM.

7. Demand and sales estimation

Demand and sales estimation is crucial in SCM for optimizing inventory levels, production planning, and meeting customer demands efficiently. Applications of ML and DL in this area have significantly improved accuracy through examining historical data, and so on. These technologies enable precise demand forecasting and sales predictions, helping businesses align their strategies accordingly. However, challenges such as data quality, integrating diverse data sources and adapting to rapidly changing market conditions persist. Key performance metrics include forecast accuracy, mean absolute percentage error (MAPE), sales variance, and customer satisfaction levels. Effective demand and sales estimation enhances operational effectiveness however supports superior decision-making as well as competitive advantage in the market.

(Suemitsu et al., 2024) introduced a three-phase approach. The mixed integer linear programming addresses issues as well as

Table 7
Summary of inventory control techniques employed in SCM.

Ref. No.	Approach	Contribution	Findings	Merits	Demerits
(Yan et al., 2022)	Complete appraisal	Determine relevance of RL method in logistics	Perform classification of preceding research	Evaluate present demands	Time consumption not reduced
(Cai et al., 2013)	New incentive scheme	Perform supply chain management	Estimate demand level	Contract between producer and distributor	Complexity level not reduced
(Tian et al., 2024)	Replenishment model termed IACPPO	To attain replenishment strategy	Extract information	Determine ecological state series	Time complexity not reduced
(Nya and Abouaissa, 2023)	Model-free control	To address SCM problem	Compute demand and sales estimation	Address demand in efficient manner	Time complexity not minimized
(Mohamadi et al., 2024)	Advantage Actor-Critic (A2C) algorithm	To handle continuous action space	Performs inventory allocation	Analyze empirical data from blood supply chain	Accuracy level not improved

determines perfect inventory quantities. Designed approach updates perfect inventory quantities depending on estimated shortages. However, the computational complexity is not reduced by a three-phase approach. (Chiang et al., 2023) designed a regression method through product-level industry information. The designed method reveals the practical implications for handling business. However, the regression method has not enhanced the accuracy level. (Lim and Chen, 2024) designed a supply and production (S and P) DT scheme to improve the resilience as well as disturbance administration at multi-echelon networks. S and P DT scheme increased demand achievement rate as well as minimized make span to improve operational permanence. However, the time complexity is not minimized by the designed DT system. The mathematical model presented in (Villa, 2022) aimed to assess supplier responsiveness, customer overreaction, and capacity allotment in competitive systems, focusing on their impact on retailer decisions. The results highlighted the complexity of accurately predicting these variables within dynamic market environments. Despite the model's design to integrate various factors affecting supply chain dynamics, such as supplier behavior and customer responses, achieving high accuracy proved challenging. The intricacies of real-world interactions, including unforeseen market shifts and behavioral nuances, posed significant obstacles. Challenges included capturing the full spectrum of supplier responsiveness, accurately predicting customer reactions, and dynamically adjusting capacity allotment strategies. These findings underscored the ongoing need for refined modeling techniques and robust data sources to enhance predictive accuracy and better inform retailer decisions in competitive supply chain settings.

According to the literature analysis, demand estimation in supply chain management (SCM) involves planning and forecasting the required goods and materials, and several ML/DL methods are employed for the same. Accurate demand estimation leads to better business outcomes and increased profitability. It also helps manage customer demand effectively to meet future needs. Additionally, demand estimation aids in determining the quantity of specific goods or services needed for current promotions, ensuring that supply aligns with sales expectations. Table 8 illustrates the summary of demand and sales estimation in SCM.

8. Review discussion and summary

The supply chain has faced significant challenges due to increasing demands and restricted logistics capabilities (Tsolaki et al., 2023; Yan et al., 2022; Chiang et al., 2023; Lim and Chen, 2024; Villa, 2022). These challenges are exacerbated by market volatility, which leads to risks within SCM. Factors such as fluctuating consumer demand, climate variation, environmental regulations, economic uncertainties, and industrial unrest contribute to the demands as well as risks faced by supply chains. In summary, the key challenges in managing supply chains include:

8.1. Current challenges facing SCM

- **Resource Management:** Poor resource management is a significant challenge in supply chain management (SCM). Efficiently allocating and utilizing resources such as raw materials, manpower, and machinery is critical for maintaining smooth operations. Resource shortages or mismanagement can lead to delays, increased costs, and operational inefficiencies, affecting the overall performance of the supply chain.
- **Unexpected delays:** Global supply chains span large distances and involve numerous steps, making them highly susceptible to delays. The extended transit times for goods increase the likelihood of unexpected delays, which can disrupt the entire supply chain process.
- **Cost control:** Controlling costs is crucial as raw material prices and shipping costs continue to spike globally. Businesses must tighten cost controls to ensure uninterrupted manufacturing operations and the consistent delivery of quality goods at reasonable rates.
- **Data Collaboration across Supply Chain:** Efficient SCM relies heavily on access to accurate and timely information. Given the vast number of data points in global supply chains, effective information management is essential to streamline operations and enhance decision-making processes.
- **Increasing Freight Prices:** Rising energy prices and higher demands for container shipping have driven up the cost of goods. This increase in freight prices presents a significant challenge for businesses striving to maintain cost efficiency.
- **Difficult Demand Forecasting:** The COVID-19 pandemic and subsequent supply chain disruptions have made demand forecasting more difficult. It has become challenging to accurately predict manufacturing needs and manage inventory levels, complicating the planning process.

Table 8
Summary of Demand and Sales Estimation Techniques employed in SCM.

Ref. No.	Approacg	Objective	Findings	Merits	Demerits
(Suemitsu et al., 2024)	Three-phase approach	To determine perfect inventory quantities	Updated perfect inventory quantities	Estimated shortage	Computational complexity is not reduced
(Chiang et al., 2023)	Regression method	To perform practical implications	Improved product-level industry information	Handling business	Accuracy level not enhanced.
(Lim and Chen, 2024)	Supply and production (S&P) DT scheme	To improve operational permanence	Improve resilience and disturbance administration at multi-echelon networks	Increased demand achievement rate and minimized make span	Time complexity not minimized by designed DT system
(Villa, 2022)	Mathematical Model	To estimate supplier responsiveness	Perform customer overreaction	Capacity allotment on retailer decisions	Accuracy not improved

- **Digital Transformation:** Implementing digital technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) is crucial for enhancing supply chain operations. The primary demand in SCM is the successful execution of these technologies across various supply chain functions.
- **Port Congestion:** The pandemic has led to limited loading and unloading operations, causing port congestion. This congestion has resulted in delayed dispatches and deliveries, affecting the overall efficiency of supply chain operations.
  - Environment navigation of persistent unpredictability
  - Labor shortages
  - Ripple effects of global bottlenecks
  - Equipment accessibility
- SCM must handle an environment of persistent unpredictability, addressing labor shortages, ripple effects of global bottlenecks, and equipment accessibility issues (Gaida et al., 2022; Toorajipour et al., 2021).
- **Supplier Relationship Management:** Effective supplier relationship management requires expertise in negotiation, communication, and coordination. Less effective supplier interactions can potentially impact the reliability and performance of the supply chain.
- **Quality and Safety:** Maintaining high standards of quality and safety while meeting tight deadlines is a considerable challenge in supply chain management. The pressure to deliver products on time to keep the supply chain moving often conflicts with the need for thorough quality checks and safety measures. Balancing these priorities is essential to ensure that products meet quality standards without compromising safety or delivery schedules.
- **Inventory Management:** Inventory management involves the delicate task of timing purchase orders to ensure smooth operations without overstocking. Proper inventory management requires predicting demand accurately to avoid excess inventory that may not be used or needed, which can tie up capital and storage space. Conversely, insufficient inventory can lead to stockouts and disruptions in operations. Achieving this balance is crucial for maintaining efficient and cost-effective supply chain operations.

8.2. *Analysis on growth and impact of ML/DL technologies in SCM*

Table 9 provides the summary of the reviewed techniques in terms of key metrics and data. The use of ML and DL in SCM is becoming more advanced, leveraging data from sensors, IoT devices, and interconnected logistics networks to predict potential issues, optimize routes, and enhance operational efficiency. Companies are advancing from basic data collection to employing real-time analytics for more accurate demand forecasting. ML/DL techniques enable the creation of highly

Table 9
Summary of the reviewed techniques in terms of key metrics and data.

Technique	Reference	Data Frequency	Time range	Application	Performance Metric	Challenges
ML-with-AHP	(Abdulla et al., 2019)	Daily	January 1, 2017- January 3, 2019	Short-term Forecasting	Error, Accuracy	Not efficient cost control
ML-SVM method	(Zhao et al., 2021)	Daily	June 1, 2015- June 3, 2018	Prediction	Time complexity	Inefficient demand prediction
ML-with-MARCOS method	(Abdulla et al., 2023)	Weekly	February 1 2020- January 31, 2023	Short term prediction	Accuracy	Difficult demand prediction
Integrated RF-model	(Ali et al., 2023)	Daily	April 1 2014- March 31, 2017	Prediction	Complexity	Unexpected delay
Two-stage solution approach	(Islam et al., 2021)	Weekly	February 1 2022- January 31, 2023	Forecasting	Precision	Difficult digital transformation
SVM-DT- combined	(Radivojevic et al., 2022)	Daily	May 15 2020- April 30, 2023	Short-term prediction	Recall	Inefficient port congestion
Conceptual framework	(Raj et al., 2022)	Monthly	December 1 2021- November 30, 2022	Prediction	Accuracy	Maximum freight prices
Conditional generative adversarial networks	(Lin et al., 2022)	Quarterly	July 15 2020- August 31, 2022	Forecasting	Accuracy, time consumption	Difficult price prediction
SCM-CAT	(Xu et al., 2024)	Monthly	December 31 2020- December 31, 2021	Prediction	Precision	Difficult collaboration
Service-driven digital global supply chain management	(Guchhait and Sarkar, 2024)	Weekly	November 1 2022- October 31, 2023	Short-term prediction	Recall	Difficult transformation
Conceptual framework	(Mahmoud et al., 2024)	Daily	February 1 2019- January 31, 2023	Prediction	Complexity	Considered only circular supply chain management
Fuzzy control approach	(Aslam et al., 2024)	Weekly	September 1 2020- August 31, 2022	Prediction	F-measure	Larger delay
Multi-stage stochastic programming	(Jang and Lee, 2024)	Monthly	April 14 2022- July 14, 2023	Short-term prediction	Recall	Inefficient cost control
Supply chain network design	(Niu et al., 2024)	Daily	August 1 2021- October 31, 2022	Prediction	Accuracy	Inefficient data transformation
Distributionally robust optimization (DRO) approach	(Deng et al., 2023)	Weekly	February 1 2018- March 31, 2022	Prediction	Recall, Precision	Not efficient data collaboration
Transport and logistics method	(Sirina and Zubkov, 2021)	Monthly	July 1 2019- September 30, 2021	Forecasting	Time complexity	Inadequate cost control
Fuzzy set and integrated approach	(Zulqarnain et al., 2024)	Daily	August 18 2010- October 31, 2018	Prediction	Computational cost	Inefficient port Congestion
Analytical framework	(Chen et al., 2023)	Weekly	July 14 2020- September 31, 2021	Short-term prediction	Accuracy	Higher delay
New incentive scheme	(Cai et al., 2013)	Monthly	June 15 2020- April 15, 2022	Forecasting	Recall	Higher computational cost
Replenishment model	(Tian et al., 2024)	Weekly	January 1 2021- October 31, 2023	Forecasting	Time complexity	Labor shortages
Advantage Actor-Critic (A2C) algorithm	(Mohamadi et al., 2024)	Monthly	July 12 2016- November 31, 2018	Prediction	Precision, time consumption	Data Collaboration
Three-phase approach	(Suemitsu et al., 2024)	Daily	March 15 2017- October 31, 2019	Short-term prediction	Computational cost	Higher ripples

personalized forecasts by integrating historical data with real-time variables such as social media trends, weather conditions, and local events. This capability enhances the ability of businesses to predict demand shifts and adjust inventory levels more effectively. The market for ML/DL in SCM is expanding, where ML models continuously refine and adapt based on real-time data and feedback. This will facilitate autonomous process optimization and adaptability to changing conditions. Moreover, ML is expected to play a pivotal role in making logistics more sustainable by optimizing delivery routes, reducing empty truck miles, and supporting eco-friendly packaging solutions. As these technologies evolve, they are likely to contribute to more resilient, efficient, and environmentally aware supply chains, capable of swiftly addressing global challenges and market fluctuations.

Table 10 provides a detailed summary analysis of the SCM literature in terms of objectives, performance results, and limitations. ML and DL technologies play a crucial role in SCM by enhancing supplier selection and monitoring. It evaluates various factors, including performance, quality, pricing, and reliability, to make informed decisions. In logistics, ML/DL optimizes transportation routes by considering variables such as traffic conditions, weather, delivery schedules, and vehicle capacities. This leads to reductions in fuel consumption, faster delivery times, and lower operational costs. Logistics companies are increasingly adopting AI and ML technologies to improve their services and offer more efficient transportation solutions. Despite its advantages, ML/DL in SCM faces several challenges, including concerns about data security and privacy, as well as the complexity of integrating ML with existing systems. Successful implementation of ML relies on high-quality, clean data. The process of aggregating data from various sources, ensuring its accuracy, and integrating it with existing systems can be intricate and time-consuming. Additionally, ML algorithms can inadvertently reinforce biases present in the training data, leading to potentially unfair decisions in areas such as supplier selection or demand forecasting, which may impede market growth. From the survey table, it is clear that further research is required by incorporating ML and DL concepts for performing efficient management of supply chain functionalities. ML in SCM Market was valued at USD 1.5 billion in 2023 and is estimated to register a CAGR of over 29% between 2024 and 2032. The major factors driving market adoption include enhanced demand forecasting, inventory optimization, and risk management. Machine learning algorithms analyze extensive data sets, such as historical sales, market trends, and social media sentiments, to predict demand accurately, optimize inventory levels, and minimize stock-outs. This leads to cost savings, increased efficiency, and improved customer experience.

Practicalapplications: According to the review analysis, the key adaptive practical applications of ML and DL in SCM can be summarized as follows.

- **Forecasting and Predictive Analytics:** The ML and DL models enhance demand forecasting through predictive analytics by analyzing past demand data to uncover hidden trends. These algorithms enable businesses to anticipate issues before they impact operations, ensuring they have the resources and insights needed to address challenges promptly. Effective forecasting systems not only prepare companies for potential threats but also enhance their ability to respond quickly and efficiently.
- **Production control and quality:** The ML and DL technologies enable automated quality inspections by using image recognition to detect manufacturing equipment faults and package damage, reducing reliance on manual checks at logistics hubs. This automation minimizes the risk of delivering defective or substandard products, ensuring higher quality control and reliability.
- **Customer Experience:** Integrating deep analytics, IoT, and real-time monitoring with ML significantly enhances supply chain visibility. This approach allows businesses to improve customer experiences through faster delivery by analyzing historical data and identifying connections within the supplier value chain.
- **Production Planning:** ML/DL optimizes production planning by analyzing existing production data to identify inefficiencies and waste. Advanced algorithms help streamline complex production processes and enable the supply chain to adapt effectively to disruptions, enhancing overall operational efficiency.
- **Reducing Costs and Response Times:** By enhancing communication with logistics providers and standardizing freight and storage operations, ML helps lower administrative and operational costs within the supply chain.
- **Effective Warehouse and Inventory Management:** Effective warehouse and inventory management is crucial for successful supply chain planning. ML improves this by addressing issues of overstocking and under-stocking through advanced forecasting and modeling techniques. AI and ML also facilitate the creation of data warehouses, enabling faster data analysis and reducing human error.
- **Fraud Detection and Prevention:** The ML and DL techniques enhance financial fraud detection by automating auditing and inspection procedures and performing real-time analysis to identify anomalies. This technology also helps prevent breaches caused by misuse of privileged credentials, thus improving the overall security and integrity of the global supply chain.

8.3. Performance analysis of different ML/DL methods in SCM

To assess the performance of different ML/DL methods in SCM, we have performed an experimental evaluation of ten different techniques, namely RF-model (Ali et al., 2023), ML-with-MARCOS method (Abdulla et al., 2023), ML-with-AHP (Abdulla et al., 2019), ML-SVM method (Zhao et al., 2021), two-stage-solution approach (Islam et al., 2021), SVM-DT-combined (Radivojevic et al., 2022), P-SVM-DT (Tirkolaee et al., 2021), MLP-model (Mitrovic et al., 2021), RF-ranking-model (Wilson et al., 2020), LR-optimization (Gaida et al., 2022) are implemented using Java language. Different evaluation metrics are employed to assess the supply chain management model using a traffic image dataset. The employed performance metrics include accuracy, time complexity, and error rate. Fig. 12, 13, and 14 present the performance analysis results in terms of accuracy, time complexity, and error rate for the ten different methods compared. The overall performance results are summarized in the Table 11.

The comparative analysis indicate that the RF-model demonstrates the highest accuracy (96%) with a low error rate (4%) and moderate time complexity (15 ms). This reveals a good performance with reasonable computational demands. ML-with-MARCOS and ML-SVM also show high accuracy (95%) and have similar error rates (5%), but with slightly higher time complexity (18 ms and 20 ms, respectively). In contrast, the Two-stage-solution method has the lowest accuracy (91%) and the highest error rate (9%), with a notable increase in time complexity (25 ms). The SVM-DT-combined and P-SVM-DT methods provide moderate accuracy (93% and 92 %) and error rates (7% and 8%) but with varied time complexities (21 ms and 18 ms). The MLP-model, RF ranking model, and LR optimization methods all offer similar accuracy (93% and 94%) with higher error rates (6–9%) and time complexities (20–27 ms). Overall, while methods like RF-model provide a balance of high accuracy and low error rate with moderate time complexity, others like the Two-stage-solution method and MLP-model face challenges with lower accuracy and higher error rates, reflecting trade-offs between performance and computational cost.

Table 12 and Fig. 15 present the overall comparative results of different ML and DL methods in SCM. The result reveals distinct differences in performance across Accuracy, Error Rate, and Time Complexity. Among ML methods, the SVM achieves a moderate accuracy of 87%, a higher error rate of 13%, and a substantial time complexity of 25 ms. In contrast, the Bayesian Network has an accuracy of 88%, with a reduced error rate of 12% and a decreased time complexity of 22 ms. The Neural Network outperforms both ML methods with a higher accuracy of 92%, a lower error rate of 8%, and a

Table 10
Literature Table for SCM.

Ref. No	Approach	Objective	Metrics												Limitations
			A	F-score	P	R	AUC	T	E	C	Cost	S	PRC	MCC	
(Ali et al., 2023)	Integrated RF-model	Find critical criteria choosing the suppliers based on requirements	√	√										√	ML classifiers like SVM, Naive Bayes, Decision Tree can be used to evaluate performance
(Abdulla et al., 2023)	ML-with-MARCOS method	Choose the suppliers in line with human e valuators	√	√	√	√	√	√				√			The designed approach cannot be applied for limited data or poor quality data.
(Abdulla et al., 2019)	ML-with-AHP	Used decision tree classifier to classify suppliers into good and bad to determine features	√	√	√	√	√			√				√	Integrated approach not used to explore hybrid methodology delivered in service-based application.
(Zhao et al., 2021)	ML-SVM method	Study the credibility of expert from historical data	√			√		√		√					Appropriate kernel parameters not identified to improve SVM classifier model
(Islam et al., 2021)	New two-stage solution approach	Perform supplier selection and order allocation planning	√		√			√					√	√	Comprehensive models are not used in forecasted factors.
(Radivojevic et al., 2022)	SVM-DT- combined	Selects the supplier		√		√			√			√		√	Combined model is not used to select the criteria and supplier in supply chain
(Tirkolaee et al., 2021)	P-SVM-DT	Select and segment suppliers for predicting the supply chain risks	√		√		√				√				Efficient solution for SCM problem is too expensive or difficult due to the inherent complexity and ill-structured nature
(Mitrovic et al., 2021)	MLP-model	Group one hundred suppliers		√					√				√		Multilayer Perceptron model does not indicate the best suppliers but categorize into efficient or inefficient group
(Wilson et al., 2020)	RF-ranking- model	Shapes industry and helps in operations.				√		√			√			√	Different classifiers and data are not used for calculating the best suppliers for industry.
(Gaida et al., 2022)	LR- optimization	Best supplier selection	√		√			√					√		Technological tools are not used to improve efficiency and accuracy results.
(Toorajipour et al., 2021)	AI	Enhance the study and practice of SCM					√				√				single-technique evaluation is highly recommended
(Raj et al., 2022)	Conceptual framework	Examine challenges and pertinent mitigation strategies	√	√									√	√	Time consumption is not minimized by designed framework
(Lin et al., 2022)	Dynamic supply chain member selection algorithm	Perform decision analysis		√				√					√		Though complexity was minimized, the computational cost was not minimized.
(Seuring et al., 2022)	Status quo of theory development	Perform stakeholder management		√			√				√				The accuracy level is not improved.
(Jasrotia et al., 2024)	PLS-based structur equation modellingapproach	Investigate hypothesis relationship between stage-wise green supply chain	√			√				√			√	√	The error rate is not reduced by PLS-based structural equation modelling approach.
(Li et al., 2024)	Enterprise digital transformation	Strengthen supply chain management		√			√				√			√	The complexity is not minimized by

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Table 10 (*continued*)

Ref. No	Approach	Objective	Metrics												Limitations
			A	F-score	P	R	AUC	T	E	C	Cost	S	PRC	MCC	
		with research perspective													enterprise digital transformation.
(Xu et al., 2024)	SCM-CAT	Perform bliometric analysis and content analysis			√			√				√			Considered SCM under cap-and-trade regulation perspective
(Sun et al., 2024)	Technology- driven logistics	Perform supply chain management		√			√			√			√	√	Explored SCM under social aspects only
(Guchhait and Sarkar, 2024)	Service-driven digital global supply chain management	Identify the intriguing factors	√		√			√					√		Time complexity is not minimized by service-driven digital global supply chain management.
(Li and Zhao, 2024)	Digital transformation	Optimize supply-demand matching and minimize transaction costs		√		√			√			√			The recall is not improved during digital transformation
(Burgess and Sunmola, 2023)	Supply chain quality management	Identified supply chain quality management practices	√		√		√		√		√				sensitivity analysis is not carried out
(Duan et al., 2024)	Technology Acceptance Model	Integrated blockchain technology		√					√				√	√	The complexity level is not minimized by Technology Acceptance Model.
(Chen and Hammad, 2023)	Modelling techniques	Perform supply chain management				√		√			√	√			Computational complexity is not reduced by modeling methods.
(Abualigah et al., 2023)	Metaheuristics algorithms	Perform sustainable supply chain management	√	√											The efficiency level is not improved by metaheuristic algorithm
(Mahmoud et al., 2024)	Conceptual framework	Studies the stochastic nature of CSCM environment			√		√		√		√			√	Complexity level is not reduced by conceptual f ramework.
(Aslam et al., 2024)	Fuzzy control approach	Guarantee stability through positive matrix identification	√	√						√			√		Stability level is not improved by fuzzy control approach.
(Drljavca and Sesar, 2023)	Unfolding of supply chain	Balance between supply and demand on market with negative consequences	√					√				√			The sensitivity analysis is not improved
(Jang and Lee, 2024)	Multi-stage stochastic programming (SP)	Computed demand uncertainty and transportation capacity		√			√		√		√				Time complexity is not reduced by multi-stage SP
(Fu et al., 2023)	Partial least squares structural equation	Analyze data based on relationship	√			√				√			√	√	The efficiency level is not improved by partial least squares structural equation.
(Matenga and Mpofu, 2022)	Industrial DevOps	Merge industry 4.0 technologies		√			√							√	The computational cost was not minimized.
(Niu et al., 2024)	Supply chain network design	Perform capacity sharing with third-party manufacturers			√			√				√			Accuracy was not improved by efficient design
(Deng et al., 2023)	DRO approach	Identify demands and pipeline working status	√		√			√		√			√		The storage cost is not minimized by DRO approach.
(Sirina and Zubkov, 2021)	Transport and logistics method	Perform transport services management		√		√			√			√			F-measure is not increased by designed method
(Peng et al., 2022)	Big data technology	Integrated transportation planning and retailing optimization	√		√		√	√			√				Complexity level is not reduced by big data technology
(Zulqarnain et al., 2024)	Fuzzy set and integrated approach	Perform Einstein aggregation		√					√				√		Accuracy level is not improved by fuzzy set

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Table 10 (*continued*)

Ref. No	Approach	Objective	Metrics												Limitations
			A	F-score	P	R	AUC	T	E	C	Cost	S	PRC	MCC	
															and integrated approach.
(Mohd Anwer, 2022)	Quantitative methodology	Gather and analyze the primary data				√		√			√			√	Time complexity is not reduced by quantitative methodology.
(Wang et al., 2022)	In-depth analysis	Address transportation capacity shortage issue	√		√		√						√		Time consumption is not reduced by in-depth analysis.
(Li et al., 2023)	Descriptive statistical analysis	Discuss statistical analysis					√				√				Computational cost was not reduced by statistical analysis
(Fartaj et al., 2020)	Transportation disruption factors	Perform supply chain of automotive parts	√	√									√		The error rate is not reduced by transportation disruption factors.
(Chen et al., 2023)	Analytical framework	Assessing supply chain restructuring and domestic capacity expansion				√		√						√	The precision level is not improved by analytical framework
(Tsolaki et al., 2023)	Current transportation	Present the evolution through time		√			√				√				Accuracy level is not improved
(Yan et al., 2022)	RL method	Discusses current challenges	√			√				√			√		The time consumption is not reduced.
(Cai et al., 2013)	New incentive scheme	Perform wholesale-price-discount sharing		√			√							√	Complexity level is not reduced by new incentive scheme
(Tian et al., 2024)	Replenishment model	Analyze data state space for probabilistic modeling			√			√				√			Time complexity is not reduced by IACPPO
(Nya and Abouaissa, 2023)	Model-free control	Address supply chain management (SCM) problem	√		√			√					√		Time complexity is not reduced by model-free control.
(Mohamadi et al., 2024)	Advantage Actor-Critic (A2C) algorithm	Handle continuous action space in inventory allocation		√		√			√			√			The accuracy level is not improved by A2C algorithm
(Suemitsu et al., 2024)	Three-phase approach	Determines ideal inventory quantities	√		√		√				√				The computational complexity is not reduced by three-phase approach.
(Chiang et al., 2023)	Regression method	Development of inventory dynamics		√					√				√		The regression method not enhanced accuracy level.
(Lim and Chen, 2024)	Supply and production (S&P) digital twin (DT) system	Improve the resilience and disruption management				√		√			√				The time complexity is not minimized by designed DT system.
(Villa, 2022)	Mathematical model	Estimate the supplier responsiveness	√	√				√				√			The accuracy is not improved by designed model

reduced time complexity of 20 ms. The Deep Belief Network excels further, with the highest accuracy of 95% and the lowest error rate of 5%, while also achieving the shortest time complexity of 15 ms. This analysis shows that DL methods generally provide superior performance compared to ML methods, highlighting their efficiency and effectiveness in enhancing supply chain operations and management.

8.4. *Case studies and real-world applications of SCM*

Based on the study and findings, the DL and ML are essential one for the rapid increase of data in SCM. This review increased the research advances and business growth for both academic researchers and practitioners. In addition, it provides a solid background of DL and ML applications in SCM. Subsequently, it is a reference for scholars to have an overview of different applications of SCM using DL and ML algorithms. The study contributes to the literature on SCM by focusing on the applications of DL and ML in SCM. Organizations evolve their SCM continuously to stay at the top. They are exposed to a wealth of knowledge from new business trends. It comprised innovations in businesses, uncertainties together with shorter and tougher business cycles, expanding and demanding consumer base, converging wages, and increasing costs. The supply chain leaders discuss the trends and their potential implications on the business. The supply chain strategy is studied by considering the design of future logistics networks by improving the responsiveness of the supply chain.

One example of a successful SCM is Walmart. It has implemented a highly efficient supply chain system. Walmart has a classy inventory management system to optimize inventory levels and minimize waste. The company employs a network of distribution centers to guarantee that products are accessible in stores when needed. In addition, Walmart

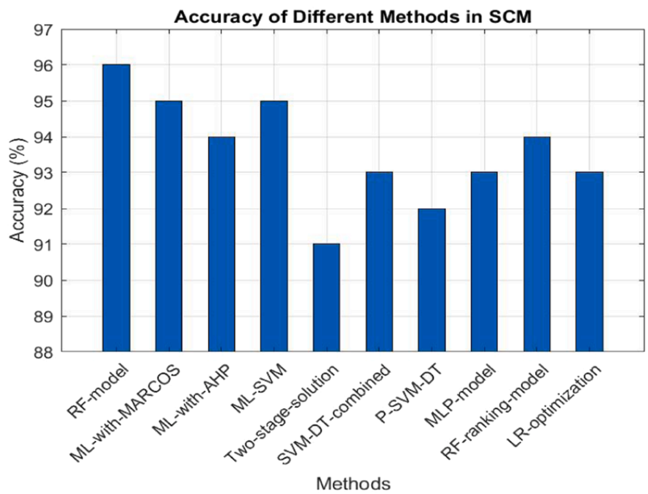

Fig. 12. Performance Analysis on Accuracy.

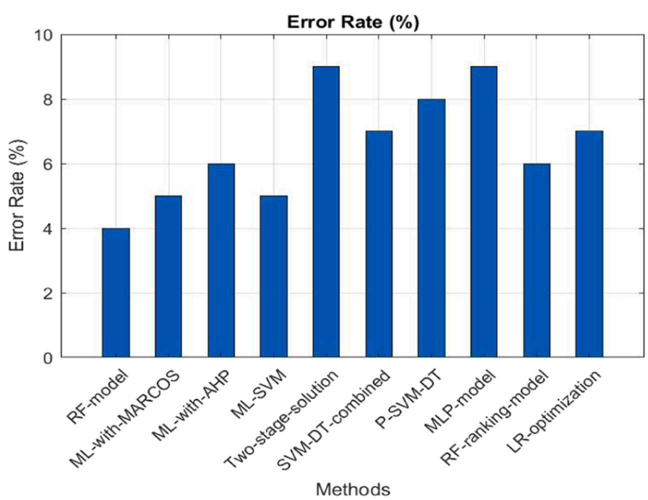

Fig. 13. Performance in terms of Error Rate.

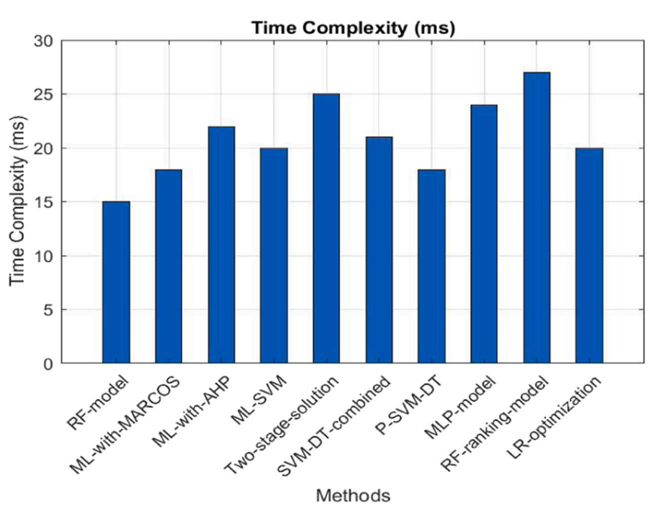

Fig. 14. Performance in terms of Time Complexity.

used the collaborative approach with its suppliers to obtain improved product quality and innovation. Another example of a successful SCM is Apple Inc. Apple has a complex supply chain system with multiple

Table 11
Summary results in terms of accuracy, time complexity, and error rate.

Techniques	Accuracy (%)	Error Rate (%)	Time Complexity (ms)
RF-model	96	4	15
ML-with-MARCOS	95	5	18
ML-with-AHP	94	6	22
ML-SVM	95	5	20
Two-stage-solution	91	9	25
SVM-DT-combined	93	7	21
P-SVM-DT	92	8	18
MLP-model	93	9	24
RF-ranking-model	94	6	27
LR-optimization	93	7	25

Table 12
Overall comparison of ML and DL methods.

Metric	Machine Learning		Deep Learning	
	SVM	Bayesian Network	Neural Network	Deep Belief Network
Accuracy	87%	88%	92%	95%
Error Rate	13%	12%	8%	5%
Time Complexity	25 ms	22 ms	20 ms	15 ms

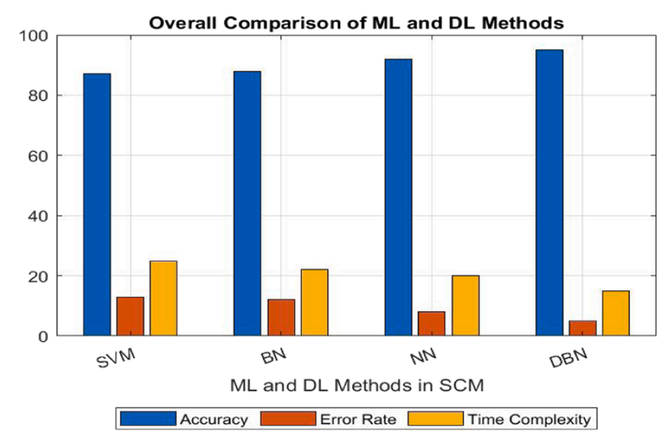

Fig. 15. Performance comparison of ML and DL methods.

suppliers and manufacturers across the globe. But, the company needs to streamline its supply chain operations to guarantee that products are sent to the customers on time and at a reasonable cost. Apple functioned closely with its suppliers to guarantee that they addressed the company standards. A third example of SCM is Amazon. The company has a large network of warehouses and distribution centers for delivering products to customers quickly and efficiently. Amazon employed advanced technology like robotics and artificial intelligence to optimize the supply chain operations. The company has implemented a customer-centric approach to SCM to deliver a seamless and personalized experience to its customers.

Case Study 1: Streamlining the Supply Chain Process for Improved Efficiency: A company in the automotive industry implemented a supply chain management system to streamline their supply chain process. The system has centralized planning and scheduling tools to enhance the communication and collaboration between suppliers and key stakeholders. The company minimizes the inventory level, increases production efficiency and enhances customer satisfaction. The supply chain management system allowed the company to identify and address the bottlenecks in the supply chain process. Through analyzing the data from the system, the company identified the areas where delays occurred and took corrective action to stop them from happening in the future. It minimized the costs associated with delays and disruptions in the supply chain.

Case Study 2: Implementing a Lean Inventory System to Reduce Costs:A manufacturer of consumer goods used the lean inventory system to reduce costs. The system eliminated the excess inventory and minimized lead time with significant cost savings. The company used a just-in-time (JIT) delivery system to reduce waste and improve efficiency. In the lean inventory system, the manufacturer improved their customer service levels by reducing the time to fulfill orders. JIT delivery system allowed the company to collect the materials and supplies on time for production, minimizing storage space and overstocking risks. The company identified and eliminated the inefficiencies in its supply chain for cost savings and improved overall performance.

Case Study 3: Enhancing Collaboration between Suppliers for Improved Product Quality: A manufacturer of electronic components used the collaborative approach with their suppliers to improve product quality. The company worked closely with its suppliers to recognize and address the quality issues. It also provided training and support to their suppliers. The company improved the product quality and minimized the number of defects. The collaborative approach minimized production costs. Through working with suppliers, the company identified the areas where costs get reduced without compromising on quality.

8.5. Challenges on implementing ML and DL in SCM

- ML and DL optimization in the SCM requires quality and large datasets for the training process to be effective. DL and ML models depend on the quality and availability of data for decision-making. In SCM, data is collected from disparate sources like ERP systems, sensors, and third-party providers. Ensuring data accuracy, completeness, and consistency across diverse sources is a significant challenge. Poor data quality resulted in inaccurate prediction, sub-optimal decisions, and unreliable insights.
- Whenever organizations decide to leverage ML and DL, security and privacy become a challenge in supply chains. Supply chain data are confidential with customer information, cost structures and strategies, and patents and copyrights. DL and ML deployments risk exposing confidential data or being vulnerable to cyber threats that compromise data security and privacy. To address these risks, supply chain data remain protected through proper data governance, encryption as well as proper access controls.
- Lack of Skilled Talent: DL and ML implementation in SCM requires a multidisciplinary team with expertise in data science, supply chain operations, and domain-specific knowledge. While implementing DL and machine learning in supply chain-based solutions, organizations have many challenges related to talent management and recruitment.
- Complexity and Scale: Supply chain network complexity and scale pose challenges for DL and machine learning in supply chain models because of many interconnected processes, stakeholders, constraints, and variables. Creating models addressed the contingencies and collected interactions.
- Interpretability and Trust: ML and DL in supply chain models are considered as black boxes to understand and interpret decision-making process. The lack of transparency resulted in mistrust among supply chain professionals and hindered the widespread adoption of technologies. The trust-building in DL and ML in supply chain systems requires interpretability for recommendations generated.
- Integration with Legacy Systems: Many supply chain organizations have spent significant time and resources on developing and deploying legacy systems. Integration of DL and ML presents several hurdles like compatibility, data structures, and format and customizations.

8.6. Research gaps and future research directions

Several industries are still at the nascent stage of utilizing ML/DL techniques to enhance their supply chain processes. For instance, the renewable energy supply chain offers substantial potential for future research and development. Additionally, integrating mathematical optimization models with ML for supply chain design and optimization presents a promising avenue for future studies in various industries. Despite the presence of AI over the last half-century and its recent application in SCM, research on the specific roles of AI in different supply chain areas remains sparse. The choice of an appropriate algorithm is significantly influenced by the nature of the industry and the type and volume of data. Therefore, executives must carefully select algorithms that align with the data characteristics and ensure their interpretability for the industry in question.

Given the projected trends in AI research, further investigation into the use of RL techniques for real-time pricing is recommended. Currently, ML applications in SCM are largely confined to well-defined, operational, and tactical problems. Future research should explore the application of ML techniques, particularly agent-based systems, to address complex and strategic SCM issues. These include outsourcing relationships, supplier relationship management, supply chain coordination, and strategic alliances among supply chain partners. The main challenge in providing efficient solutions for SCM problems lies in their inherent complexity and ill-structured nature, which makes them either too costly or difficult to resolve.

The application of DL in SCM is in a developmental phase, with the potential benefits still largely unexplored. Despite the frequent use of DL algorithms in SCM, their applications have been unevenly distributed, with a significant focus on forecasting and quality management problems, while other areas of the supply chain remain under-researched. Specifically, functions such as warehousing and logistics, which are both costly and crucial, have not received as much attention compared to manufacturing and retailing. Furthermore, most studies have centered on developing theoretical models and validating them through simulations and experimental analysis, with relatively few papers presenting practical applications of DL methods in SCM. There is also an opportunity to integrate DL with other technologies like IoT and blockchain to enhance the performance and integrity of supply chains.

Considering the gaps in existing literature, further studies should mainly focus on the following aspects of SCM, among others:

- **Optimizing Financial Resources:** In today's uncertain competitive landscape, financial management has emerged as a significant challenge, often constraining company growth due to limited human and capital resources. Supply Chain Financial Management focuses on optimizing the cost of capital and ensuring efficient cash flow management within the supply chain. Future research should conduct in-depth study on improving aspects such as capital structure, cash flow management, bank financing, payment terms, and collection strategies.
- **Mitigating Supply Chain Disruptions:** Recent emphasis on Supply Chain Risk Management highlights its critical role in shielding supply chains from disruptions. It aims to predict potential risks, minimize their impact, and enhance the transparency and resilience of value-added processes. This helps to counteract or even prevent supply chain interruptions. Future research should address gaps by utilizing DL-based strategies for managing delay/shortage risks, operational risks, out-of-stock risks, and demand risks to better identify and mitigate potential threats.
- **Strategic Coordination and Planning:** Supply Chain Planning remains crucial for effective business operations, coordinating assets to maximize the delivery of goods, services, and information while balancing supply and demand. Future research should explore comprehensive planning concepts, including supply planning, production planning, warehouse planning, logistics planning, and

demand fulfillment planning within frameworks like sales and operations, integrated business and material requirements.

- **Optimizing Execution for Customer Satisfaction:** With the demand for faster product delivery from global customers, Supply Chain Execution (SCE) has become increasingly vital. SCE encompasses supplier relationship management, production management, inventory management, service delivery management, and customer relationship management, both within the enterprise and across the extended supply chain (Vlachopoulou and Manthou, 2005). To accelerate the adoption of deep learning applications in SCM, future research should ensure a balanced focus on all aspects of supply chain execution.
- **Addressing Emerging Trends:** As companies aspire to stay ahead of global trends affecting their products and services, there is a need for detailed information on key supply chain hotspots. These include supply chain resiliency, sustainability, visibility, coordination, transparency, green supply chains, closed-loop supply chains, and reverse supply chains. Despite their significant impact on SCM, these areas have been under-researched and deserve more focused investigation in future studies.
- **Technological Transformation and Digital Innovations:** The past decade has seen transformative changes in supply chain digitization, driven by next-generation technologies that enhance efficiency, revenue growth, and customer experiences. As supply chain leaders are called upon to leverage new technologies, such as Blockchain, Internet of Things (IoT), Industry 4.0, and AI, there is a need for more research to support companies in adapting to the evolving digital landscape. Researchers should focus on how these technologies can revolutionize global business operations.

9. Conclusion

This paper aims to provide a comprehensive analysis of the contributions of DL and ML techniques in various aspects of SCM, including supplier selection, production, inventory control, transportation, demand and sales estimation, and others. The extensive review presented in this work delivered an in-depth examination of the integration of DL and ML with SCM, highlighting strategies for enhancing operational efficiency, addressing current limitations, and identifying future research opportunities. The application of ML and DL techniques significantly enhances supplier evaluation by identifying key features and streamlining classification processes. Application of ML and DL has also helped in risk prediction and mitigation, promoting supply chain resilience and profitability, demand forecasting, reducing inventory costs through accurate estimations, and optimizing logistics and transportation by improving delivery routes and minimizing damage. Additionally, these techniques helped in advancing production planning by balancing workflow constraints and enhancing scheduling accuracy. However, the implementation of these technologies comes with challenges such as computational cost and time complexity, which must be managed to achieve efficiency. Our findings also reveal that consumer goods, food, and agricultural supply chains are the most frequently studied areas within SCM. The study also highlights the substantial potential of DL techniques to address challenges across various supply chain sectors. As vast amounts of data are generated and stored, DL methods can leverage this data to enhance decision-making from operational to strategic levels. Among DL techniques, RNNs, particularly LSTM, are widely used for forecasting, while CNNs are applied to quality management and forecasting. Recent trends include combining multiple DL methods to leverage their strengths and overcome individual limitations. Additionally, integrating DL with technologies such as IoT and blockchain can further enhance supply chain performance and integrity, contributing to the development of smart supply chains. ML methods like RF, SVM, and NNs are often compared with DL methods, with metrics such as Accuracy, F1-Score, RMSE, Precision, and MAE being the most commonly used for evaluation. Despite the frequent use of DL in SCM, its application remains uneven, emphasizing the need for careful selection of algorithms based on data characteristics and industry requirements.

The results of this study showed that ML and DL applications in SCM are still in the developmental phase. DL and ML algorithms frequently used in SCM and their applications are discussed in an unbalanced way. The review suggests several research gaps in this area including using DL delay/shortage risk, operational risk, out-of-stock risk, delay risk, and demand risk to identify potential risks. In addition, it is found that many papers addressed forecasting and quality management problems while the other areas of supply chains are not well-studied using ML and DL techniques. Additionally in terms of supply chain functions, manufacturing, and retailing have been dealt with by many researchers. SCM optimizes both the cost of capital and the availability of suppliers and buyers by managing the cash flow of transaction activities and processes in the supply chain. However, other functions especially warehousing and logistics are two costly functions of supply chains that need to be studied more in the future. Meanwhile, DL and ML methods need to be integrated with other technologies to improve the performance and integrity of supply chains. This study has shown the potential capabilities of applying ML and DL in SCM. Our future research will focus on a detailed exploration of ML and DL concepts in SCM, particularly from the perspectives of data understanding and evaluation.

Funding

This research received no specific grant from any commercial, public, or non-profit funding source.

Ethical approval

None.

Availability of data and material

None.

Authors’ contributions

All authors contributed to the study conception and design. 640 All authors read and approved the final manuscript.

Ethical statement for solid state ionics

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I agree with the above statements and declare that this submission follows the policies of Solid State Ionics as outlined in the Guide for Authors and in the Ethical Statement.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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