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Review Article

Application of Artificial Intelligence in Supply Chain Management: A Review on Strengths and Weaknesses of Predictive Modeling Techniques

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About Article

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ABSTRACT

This study examines and summarizes the body for studies on supply chain management (SCM) applications of artificial intelligence (AI) predictive modeling techniques. It does this by examining 55 pertinent publications that were published between July 2024 and 2015. Sources for the literature included reputable research resources such as Google Scholar, IEEE Xplore, Web of Science, Science Direct, and Scopus. With an emphasis on machine learning algorithms, deep learning frameworks, and conventional statistical techniques, the paper demonstrates the wide variety of predictive modelling techniques used in the field. The results show that the use of machine learning techniques is becoming more common, and these techniques have been shown to offer a great deal of promise for enhancing SCM decision-making and forecasting accuracy. Deep learning frameworks are becoming increasingly potent instruments as well, especially for handling big datasets and identifying intricate linkages in the supply chain. This review provides a thorough resource for researchers and practitioners who wish to understand the advantages and disadvantages of various prediction modeling techniques in AI for SCM. It also highlights some noteworthy weaknesses, such as issues with data quality, model interpretability, and the requirement for domain-specific knowledge. Lastly, the synthesis of findings shows that although AI-driven prediction models can improve efficiency and responsiveness in SCM, their successful implementation requires careful consideration of organizational context and operational constraints.

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1. INTRODUCTION

Artificial intelligence (AI) has become a disruptive force in supply chain management (SCM), allowing organizations to improve operational efficiency, accuracy, and responsiveness. Managing enormous volumes of data and producing useful insights requires the application of AI technologies, which are becoming more and more complicated and integrated as global supply chains get bigger. Artificial intelligence (AI) is revolutionizing supply chain operations and creating new avenues for optimization with its powers in machine learning, natural language processing, and predictive analytics (Chong *et al.*, 2017; Dubey *et al.*, 2019; Kudama *et al.*, 2021). SCM is among the sectors most affected by the gradual use of AI technology across a range of industries. With the introduction of AI, businesses are now able to automate procedures, make better decisions, and foster collaboration throughout the supply chain. AI-driven systems, for example, can estimate demand, optimise inventory levels, and spot possible disruptions by analysing historical data (Naz *et al.*, 2022; Pournader *et al.*, 2021; Wang *et al.*, 2016). By offering real-time insights into supply chain dynamics, artificial intelligence (AI) in supply chain management (SCM) not only lowers operating costs but also improves service levels (Kamble *et al.*, 2020). Furthermore, AI technologies are set to become increasingly more crucial in navigating uncertainties and enhancing responsiveness as businesses work to improve the agility and resilience of their supply chains (Kamble, Gunasekaran, & Sharma, 2021). Effective SCM decision-making requires the use of predictive modeling techniques, which allow organizations to project future events based on existing data. Precise forecasting can result in enhanced demand estimation, optimized inventory control, and superior supplier selection (Sodhi & Tang, 2019). Although traditional statistical approaches have been used for these goals for a long time, they are not always sufficient to handle the non-linearities and complexity found in contemporary supply chains (Kourentzes, 2019). Forecast accuracy has increased as a result of the greater effectiveness of AI-driven prediction models, such as machine learning algorithms, in identifying patterns and relationships within huge datasets (Hazen *et al.*, 2014). Organizations may improve decision-making, cut waste, and boost overall supply chain efficiency by utilizing these cutting-edge modeling tools (Wang *et al.*, 2018).

This systematic literature review aims to identify important trends, methodologies, and findings related to AI-driven prediction models by methodically analysing existing studies. The primary purpose of the review is to evaluate and synthesize current literature on predictive modelling techniques in AI for SCM.

2. LITERATURE REVIEW

The growing realization of artificial intelligence's (AI) revolutionary potential has led to a major expansion of the literature on AI in supply chain management (SCM) in recent years. The definition, application, and historical development of AI in SCM are highlighted in this section's overview.

2.1. An Overview of Supply Chain Management using Artificial Intelligence

2.1.1. Definition and Scope

The term "artificial intelligence" describes how computers, specifically computer systems, can simulate human intelligence processes. Russell and Norvig (2016) list learning, reasoning, and self-correction as some of these processes. In the context of SCM, AI encompasses a variety of technologies and techniques, including machine learning, natural language processing, robotics, and expert systems, all aimed at enhancing various aspects of supply chain operations (Kamble *et al.*, 2020). The application of artificial intelligence (AI) in supply chain management (SCM) is wide-ranging and affects many different functions, including demand forecasting, inventory management, logistics optimisation, and supplier relationship management (Wang *et al.*, 2020). For example, machine learning algorithms can improve demand forecasting accuracy by analysing historical sales data and identifying trends, and natural language processing can improve communication with suppliers and customers through automated chatbots (Hazen *et al.*, 2014). Consequently, the integration of AI into SCM not only improves operational efficiency but also supports more flexible and responsive supply chain strategies (Dubey *et al.*, 2020).

2.1.2. Historical Context and Evolution

The early advancements in computers and data analysis can be linked to the development of AI in SCM. The first ideas of artificial intelligence surfaced in the 1950s and 60s, with a primary emphasis on logical thinking and problem solving (Russell & Norvig, 2016). But AI didn't start to have a substantial impact on SCM procedures until the 21st century, with the introduction of huge data and sophisticated computing technology. An important turning point for AI in SCM occurred in the early 2000s, when businesses began to realize how data analytics and predictive modelling could influence choices. Businesses started implementing AI technology to improve their supply chain processes as a result of the growing amount of data available and the advances in processing capacity (Kamble, Gunasekaran, & Sharma, 2021). Companies such as Amazon and Walmart, for instance, have set new industry norms for efficiency and responsiveness by leveraging AI to optimise their logistics and inventory management (Mishra *et al.*, 2017). The uses of AI in supply chain management (SCM) have grown as these technologies develop. New developments in deep learning and machine learning have made it possible for enterprises to use more advanced predictive analytics, which improves risk management and demand forecasting accuracy (Sodhi & Tang, 2019). Furthermore, real-time supply chain monitoring and control have been made easier by the integration of AI with the Internet of Things (IoT), improving visibility and collaboration throughout the supply chain (Kamble *et al.*, 2020). This development demonstrates the continuous possibility of artificial intelligence to transform supply chain procedures and spur industry innovation.

2.2. Predictive Modeling Techniques

The application of predictive modelling techniques is essential to improving supply chain management (SCM) decision-making procedures. These models fall into two categories: conventional statistical techniques and cutting-edge AI-driven strategies, each with unique traits and uses. This section looks at the various kinds of prediction models used in SCM and compares and contrasts these models.

2.2.1. AI-Driven vs. Traditional Models

The main statistical methods used in traditional SCM prediction models are moving averages, time series analysis, and linear regression. Because of their simplicity and interpretability, these techniques have been frequently employed for inventory management and demand forecasting (Snyder *et al.*, 2016). Though they frequently make the assumption of linear correlations, classic models might not adequately represent the complexities and non-linearities found in contemporary supply chains (Kourentzes *et al.*, 2020). In contrast, AI-driven models use machine learning and deep learning techniques to analyse large datasets and identify complex patterns. These models can automatically improve their predictions as they are exposed to more data, making them particularly effective in dynamic environments (Hyndman & Athanasopoulos, 2018). AI-driven models can incorporate various data sources, such as social media trends, economic indicators, and real-time sales data, leading to more accurate and timely decision-making (Mishra *et al.*, 2017). Therefore, the shift towards AI-driven models represents a significant evolution in supply chain management (SCM), enabling organisations to achieve higher accuracy and responsiveness in their operations.

2.2.2. Types of Prediction Models in SCM

Traditional statistical methods, deep learning approaches, and machine learning techniques are some of the categories into which prediction models in SCM can be divided. Every type of model has distinct qualities and uses in the context of the supply chain.

i. Machine Learning Technique

Because machine learning (ML) techniques can analyse large volumes of data and find patterns that traditional approaches might miss, they have become increasingly popular in supply chain management (SCM). Support vector machines, random forests, and decision trees are common machine learning techniques used in supply chain management. These algorithms are particularly good at activities like demand forecasting, where they may use past sales data to make very accurate predictions about future demand (Wang *et al.*, 2020). For example, studies by Gunasekaran *et al.* (2017) and Montesalve *et al.* (2023) showed how well a random forest model forecasts demand for a retail company and supply chain financial risk assessment, leading to better inventory management and fewer stockouts, respectively. Moreover, ML approaches can be used for risk assessment and supplier selection, allowing businesses to assess possible suppliers using past performance information and other pertinent criteria (Dubey *et al.*, 2020). Machine learning models are highly adaptive, meaning that they can continuously learn from fresh data, improving their predicting power over time.

ii. Deep Learning Techniques

Neural networks having numerous layers are used in deep learning, a subset of machine learning, to model complicated relationships in data. Demand forecasting and predictive maintenance are two SCM applications where this strategy has shown promise and is especially successful with huge datasets (Zhang *et al.*, 2019). For instance, recurrent neural networks (RNNs) are best suited for sequence prediction tasks, but convolutional neural networks (CNNs) can analyse time series data for demand forecasting. An example of an RNN that is specifically intended to handle sequences with long-term dependencies is the Long Short-Term Memory (LSTM) network. Sezer *et al.* (2020) presented a noteworthy use of deep learning in supply chain management (SCM), wherein an LSTM model demonstrated a considerable superiority over conventional forecasting techniques in the prediction of product demand inside a retail setting. Deep learning models hold special value in complicated supply chain settings due to their capacity to catch complex patterns in data.

iii. Statistical Techniques

Time series analysis, ARIMA models, and other statistical techniques are widely used to forecast demand and manage inventory levels in supply chain management (SCM) contexts (Hyndman & Athanasopoulos, 2018). These techniques are valued for their accessibility to practitioners due to their simplicity and ease of interpretation; however, traditional statistical models often rely on assumptions about data distributions and linear relationships, which can limit their applicability in complex supply chain environments (Kourentzes *et al.*, 2020). Despite these drawbacks, statistical methods are still valuable, especially in situations where interpretability is critical and data availability is constrained. The unique application, the intricacy of the data, and the requirement for interpretability all play a role in the prediction modelling technique selection process in SCM. The rising adoption of AI-driven methodologies by organisations is anticipated to improve the efficacy and precision of supply chain management prediction models through the integration of machine learning and deep learning techniques.

2.3. Applications of Predictive Modeling in SCM

In many supply chain management (SCM) applications, prediction modelling approaches are essential. Organisations can improve decision-making, streamline processes, and efficiently adapt to changing market conditions by utilising these models. The main uses of prediction modelling in supply chain management (SCM) are discussed in this section, including risk management, supplier selection, inventory control, and demand forecasting.

2.3.1. Demand Forecasting

One of the most important uses of prediction modelling in supply chain management (SCM) is demand forecasting, which has a direct impact on customer satisfaction, production planning, and inventory management (Hyndman & Athanasopoulos, 2018). Traditional methods, like time series analysis and moving averages, have been widely used for demand forecasting, but they frequently struggle to adapt to changes in market conditions and consumer behavior (Kourentzes *et al.*, 2020). In recent years, machine learning and deep learning techniques have gained traction in demand forecasting because of their capacity to analyse large datasets and identify complex patterns. For instance, Wang *et al.* (2020) showed that when compared to conventional techniques, machine learning algorithms like random forests and gradient boosting greatly increased forecasting accuracy. Furthermore, to further improve demand prediction skills, long-term dependencies in time series data have been captured using deep learning techniques such LSTM networks (Zhang *et al.*, 2019). Businesses can obtain more accurate demand projections, which improves inventory control and customer service, by employing sophisticated prediction models.

2.3.2. Inventory Management

Retaining operational effectiveness and cutting expenses in supply chain management depend on efficient inventory management. Through the prediction of future demand and the identification of ideal reorder points, prediction modelling approaches allow organisations to optimise their inventory levels. Stocking up tactics are influenced by accurate demand projections, which assist businesses in keeping the proper quantity of inventory on hand to satisfy consumer demand while reducing carrying costs (Snyder *et al.*, 2016). By evaluating past sales data, seasonality, and other pertinent variables to guide replenishment decisions, machine learning algorithms can be very helpful for inventory management (Dubey *et al.*, 2020). For example, a study by Gunasekaran *et al.* (2017) demonstrated how machine learning models may be used to optimise inventory levels for a retail business, leading to a decrease in stockouts and an increase in service quality. Additionally, according to Chong *et al.* (2017), predictive analytics can help detect outmoded or slow-moving inventory, allowing businesses to make data-driven decisions about markdowns or termination.

2.3.3. Risk management and supplier selection

Supplier selection and risk management are crucial components of SCM, as it directly impact the quality, cost, and reliability of the supply chain. Prediction modeling techniques can aid organizations in evaluating potential suppliers based on various criteria, including price, quality, delivery performance, and financial stability. By employing machine learning algorithms, organizations can analyze historical supplier performance data and predict future supplier reliability, helping them make informed sourcing decisions (Dubey *et al.*, 2020). Additionally, predictive modeling can also enhance risk management in the supply chain. By identifying potential risks, such as supplier failures or geopolitical disruptions, organizations can proactively develop strategies to mitigate these risks (Wang *et al.*, 2020). For example, a study by Singh *et al.* (2019) demonstrated the use of machine learning models to assess supplier risk by analysing factors such as financial performance, delivery history, and geopolitical factors. Using these advanced techniques, organisations can enhance their supplier selection processes and ensure a more resilient supply chain.

2.4. Challenges and Limitations of Current Research

Despite the promising advancements in prediction modelling techniques for supply chain management (SCM), certain challenges and limitations persist in current research. These challenges can hinder the effective implementation and adoption of predictive analytics in real-world applications. This section discusses key challenges, including data quality and availability, model interpretability, and integration with existing systems.

2.4.1. Data Availability and Quality

The quality and availability of data is one of the main issues with prediction modelling for supply chain management. Building accurate prediction models requires dependable, high-quality data, although many organisations suffer with inconsistent, outdated, or incomplete data (Kourentzes *et al.*, 2020). Inadequate data quality can result in inaccurate projections and poor decision-making, which can eventually reduce the supply chain's efficiency. Furthermore, the efficacy of deep learning and machine learning models—which need a lot of historical data to train—depends on the availability of data. Due to data silos, tight data-sharing rules, or restricted access to external data sources, many organisations may not have comprehensive datasets (Dubey *et al.*, 2020). Consequently, researchers and practitioners must invest significant time and resources to ensure data is cleaned, integrated, and prepared for analysis, which can delay the implementation of predictive modeling initiatives (Wang *et al.*, 2020).

2.4.2. Model Interpretability

Model interpretability is another major barrier to the adoption of advanced predictive modelling techniques in supply chain management (SCM). Although machine learning and deep learning models frequently outperform traditional statistical methods in terms of accuracy, they are typically regarded as "black boxes" due to their complex structures and lack of transparency (Lipton, 2016). This complexity can limit supply chain managers' and decision-makers' trust in the models and their willingness to act on the insights provided. In industries where regulatory compliance and accountability are critical, the lack of interpretability can pose significant risks (Mishra *et al.*, 2017). Without a clear knowledge of how the model arrived at its conclusions, stakeholders may find it difficult to defend a decision made if a predictive model, for example, recommends a course of action that has unfavorable effects. In order to increase stakeholder trust and speed the adoption of these technologies in SCM, researchers stress the need for techniques that improve the interpretability of machine learning models, such as feature importance analysis and visualizations (Doshi-Velez & Kim, 2017).

2.4.3. Integration with Existing Systems

For organizations aiming to utilize advanced analytics in supply chain management, integrating predictive modelling methods with current systems poses an additional difficulty. According to Hazen *et al.* (2014), many businesses still use antiquated technologies that might not fit with contemporary deep learning or machine learning frameworks. This incompatibility can make it more difficult to put predictive models into practice and impede data transfer between systems, which will ultimately make the models less effective. Furthermore, it can be challenging for businesses to match their predictive analytics projects with their overall business plans and procedures. According to Chong *et al.* (2017), successful integration necessitates not only technical changes but also a cultural transformation within the company to support data-driven decision-making. Integration efforts are further complicated by the fact that there is frequently a shortage of qualified professionals that can bridge the gap between data science and business operations (Wang *et al.*, 2020). In order for organizations to fully utilize predictive modelling in their supply chains, several issues must be resolved.

3. METHODOLOGY

The research design, inclusion and exclusion criteria, literature search approach, data extraction and analysis, and analytic framework are all covered in this section of the methodology. The approach is designed to guarantee a thorough comprehension of the procedures involved in obtaining and evaluating data pertinent to supply chain management (SCM) prediction modelling.

3.1. Research Design

A systematic literature review (SLR) was used as the research design for this work in an effort to compile the body of knowledge regarding predictive modelling approaches in SCM. As seen in Figure, this method enables an organized analysis of the literature, making it easier to spot patterns, regions lacking in knowledge, and topics for further investigation on the fifty-five (55) prior literature pieces covering a ten-year period from July 2015 to July 2024. To guarantee the validity and reliability of the results, the systematic review procedure entails formulating precise research questions, creating inclusion and exclusion criteria, and adhering to a strict search and analysis strategy.

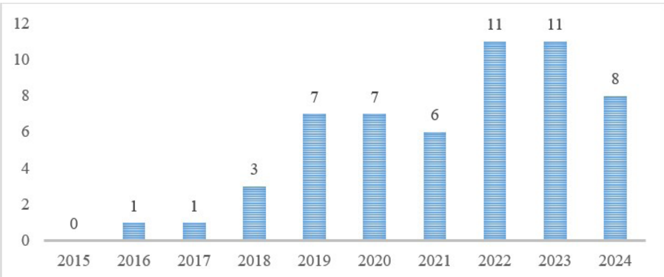

Figure 1. Distribution of studies over time

3.2. Inclusion and Exclusion Criteria

As shown in Table 1, inclusion and exclusion criteria are critical for determining which studies are relevant to the research questions.

These criteria ensure that the review focuses on high-quality, relevant research that contributes to the understanding of prediction modeling in SCM.

3.3. Literature Search Strategy

The literature search strategy is designed to identify relevant studies systematically. This process involves selecting appropriate databases and keywords to maximize the retrieval of pertinent literature.

3.3.1. Databases and Keywords Used

The primary databases utilized for the literature search include five as shown in Figure 2.

Table 1. Criteria for Inclusion and Exclusion

Inclusion Criteria	Exclusion Criteria
The inclusion criteria for this review are as follows:- - Studies published in peer-reviewed journals focusing on prediction modeling techniques in SCM - Research articles published within the last ten years to ensure the relevance and timeliness of the findings - Studies that employ quantitative or qualitative methods to analyze prediction models	Conversely, the exclusion criteria include: - Articles not published in English - Studies that do not specifically address prediction modeling techniques or its applications in SCM - Conference papers, theses, and dissertations that lack peer-reviewed status

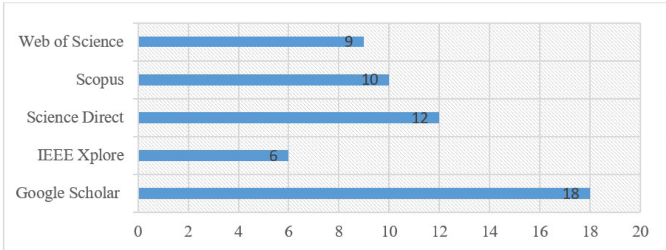

Figure 2. Distribution of studies over various research databases

Keywords used in the search include combinations of terms such as (prediction modeling, (supply chain management, (machine learning, AND/OR (deep learning, AND (demand forecasting, AND (inventory management). Boolean operators (AND, OR) are employed to refine the search results and ensure comprehensive coverage of the topic.

3.3.2. Review Process

Figure 3 illustrates the many steps of the review process, which include data extraction, full-text evaluation of chosen publications, and preliminary screening of titles and abstracts. The full-text review evaluates the quality and relevance of the chosen publications, whereas the initial screening concentrates on finding research that fit the inclusion criteria. Only the most relevant studies are considered in the final analysis thanks to this methodical process.

3.3.3. Framework for Analysis

In order to find patterns, obstacles, and gaps in the literature, the gathered data must be synthesized according to the analysis framework. The analysis is organized around major issues, including how well various prediction modelling approaches work, how data quality affects model performance, and how predictive analytics might be incorporated into current supply chain management procedures. The present state of prediction modelling in SCM may be more fully understood thanks to this thematic analysis, which also identifies areas that warrant further investigation.

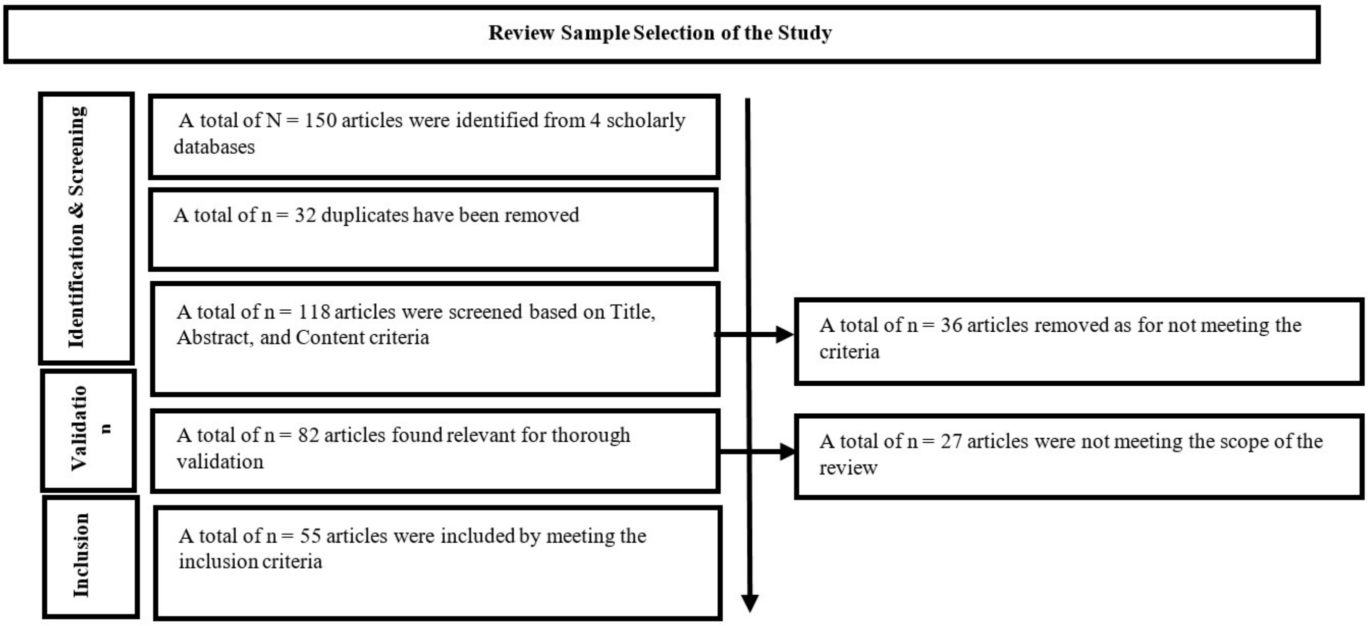

Figure 3. PRISMA sampling flowchart of the study

4. RESULTS AND DISCUSSION

The findings of the comprehensive literature review on supply chain management (SCM) prediction modelling approaches are shown in this section. In addition to offering a comparative review of the many prediction modelling strategies found in the literature, it highlights the most important findings from a few chosen studies. A variety of research that examine various predictive modelling strategies used in SCM were found by the systematic review. These studies demonstrate how different models work well for tackling particular supply chain problems like inventory control, supplier selection, and demand forecasting.

4.1. Key Findings on Prediction Modeling Technique

According to the review, machine learning techniques are becoming more and more popular because of their capacity to analyse big datasets and identify intricate patterns (see Table 1 for further information). For example, research has demonstrated that, in comparison to conventional statistical techniques, algorithms like random forests and support vector machines greatly increase predicting accuracy (Wang *et al.*, 2020). Long Short-Term Memory (LSTM) networks, in particular, have shown higher performance in time series forecasting challenges, further demonstrating the effectiveness of deep learning approaches in capturing long-term relationships in data (Zhang *et al.*, 2019). Furthermore, to improve model interpretability and offer a reference point for comparison, conventional statistical methods—while still relevant—are frequently employed in conjunction with machine learning techniques (Monsalve *et al.*, 2023). For instance, because of its simplicity and interpretability, linear regression is still a popular option, especially when stakeholders need concise explanations of the model's results (Kourentzes *et al.*, 2020). By combining these techniques, organisations can take use of the advantages of each strategy, creating prediction models that are stronger.

4.2. Comparative Analysis of Techniques

A comparison study of the recognized prediction modelling methods, as shown in Table 1, identifies unique advantages and disadvantages for every strategy.

4.2.1. Machine Learning Techniques

These models are excellent at managing massive amounts of data and are able to adjust to evolving patterns over time, according to the review results displayed in Table 1. But if not adjusted properly, it may have problems associated with overfitting and frequently requires a great deal of preprocessing of the data (Mishra *et al.*, 2017). Furthermore, these models' complexity may impede their interpretability, making it difficult for decision-makers to comprehend the reasoning behind projections.

4.2.2. Deep Learning Techniques

Neural networks, in particular, are deep learning models that have demonstrated impressive performance in challenging predicting tests. They are able to identify complex patterns that conventional approaches would overlook because of their capacity to learn hierarchical representations of data. However, for effective training, it requires a significant amount of processing power and vast datasets, which may not be possible for all organizations (Hyndman & Athanasopoulos, 2018).

4.2.3. Statistical Techniques

Conventional statistical methods, such time series analysis and linear regression, are frequently simpler to understand and offer insightful information about the correlations between variables. It might, however, find it difficult to handle the complex interconnections and non-linear correlations found in contemporary supply chains (Snyder *et al.*, 2016). Because of this, these approaches are still helpful, but machine learning techniques are increasingly being used in addition to these to improve prediction accuracy. In conclusion, the comparative study suggests that the best approach for prediction modelling in SCM may be a hybrid one that combines sophisticated machine learning and deep learning approaches with conventional statistical methods. Through this integration, organisations can take use of the predictive power of contemporary algorithms and the interpretability of conventional approaches.

Table 2. Techniques and Model Assessment

Technique	Proposed Model	Strength	Weakness	Source
Three machine learning classifiers were applied: Decision Tree, Random Forest, and Ensemble learning, and the Random Forest classifier	AI-based learning prediction model	The Random Forest classifier achieved the highest accuracy (87.5%), which is a strength of the methodology	However, the study was conducted on a small sample size, and the results may not be generalizable to larger populations	(Lokare & Jadhav, 2024)
Utilized AI and explainable AI (XAI) methods, including autoencoders, light gradient-boosting machines (LightGBM), and Shapley additive explanations (SHAP). Used a compact nuclear simulator (CNS) to gather abnormal scenario data for AI training.	Combines AE, LightGBM, and SHAP models to predict the remaining time until a reactor trip occurs and provide diagnostic information.	High accuracy and explainability of AI models. Effective use of XAI to provide rationale for AI predictions.	Limited by the availability of real-world data. Potential biases due to the use of simulated data.	Oh, *et al.*, (2024).
Utilized a publicly available dataset with 15,300 records from 2013-2018. Included outlier removal, data normalization, and handling class imbalance using SMOTE. Logistic Regression, XGBoost, Decision Tree, Random Forest, and LGMBoost. Employed LIME to provide transparent model predictions.	LGMBoost learning model with 91% accuracy.	High accuracy (91% with LGMBoost), use of explainable AI for transparency, comprehensive preprocessing steps.	Potential overfitting in some models, limited dataset scope.	Kasthuri, *et al.*, (2024).
Polynomial regression (PR), support vector regression (SVR), Gaussian process regression (GPR), and artificial neural networks (ANN). Cutting speed, depth of cut, and feed rate. Minimum quantity lubrication (MQL) and high-pressure coolant (HPC). Statistical error analysis methods.	The study proposes regression-based machine learning models (PR, SVR, GPR) and ANN for predicting machining responses.	Comprehensive comparison of multiple machine learning techniques; use of real experimental data; focus on sustainable manufacturing.	Limited to specific machining conditions and materials; potential overfitting in machine learning models.	Cica, *et al.*, (2024).

Technique	**Proposed Model**	**Strength**	**Weakness**	**Source**
The RTT prediction system consists of an algorithm that utilizes artificial intelligence (AI) and explainable AI (XAI) methods, such as autoencoders, light gradient-boosting machines, and Shapley additive explanations	A remaining trip time (RTT) prediction system	AI methods provide diagnostic information about the abnormal states that occur and predict the remaining time until a reactor trip occurs. The XAI method improves the reliability of AI by providing a rationale for RTT prediction results and information on the main variables of the status of NPPs	In this study, data that did not consider the operator's actions during abnormal conditions were used	(Oh *et al.*, 2024)
Prediction is done with machine learning algorithms with proper pre-processing, data normalization, and class imbalance approaches.	Explainable AI, a transparent model, is used to enhance the prediction which enables to draw inferences.	LGM Boost learning model prediction has a 91% accuracy and explainable AI framework predictions of most contributing attribute is accurate when compared to other models	The scope of this study is limited to the development and deployment of a mobile application to increase its utilization	(Kasthuri *et al.*, 2024)
Gated Recurrent Unit (GRU) model for demand forecasting, and the Bayesian Network for price prediction	Proposed the GRU BERT, GRU, models for demand forecasting and price prediction respectively	Investigating the effects of potential outliers in the Bayesian Network model's error range, it could be equally beneficial to explore how the synergy between these models within the framework could be enhanced	It remains an open question whether the complexity introduced by some of these combinations is necessary for accurate demand forecasting	(Amellal *et al.*, 2024)
An Integrated Approach of Business Analytics and Machine Learning	Employee Performance Prediction Model	This study has ascertained that the integration of business analytics and machine learning offers companies an opportunity to forecast employee performance more accurately	Nevertheless, progressive monitoring and adjustment are paramount to maintaining the model's performance over time	(Hasan, *et al.*, 2024)
Hybrid CNN-RNN model for demand forecasting	combining convolutional neural networks (CNNs) and recurrent neural networks (RNNs) models	Captures spatial and temporal dependencies	Challenges in training and tuning	Gupta *et al.* (2023)
Ensemble learning for supplier performance prediction	combined various models, including Decision Trees and Gradient Boosting, to enhance prediction accuracy	Improves robustness and accuracy	Less interpretable	Niazi *et al.* (2023

Technique	Proposed Model	Strength	Weakness	Source
Genetic algorithm based heuristic optimization	A mixed-integer nonlinear programming model to represent the BAP with the given restrictions	Proposes a GA-based technique that can handle the nonlinearity and complexity of the problem,	Does not provide any theoretical analysis or comparison with other existing methods for solving the BAP or similar problems, it also does not consider any uncertainty or variability in the supply, demand, or delivery cost	(Deb & Gupta, 2023)
Genetic algorithm based heuristic optimization	A mixed-integer nonlinear programming model to represent the BAP with the given restrictions	Proposes a GA-based technique that can handle the nonlinearity and complexity of the problem,	Does not provide any theoretical analysis or comparison with other existing methods for solving the BAP or similar problems, it also does not consider any uncertainty or variability in the supply, demand, or delivery cost	(Deb & Gupta, 2023)
Machine Learning Algoriths (Random Forest, and Support Vector Machine) to calibrate the models by applying the transformations to spectral and chemical data	Machine Learning Models for prediction of organic carbon and nitrogen in soil from hyperspectral imagery in laboratory	It can handle high-dimensional and noisy data, and produce acceptable results with low error and high R2	It require a large amount of data for training and testing, and sensitive to the choice of parameters and transformations	(Monsalve *et al.*, 2023)
Golden Eagle Optimization-based Deep AlexN*et Al*gorithm for predicting the parameter variation and its effect on absorbance, and Principal Component-Autoencoder method for extracting the features of WTa-SiO2	Metasurface-based Solar Absorption Prediction System using AI	It can achieve high absorption efficiency, reduce computational time, and provide accurate prediction results	It requires a large amount of data for training the deep learning model, and may not be applicable to other types of metasurface designs or materials	(Alam *et al.*, 2023)
Fifteen different algorithms have been considered to evaluate the most appropriate algorithms to use in agriculture, and a new feature combination scheme-enhanced algorithm is presented	AI-based crop analysis and prediction	Achieve a classification accuracy of 99.59% using the Bayes N*et al*gorithm and 99.46% using Naïve Bayes Classifier and Hoeffding Tree algorithms	Many research analyses did not consider a real problem for which to perform classification and performance evaluation	(Elbasi *et al.*, 2023)
The study employs deep learning, specifically a 2D Convolutional Neural Network (2D-CNN), for predictive modeling	A 2D Convolutional Neural Network (2D-CNN), for predictive modeling	This architecture excels in extracting intricate spatial features from sensor data. Training is conducted under the guidance of an Asymmetric Gaussian loss function, custom-tailored to accommodate the idiosyn- crazies of real-world sensor data	Other sources of data could be used as this study sourced data from sensor	(Che *et al.*, 2023)

Technique	**Proposed Model**	**Strength**	**Weakness**	**Source**
Hybrid model (ARIMA & Random Forest)		Captures linear and non-linear patterns	Complexity in analysis and tuning	Li *et al.* (2023)
Transformer networks for demand forecasting	Transformer networks Model	Effectively captures long-range dependencies	Computationally intensive	Liu *et al.* (2023)
Multi-agent system for inventory optimization	A multi-agent system (MAS)	Greater flexibility and responsiveness	Challenges in agent design and coordination	Kim *et al.* (2023)
AI-based customer churn prediction model employs a Chaotic Salp Swarm Optimization-based Feature Selection, Fuzzy Rule-based Classifier, and Quantum Behaved Particle Swarm Optimization	AI-based Customer Churn Prediction Model for telecommunication companies	It can handle massive amount of data, utilize both unstructured and structured inputs, and improve the prediction performance of the model	It may be complex, expensive, and difficult to implement	(Banu *et al.*, 2022)
Principal Component Analysis, Dynamic mutation particle swarm optimization algorithm to optimize	AI Application Model for SC Financial Risk Assessment	It can solve problem of high-dimensional data in SC finance, avoid the problem of particles falling into a local minimum in the process of optimization and improve the performance of the model	It also has some limitations, such as the selection of the optimal number of principal components, the choice of the mutation probability, and the sensitivity of the model to outliers and noise.	(Luo *et al.*, 2022)
Cognitive Cycle Model to describe the cognitive radio system, and design an access control algorithm based on dynamic pricing and multi-criteria decision making	Heterogeneous Wireless Network and AI-based SC Efficiency Optimization Application	Achieve better communication quality, load balancing, and SC efficiency than the existing methods, and provides some numerical results and figures to support this claim	Does not provide a clear explanation of how cognitive radio system and the AI algorithms are integrated and does not compare the proposed algorithms with other state-of-the-art methods in the literature	(Yuan, 2022)
Dynamic SC member selection algorithm based on conditional generative adversarial networks (CGANs) and innovative machine learning	An Innovative Machine Learning Model for SCM	It can effectively solve the problems of incompleteness, uncertainty and subjectivity of decision-making information, as well as the dynamic selection of SC partners	However, it does not provide any empirical evidence or experimental results to support these claims, nor does it compare the proposed method with existing methods or benchmarks	(Lin *et al.*, 2022b)
Two datasets to benchmark different Unsupervised Machine Learning Algorithms with different input attributes, such as speed, acceleration, heading change, and stop duration. It also tested feasibility of using a pre-trained model for unlabeled real data	Benchmarking Machine Leaning Algorithms by inferring transportation modes from unlabeled data	It can infer transportation modes from unlabeled GPS data without requiring any prior knowledge or user input	It depends on the quality and quantity of the data, the choice of the input attributes, and the parameters of the algorithms	(Dabbas & Friedrich, 2022)

Technique	Proposed Model	Strength	Weakness	Source
Graph neural network for disruption prediction	A graph neural network (GNN) model	GNNs effectively capture complex relationships and can model the dynamic nature of supply chains, providing insights into potential disruptions.	Graph construction can be complex and requires accurate data on the supply chain structure, which may not always be available.	Zhao *et al.* (2022)
Deep reinforcement learning for logistics	A deep reinforcement learning (DRL)	Adaptive learning in complex environments	Time-consuming training, high computational cost	Wang *et al.* (2022)
Deep reinforcement learning for logistics	A deep reinforcement learning (DRL)	Adaptive learning in complex environments	Time-consuming training, high computational cost	Wang *et al.* (2022)
Convolutional neural networks (CNNs)		Recognizes patterns effectively in time-series data	High computational cost, extensive preprocessing	Santos *et al.* (2022)
Artificial neural networks (ANN) as the algorithm and model for forecasting the flowtime of job shops	Artificial neural networks Model	It applies the ANN model, which is a powerful and flexible technique for data analysis and prediction, and can learn from data and experience	It does not specify the parameters or the configuration of the ANN model, such as the number of layers, the number of neurons, the activation function, the learning rate or the error function	(Modesti & Borsato, 2022)
Clustering Optimization Algorithm for Data Mining Based on Artificial Intelligence Neural Network	Implements four neural network models for data mining: two-layer perceptron, backpropagation (BP) neural network, RBF radial basis function network, and self-organizing map (SOM) self-organizing neural network	It uses neural network models, which have the advantages of self-adaptation, self-organization, parallel processing, and nonlinear mapping, for data mining clustering. It uses the RBF neural network for node selection, which can handle nonlinear and complex data and achieve high accuracy and stability	It relies on the choice of appropriate parameters, such as the number of hidden nodes, the learning rate, and the activation function, which may affect the performance and convergence of the neural network models. It does not consider the influence of noise, outliers, or missing values on the data mining clustering results, which may reduce the quality and reliability of the clustering.	(Zhang & Duan, 2022)
Developed a mathematical model of the golden eagle's spiral trajectory and speed adjustment, and used it to design the Golden Eagle Optimizer (GEO) algorithm	A mathematical model of the golden eagle's spiral trajectory and speed adjustment	It is simple and easy to implement, and it can handle different types of optimization problems.	Does not have any mechanism to deal with constraints or noise in the objective functions	(Mohammadi-Balani *et al.*, 2021)
Applying artificial neural networks (ANNs) to solve solid waste-related issues	Various ANN models, such as multilayer perceptron, radial basis function, self-organizing feature map, etc.	A detailed and quantitative analysis of the ANN model configurations and performance indicators; a graphical representation of the ANN model framework	A possible oversimplification or generalization of the ANN model configurations and performance indicators; a possible neglect of the specificities and complexities of different solid waste-related issues	(Xu *et al.*, 2021)

Technique	Proposed Model	Strength	Weakness	Source
Reinforcement learning for inventory management		Adaptive decision-making for better control	Longer training times, computationally intensive	He *et al.* (2021)
Comparative analysis of ML techniques		Broad insights into various techniques	Lack of real-time data integration	Chen *et al.* (2021)
Golden Eagle Optimizer (GEO) algorithm	ANNs Models	It can handle different types of optimization problems.	Some drawbacks, such as the possibility of bias, incompleteness, and inconsistency in the selection and evaluation of the literature sources	Mohammadi-Balani *et al.*, 2021)
Multi-layer perceptron (MLP)		Models complex relationships, effective for non-linear data	Sensitive to overfitting	Goh *et al.* (2021)
Multi-objective meta-heuristic algorithms, Taguchi and Fuzzy methods	A Novel Fuzzy Mathematical Model for integrated SC planning using multi-objective evolutionary algorithm	These techniques can handle uncertainty, imprecision and variability of data	Computationally expensive and that it requires tuning of many parameters for the algorithms	(Alavidoost *et al.*, 2020)
Phase1: Genetic algorithm-based simulation optimization Phase2: AI-based simulation	A Novel Hybrid AI-based Decision Support Framework to predict lead time	Can provide remarkable solution and cope with any changes in the SC by using a htbrid approach that combine simulation, optimization and AI	Require high computational time and resources, and it may not be applicable to other types of SC problems	(Dosdoğru *et al.*, 2020)
A framework of an interactive machine learning algorithm that uses an ANN to provide a good initial solution for a mixed integer programming solver, CPLEX, with Relaxation Induced Neighbourhood Search Function	A Hybrid methodology based on machine learning for a SC optimization problem	It can reduce the search space of an optimization problem and find optimal solutions while saving runtime	The performance of the methods depends on the quality of the training and testing datasets and the structure of the ANN	(Duc & Nananukul, 2020)
Particle Swarm Optimization Algorithm and Ant Colony Optimization Algorithm for optimizing the extreme learning machine	A Coalmine Water Inrush Prediction Model based on AI	It can achieve fast speed, high accuracy, and good generalization ability for coalmine water inrush prediction, it can also adapt to the dynamic changes of influencing factors	It still relies on some empirical parameters, such as the number of hidden layer nodes and the activation function, it can also be affected by the quality and quantity of the data samples	(G. Wang *et al.*, 2020)
Three regression based machine learning techniques, namely, polynomial regression (PR), support vector regression (SVR) and Gaussian process regression (GPR)	Regression based machine learning models	Mathematical models of the multi-objective optimization were established based on the polynomial regression method and metaheuristic approach based on a neural network algorithm was used to obtain optimal solutions.	The performance of four methods were evaluated in terms of Predictive modeling of turning operations different statistical measures, which will be completex technique	(Cica *et al.*, 2020)

Technique	Proposed Model	Strength	Weakness	Source
LSTM networks		Strong in capturing temporal dependencies	Data requirements and interpretability issues	Kumar & Singh (2020)
Bayesian network for risk assessment		Captures uncertainty and interdependencies	Complexity in construction and validation	Tan *et al.* (2020)
Compares various Neural Architecture Search (NAS) methods based on the three dimensions: search space, search strategy, and performance estimation strategy	Neural Architecture Search	Thorough literature review, provides empirical evidence and references	Does not perform any experiments or evaluations of its own, and relies on the reported results	(Elsken *et al.*, 2019)
New Generation Metaheuristic Algorithms	Fourteen new generation metaheuristics	Covers a wide range of metaheuristics and provides pseudocode, diagrams, and tables for each algorithm	Difficult to read for beginners or non-experts	(Dokeroglu *et al.*, 2019)
Butterfly optimization algorithm (BOA), artificial bee colony (ABC), cuckoo search (CS), differential evolution (DE), firefly algorithm (FA), genetic algorithm (GA), monarch butterfly optimization (MBO), and particle swarm optimization (PSO)	Butterfly optimization algorithm	provides a comprehensive experimental analysis and comparison of BOA with other algorithms on various optimization problems	does not address the scalability and robustness issues of BOA for large-scale and dynamic problems	(Arora & Singh, 2019)
Uses a data-driven approach to create a control-oriented model of the building thermal behavior, based on a Gauss Process Regression (GPR) algorithm	Uses the GPR algorithm to develop the control-oriented model, and compares its performance with other AI techniques, such as Feedforward Artificial Neural Network, Decision Tree, Random Forest and Support Vector Machine	Uses a GPR algorithm, which can capture the non-linear and stochastic nature of the building thermal behavior, and provide uncertainty estimates for the predictions	It uses a black-box model, which may not be easily interpretable or explainable, and may not capture the physical insights or the causal relationships of the system	(Cotrufo *et al.*, 2019)
XGBoost for demand forecasting		High accuracy, effective feature selection	Complexity and hyperparameter tuning required	Raut *et al.* (2019)
A novel type of activity prediction model that is able to adapt to new prediction tasks at inference time, via under- standing textual information describing the task	Activity and property prediction models are	CLAMP yields improved predictive performance on few-shot learning benchmarks and zero-shot problems in drug discovery	Without training or fine-tuning, scientific language models could be used for such low-data tasks through announced zero- and few-shot capabilities. How- ever, their predictive quality at activity prediction is lacking.	(Seidl *et al.*, 2019)

Technique	Proposed Model	Strength	Weakness	Source
Genetic algorithm and BP neural network	A three-layer network simulation model	It combines the advantages of genetic algorithm and BP neural network to improve the accuracy and efficiency of the model. It uses wavelet decomposition to deal with the non-stationarity and non-linearity of the data. It adopts a three-layer network structure to simplify the model complexity and reduce the computation time	It does not explain how the parameters of the genetic algorithm and the BP neural network are determined or optimized. It does not provide a clear criterion or indicator to evaluate the model performance or error. It does not conduct a sensitivity analysis or a robustness test to assess the stability and reliability of the model	(Du *et al.*, 20
Use the properties of Frank t-norms and max-Frank composition to derive some necessary and sufficient conditions for the feasibility and optimality of the problem, and to present an algorithm to solve the problem	A linear optimization model with fuzzy relational inequalities as constraints	Generate random feasible test problems and applies the algorithm to an example, and	Does not compare the performance of the algorithm with other existing methods, nor does it discuss the applicability and limitations of the model and the framework in real-world scenarios	(Ghodousian, 2018)
Three Random Forest Models are trained and validate to predict mode, transit itinerary, and activity	An automated approach from GPS traces to complete trip information	It is scalable and effective in predicting trip information from large and real-world datasets	It relies on external data sources that may not be available or accurate for all locations, and that the random forest models may not capture complex interactions or nonlinear relationship among variables	Yazdizadeh, *et al.*, 2018)
Hybrid model (Random Forest & ARIMA)	Hybrid Model	Enhanced accuracy, captures non-linearities	Risk of overfitting, computationally intensive	Zhang *et al.* (2018)
Propose two novel optimization algorithms called Salp Swarm Algorithm (SSA) and Multi-objective Salp Swarm Algorithm (MSSA) for solving optimization problems with single and multiple objectives, inspired by the swarming behaviour of Salp in oceans	Salp Chain Model, which consists of a leader Salp and several follower Salp	It introduces a new and simple bio-inspired optimization technique that can handle a wide range of optimization problems with different characteristics and complexities	it does not provide a theoretical analysis of the convergence and complexity of the proposed algorithms, nor does it explain the parameter tuning and sensitivity analysis of the algorithms	(Mirjalili *et al.*, 2017)
Artificial Neural Networks (ANN) and ANN-based Modelling	A Suitable AI Model for inventory level optimization	It shows applicability and effectiveness of ANN models for inventory management and lot-sizing problem	Does not provide clear explanation of how the ANN models are constructed and trained, it also does not consider other factors that may affect inventory management, such as lead time, stockout costs, or capacity constraints	(Šustrová, 2016)

4.2. Implications for Supply Chain Management

The findings from the systematic literature review on prediction modeling techniques in supply chain management (SCM) have significant implications for enhancing operational efficiency and improving strategic decision-making. This section discusses these implications in detail.

4.2.1. Enhancements in Operational Efficiency

The application of advanced prediction modeling techniques, particularly machine learning and deep learning, has been shown to significantly enhance operational efficiency within supply chains. By leveraging predictive analytics, organizations can optimize various processes, including demand forecasting, inventory management, and logistics operations. For instance, predictive models can analyze historical sales data to forecast future demand accurately, allowing companies to adjust its production schedules and inventory levels accordingly. This proactive approach minimizes stockouts and reduces excess inventory, leading to lower holding costs and improved cash flow (Hazen *et al.*, 2014). Moreover, the integration of predictive analytics into supply chain operations facilitates better visibility and tracking of inventory as it moves through different stages, from receiving to warehousing and shipping (Duc & Nananukul, 2020). Enhanced visibility enables organizations to identify bottlenecks and inefficiencies in real-time, allowing for timely interventions that streamline operations. For example, automated inventory management systems can provide alerts for low stock levels, enabling timely replenishment and reducing the risk of disruptions in the supply chain (Alam *et al.*, 2023; Alomar, 2022).

Additionally, the use of machine learning algorithms for optimizing logistics operations can lead to significant improvements in delivery performance. By analyzing data related to transportation routes, delivery times, and customer preferences, organizations can make informed decisions that enhance route efficiency and reduce transportation costs (Belhadi *et al.*, 2022). Overall, the implementation of prediction modeling techniques contributes to a more agile and responsive supply chain, ultimately enhancing operational efficiency.

4.2.2. Strategic Decision-Making Improvements

The insights gained from prediction modeling techniques also play a crucial role in improving strategic decision-making within organizations. By utilizing big data analytics, supply chain managers can access unprecedented levels of information, enabling them to make more informed and precise decisions (Wang, 2021). For example, predictive models can provide insights into market trends, customer behavior, and potential risks, allowing organizations to develop strategies that align with its long-term goals and objectives. Furthermore, the ability to forecast demand accurately allows organizations to align its supply chain strategies with sales and financial priorities, minimizing unnecessary costs and optimizing resource allocation (Liao & Yao, 2021). This alignment is essential for maintaining competitiveness in a rapidly changing market environment, where organizations must be agile and responsive to shifts in consumer demand and market conditions. The integration of predictive analytics into strategic planning processes also fosters collaboration across departments, as stakeholders can share insights and data-driven recommendations (Alomar, 2022). This collaborative approach enhances communication and facilitates cross-functional decision-making, leading to more cohesive and effective supply chain strategies. The implications of adopting prediction modeling techniques in SCM extend beyond operational efficiency to encompass strategic decision-making improvements. By leveraging advanced analytics, organizations can enhance its responsiveness to market dynamics, optimize resource allocation, and ultimately achieve a competitive advantage in the marketplace.

5. CONCLUSIONS

The systematic literature review on prediction modeling techniques in supply chain management (SCM) has yielded valuable insights into the current state of research and practice in this field. This conclusion summarizes the key findings, discusses the relevance of these techniques in SCM, and offers final thoughts on the future of artificial intelligence (AI) in supply chain management. The review highlighted the growing importance of advanced prediction modeling techniques, particularly machine learning and deep learning, in enhancing the efficiency and effectiveness of supply chain operations. Key insights include the ability of these models to analyze large datasets, uncover complex patterns, and provide accurate forecasts that inform decision-making processes. Additionally, the integration of predictive analytics into SCM practices has been shown to improve operational efficiency, reduce costs, and enhance responsiveness to market dynamics. Moreover, the comparative analysis of various modeling techniques revealed that while traditional statistical methods remain relevant, it are increasingly complemented by machine learning approaches to achieve better predictive performance. The findings underscore the necessity for organizations to adopt a hybrid approach that leverages the strengths of both traditional and advanced modeling techniques to optimize its supply chain strategies.

Prediction modeling techniques are highly relevant in today's complex and dynamic supply chain environment. As organizations face increasing pressure to respond swiftly to changing consumer demands and market conditions, the ability to forecast accurately becomes a critical competitive advantage. These techniques enable businesses to anticipate demand fluctuations, optimize inventory levels, and streamline logistics operations, ultimately leading to improved customer satisfaction and reduced operational costs. Furthermore, the relevance of these techniques extends beyond operational efficiency; it also play a crucial role in strategic decision-making. By providing insights into market trends and customer behavior, predictive models empower supply chain managers to make informed decisions that align with organizational goals and enhance overall performance. As such, the integration of prediction modeling into SCM practices is essential for organizations aiming to thrive in an increasingly competitive landscape.

Looking ahead, the future of AI in supply chain management appears promising. The continued advancement of AI technologies, including machine learning, deep learning, and big data analytics, will further enhance the capabilities of prediction modeling techniques. As organizations increasingly adopt these technologies, it will be better equipped to manage supply chain disruptions, optimize resource allocation, and improve overall operational efficiency. Moreover, the integration of AI with emerging technologies such as the Internet of Things (IoT) and blockchain will create new opportunities for innovation in SCM. These technologies can provide real-time data and insights that enhance visibility and collaboration across the supply chain, enabling organizations to respond more effectively to challenges and opportunities. The ongoing evolution of AI and its applications in supply chain management will continue to shape the future of the industry. Organizations that embrace these advancements and invest in the necessary skills and technologies will be well-positioned to achieve sustainable competitive advantages in the marketplace.

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