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Leveraging machine learning for supply chain disruption management: Insights from recent research

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ABSTRACT

Supply chain disruptions pose significant challenges to global economic stability, necessitating advanced predictive tools for effective risk management. As Machine Learning (ML) offers promising solutions for enhancing resiliency, this study investigates its applications in supply chain management. Utilizing a systematic literature review, we examined recent research to identify effective ML models and techniques, focusing on both supervised and unsupervised learning. Our analysis covered various industries to understand the adaptability and effectiveness of these models in mitigating supply chain risks. The results highlight the growing implementation of ML in anticipating disruptions, with supervised learning demonstrating superior predictive precision under specific conditions. At the same time, unsupervised approaches offer valuable insights in data-scarce scenarios. Context-specific data surfaced as crucial in model accuracy, underscoring the need for tailored approaches. This study concludes that integrating ML with current supply chain systems can significantly enhance operational resilience, advocating for continued exploration of novel data sources and interdisciplinary collaborative efforts.

1. Introduction

In today's business environment, supply chain management plays a crucial role in the success and customer satisfaction of any company. It has the ability to enhance customer service, lower operational expenses, and enhance the financial health of a company more than ever before (Kleab, 2017). Supply chains operate in an increasingly unpredictable and competitive environment, marked by the potential for disruptive events that can significantly impact business performance (Zamani et al., 2023). These disruptions are seen as the combination of an unexpected triggering event and its subsequent effects, which greatly threaten the seamless flow of materials and regular business operations. Disruptive incidents can be classified into two main groups: natural events (like earthquakes, floods, fires, etc.) and man-made events (like terrorist attacks, accidents, supplier bankruptcy, etc.) (Katsaliaki et al., 2022). Natural disasters, such as earthquakes, floods, and hurricanes, can cause widespread damage to infrastructure, leading to transportation bottlenecks, port closures, and disruptions in raw material supply (Ashraf et al., 2024; Baryannis et al., 2019). Man-made disruptions, including terrorist attacks, accidents, and supplier bankruptcies, can also cripple supply chains. These events can result in production halts, supply shortages, and reputational damage (Baryannis et al., 2019). The EventWatch Supply Chain Disruption Report documented 1,069 instances of supply chain disruption in the first half of 2018, marking a three-year high. The 2018 EventWatch Report also showed a 36% increase in global supply chain risk events over the year (Xu et al., 2020). To address the challenges posed by these disruptions, researchers have formulated diverse strategies and models for supply chain risk management (Tang, 2006). In today's world, vast amounts of data are collected daily, making data analysis an essential aspect of business management. Previously, manual methods were employed for data analysis, leading to frustrating and often impractical processes (Ghorbani & Ghousi, 2019). Data analysis involves identifying hidden patterns and data connections to generate predictive insights within vast datasets. It is a process that aligns closely with statistics and precise data analysis (Khosrowabadi et al., 2019). Machine learning (ML) utilizes algorithms that can "learn" from past experiences. The increased processing power

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of machines enables them to analyze large quantities of data, leading to advancements in ML. Machines can now uncover hidden patterns and complex relationships in disruptive and discontinuous data, making accurate conclusions where human capabilities fall short (Thomas & Panicker, 2023).

Our study aims to analyze published literature on supply chain disruptions, employing various data mining methods as a methodology. After conducting an initial review of these articles, we determined several key research questions to guide our analysis:

- What are the key components and functionalities of the supply chain, and why is it essential to analyze and understand disruptions within these components?
- What are the most effective ML models for predicting supply chain disruptions?
- What are the comparative efficiencies of unsupervised vs. supervised learning methods in identifying supply chain disruptions?
- What features are most significant for the predictive models in various industries when predicting supply chain disruptions?
- How do different industries implement ML solutions for disruptions, and what lessons can be drawn from these implementations?

The remaining sections of this paper are formed as follows: Section 2 introduces the essential theories and principles necessary for understanding supply chain management and ML, Section 3 details the methodology employed in conducting the systematic literature review, Section 4 presents the findings related to the research questions, Section 5 discusses the implications of these findings for enhancing supply chain resilience, and Section 6 summarizes the study's contributions and proposes directions for future research.

2. Foundational Concepts

This section will delve into the fundamental concepts essential for comprehending supply chain disruptions and how ML methodologies can be applied to predictive analytics.

2.1. Supply chain disruptions

Supply chain disruptions are often caused by an unexpected event that initiates a chain reaction, putting the smooth flow of materials and normal business operations at risk (Bugert & Lasch, 2018). Highly disruptive events have underscored the importance of flexible supply planning. Manufacturing and supply chain resilience play a crucial role in enabling companies to address market disruptions and maintain competitiveness effectively. The ability to react quickly to unforeseen challenges is directly linked to performance outcomes (Arias-Vargas et al., 2022). In the past decade, the likelihood of facing supply chain disruptions has risen, leading to a surge in interest in supply chain risk management. As a result, this field has garnered increased attention from researchers and practitioners, reflected in the growing number of publications exploring potential risk mitigation strategies (Lasch, 2018). Potential risks in the business environment can significantly affect the performance of the supply chain. These risks can be divided into two main categories: uncertainty and disruption. Uncertainty typically arises from challenges in aligning demand and supply, a common occurrence in business. On the other hand, disruption involves factors such as human errors, natural disasters, terrorist attacks, and economic downturns, all of which can significantly reduce the reliability of the supply chain (Jafari-Nodoushan et al., 2024).

2.2. Key components of the Supply chain

Supply chains are intricate and dynamic systems that consist of multiple tiers . Each tier can contain various components, forming a network within the supply chain where the straightforward flow of goods is not typical. The complexity is further heightened when entities in the supply chain are part of multiple other supply chains, each with distinct requirements or goals. These supply chain systems may face challenges and difficulties as each entity operates towards different objectives or goals, often conflicting with one another. This competition and tension among entities add another layer of complexity to supply chain management (Wu et al., 2007).

2.3. Machine learning in Supply Chain Management

ML is an essential aspect of artificial intelligence, focused on analyzing historical data to detect patterns and make predictions. Unlike traditional artificial intelligence approaches, ML delves into discovering hidden patterns within data to classify or predict outcomes related to a given problem. ML and big data analytics are increasingly utilized for supply chain functions such as supplier selection, sourcing risk management, production planning and control, inventory management, demand forecasting, and demand sensing (Malmstedt & Bäckstrand, 2022). Supply chain management aims to optimize operations with minimal costs, ensuring a smooth process from procurement to the final customer (Luo, 2023). ML can enhance various stages of SCM by leveraging historical data sets. For instance, using big data in ML can improve forecasting models, given the wealth of data accessible to organizations. Additionally, enhancing the flexibility of business processes through ML can lead to cost reductions (Soltani & Bhandari, 2023).

2.4. Supervised vs. Unsupervised Learning in Disruption Detection

ML algorithms are typically categorized as either supervised or unsupervised, with the vital distinction between these classes being the presence of labels in the training data subset (Alloghani et al., 2020). In Unsupervised learning, clustering techniques are utilized, whereas supervised learning involves regression and classification techniques (Jain & Chatterjee, 2020). Supervised learning involves a designated set of inputs and corresponding outputs, known as labelled databases. The primary goal of this learning approach is to uncover the connections between the inputs and outputs during the training phase. This algorithm generates a function to effectively link data to labels, enabling accurate predictions for unlabeled data. Supervised learning is implemented when clear outputs are available for the training set (Rahmani et al., 2021). Ashraf et al. (2024) developed a hybrid Deep Learning (DL) method for detecting disruptions in a cognitive digital supply chain twin framework. They aimed to improve supply chain resilience by accurately spotting potential disruptions. Unsupervised methods do not rely on a specific class or target feature; instead, all data features are interpreted as distances rather than categories (Esmaieeli Sikaroudi et al., 2015). The method involves working with a dataset containing data samples where the desired output is ambiguous, resulting in unlabeled data. This approach focuses on discovering patterns and relationships within the data. Unsupervised learning involves comparing data based on similarity to group them into categories (Rahmani et al., 2021). In their study, Chen et al. (2023) utilized an unsupervised anomaly detection method to analyze the usual behaviours of privileged users. They created a risk score algorithm to detect anomalies and successfully showcased its effectiveness in efficiently detecting them.

2.4.1. Regression

Regression analysis is a statistical method used to determine the relationship between a dependent variable and one or more independent variables (Romero & Ventura, 2010). The primary objective of the regression problem is to train a learner using available data and establish a mapping between the input and its corresponding output to make predictions effectively or predict a real-valued output variable, such as forecasting future values in a time series based on recent or past data points (Bartschat et al., 2019; Huang et al., 2020). In a study, Camur et al. (2024) investigated the application of ML regression models in forecasting the availability dates of product orders for inbound shipments at General Electric (GE) Gas Power. Accurate predictions play a crucial role in optimizing logistics operations. The research examined different regression models, with tree-based ensemble techniques like Random Forest and Gradient Boosting Machines demonstrating superior accuracy compared to other models.

2.4.2. Classification

In the realm of data analysis, both structured and unstructured datasets can undergo classification. This process involves categorizing members of a dataset based on predefined labels or categories. For new data points, classification techniques are used to predict the appropriate label. A classifier algorithm is a tool that learns from a training set and assigns new data points to specific classes. A classification model establishes a mapping function from the training dataset, which is then used to predict labels for new data entries. Attributes or features are parameters within a given problem set that aid in creating accurate predictive models. Various classification tasks can be undertaken (Sen et al., 2020). Binary classification involves separating data into two distinct categories, such as determining whether an email is spam or not for fraud detection. On the other hand, multi-class classification entails classifying data into more than two potential outcomes, like assessing a student's academic performance as excellent, good, average, or poor (Sen et al., 2020). Lorenc et al. (2020) addressed the issue of cargo theft in railway transportation, proposing a method to analyze the likelihood of theft for each transport instance. The researchers constructed a predictive model utilizing Artificial Neural Networks and ML algorithms such as K-Nearest Neighbor, Support Vector Machine, and Boosted Trees. This model was created based on historical data on theft incidents and various transport parameters.

2.4.3. Clustering

Cluster analysis is an unsupervised learning technique to optimize an objective function by identifying feature similarities. The main aim is to identify groups with elements sharing similar features. Clustering algorithms typically employ a search method to improve the objective function. A distance metric like Euclidean or Manhattan distance can be utilized to measure the dissimilarity between each pair of elements. Determining the number of clusters is often a challenge, and it must be chosen for cluster analysis. The user can specify or estimate the number of clusters using a global distance measure, such as the sum of squared distances from cluster centers. The objective function is optimized by minimizing the within-cluster distances and maximizing the between-cluster distances. A systematic search approach is essential to identify the optimal groups (Shutaywi & Kachouie, 2021). Nikolopoulos et al. (2021) utilized clustering analysis to detect commonalities in data, group nations according to these similarities, and identify countries facing similar challenges concerning the evolution of COVID-19. They applied the K-means clustering algorithm to categorize countries into clusters based on socioeconomic status, climate conditions, and factors related to COVID-19. Subsequently, they projected the spread of the pandemic on a national level and assessed 52 different methodologies, including time-series analysis, epidemiological modeling, ML, and DL approaches.

3. Methodology

Performing a literature review is a critical component of any research endeavor. It allows the researcher to navigate and assess the pertinent academic landscape to craft a research question that advances existing knowledge (Tranfield et al., 2003). A systematic literature review is a methodical approach to identifying, evaluating, and interpreting scholarly and practitioner work within a chosen field. Its primary objective is pinpointing knowledge gaps and research needs within that area (García-Peñalvo, 2022). This study analyzes published literature on supply chain disruptions by employing various data mining techniques as the chosen methodology. The research process begins with formulating specific research questions to explore supply chain disruptions' nature, causes, and impacts. A comprehensive protocol is then developed, outlining the search strategies, inclusion and exclusion criteria, and data mining techniques to be utilized. The literature search is conducted across multiple academic databases, using targeted keywords related to supply chain disruptions. A two-step screening process involves an initial review of titles and abstracts and a thorough full-text analysis. To ensure the study's credibility, a quality assessment is performed, evaluating the methodological soundness and relevance of the selected articles. Relevant data is then extracted from the included studies, focusing on critical aspects of supply chain disruptions. The extracted data is synthesized using various data mining methods to identify patterns, trends, and insights within the literature. Finally, the results are analyzed and interpreted in the context of the research questions, providing a comprehensive overview of the current knowledge on supply chain disruptions and identifying potential areas for future research. Figure 1 provides a visual representation of the detailed protocol.

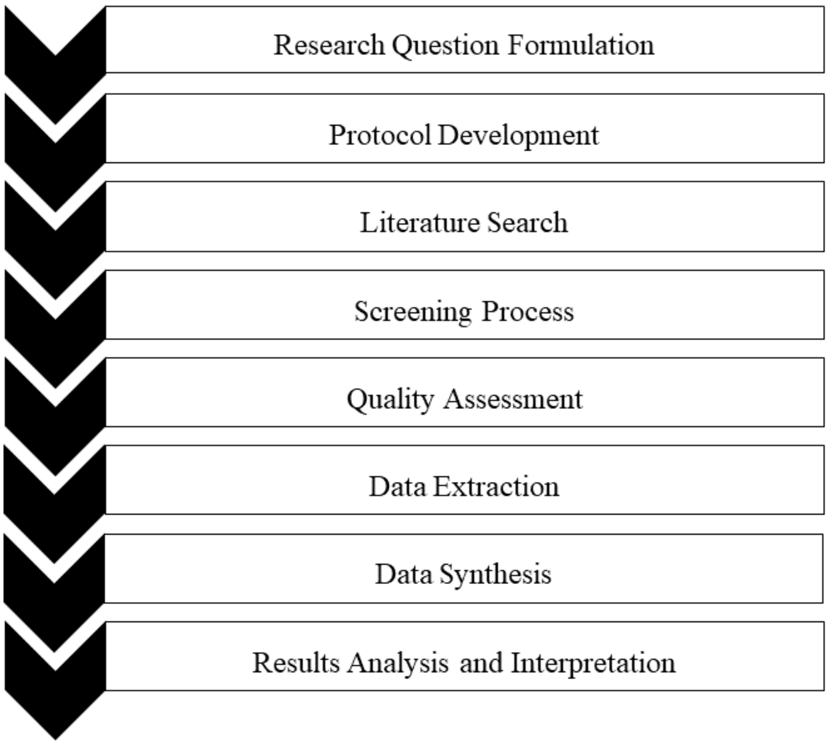

Fig. 1. Research methodology based on SLR

In conducting this review, a compilation of scholarly articles from three reputable databases – Google Scholar, Scopus, and Web of Science – was analyzed to encompass a diverse range of literature. Search queries were formulated based on commonly used keywords in the field and relevant to the review subject. A methodical refinement strategy was employed, beginning with broad terms and progressing towards more precise phrases, as outlined:

- Scopus: TITLE-ABS-KEY ("supply chain disruption*" AND ("machine learning" OR "deep learning") AND "predict*") AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English"))
- WoS: "supply chain disruption*" AND ("machine learning" OR "deep learning") AND "predict*" (All Fields) and Article (Document Types) and English (Languages)

The selection criteria for this review include English journal articles focusing on using ML methods to detect supply chain disruptions without any limitation on publication year. Conversely, conference papers, book chapters, and studies that need to address the application of ML methods in identifying supply chain disruptions or duplicate studies across databases are excluded. These criteria are implemented to ensure the inclusion of top-notch, relevant studies that significantly enhance the examination of ML techniques in supply chain management. Fig. 2, a visual representation of the literature review process, guides the reader, enhancing their understanding of the methodology.

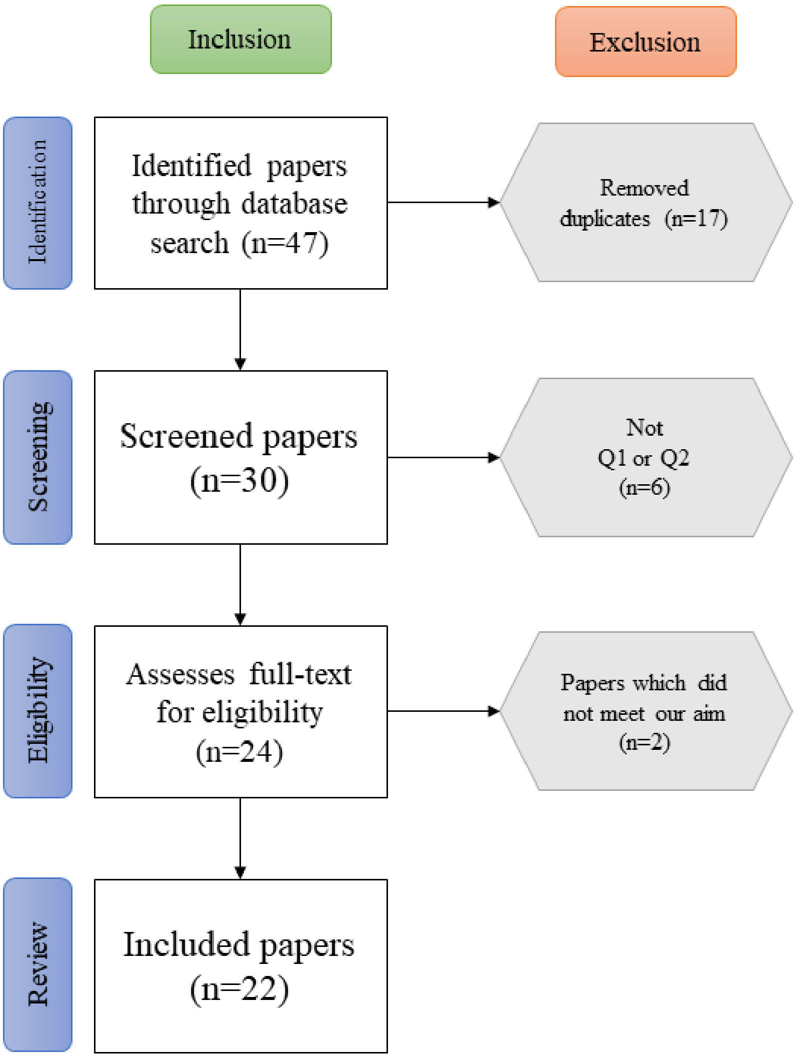

Fig. 2. Literature review process

4. Insights and Analysis

In this section, we will explore the purpose of our research questions, which focuses on investigating the fundamental aspects of supply chain disruptions and the utilization of ML for prediction and mitigation. Our analysis will delve into supply chains' key components and functionalities and examine different ML models for disruption forecasting. We will also compare the effectiveness of unsupervised and supervised learning methods within this context. Additionally, we will investigate the most influential features in predictive models across various industries and examine how different sectors implement ML solutions to address supply chain disruptions. Our objective is to provide valuable insights that will enhance comprehension of supply chain resilience and facilitate future advancements in predictive analytics for supply chain management. Table 1 provides the key insights and findings from the literature review, highlighting significant contributions and gaps in the existing research.

Table 1
Literature review

Article	*Aim of the study*	*Supply Chain Components Analyzed*	*Disruption Types*	*ML Model used*	*Learning Method*	*Key Features for Prediction*	*Industry Sector*	*Implementation Insights*
(Cavalcante et al., 2019)	Develop a hybrid simulation and ML technique for resilient supplier selection.	Supplier selection, order allocations	Supplier disruptions, delivery delays	LR, KNN, Hybrid	Supervised	Delivery time, order quantity	Digital Manufacturing	Combining simulation and ML to create digital supply chain twins for better supplier selection and delivery reliability. Advancing risk mitigation and supplier portfolio expansion.
(Handfield et al., 2020)	Use newsfeed data for long-term supply risk assessment in LCCs.	Supply base risk in LCCs	Human resource and safety risks, inflation	Machine-Based Learning	Supervised	Risk impact and probability	Apparel Sector	Converts unstructured data into risk scores and visual maps, predicting risks and aiding sourcing decisions. Provides method for regional supply risk assessment.
(Brintrup et al., 2020)	Utilize data analytics to forecast supply chain disruptions from an OEM using historical data	First-tier supply chain components (suppliers)	Order delays	RF, SVM, LR, KNN, Linear regression	Supervised	Engineered features including agility	Complex asset manufacturing	Importance of feature engineering and domain knowledge; challenges of class imbalance, curse of dimensionality; promise in using augmented features for better prediction accuracy
(Nikolopoulos et al., 2021)	Develop predictive analytics for forecasting & planning during COVID-19.	Various supply chain components impacted by pandemic-driven excess demand	Pandemic-induced disruptions (demand fluctuations, supply interruptions)	MLR, Ridge, DT, RF, NN, SVM, LSTM, PC-NN, CPC-NN	Supervised	Country-specific COVID-19 data, Google trends data	Cross-industry; applicable to any sector dealing with pandemic impacts	Evaluates 52 forecasting methods, introduces hybrid method with cross-country information, emphasizes need for homogeneous database for accurate forecasting
(Aboutorab et al., 2022)	Using reinforcement learning for proactive risk identification in supply chain operations.	Operational data related to supply chain disruptions	Disruption risks affecting SC operations	Q-learning	Reinforcement	External and internal risk data, news articles, environmental changes	Can be applied across multiple sectors, including SC and possibly stock markets	RL-PRI model uses AI for risk detection, outperforms manual methods, considers wider risk categories, and can incorporate social media and NLP for better accuracy.
(Zamiela et al., 2022)	Analyzing and ranking resilience indicators in healthcare supply chain using MCDM & unsupervised learning to tackle future disruptions like COVID-19	Medical supplies supply chain within healthcare	Disruptions caused by pandemics, specifically COVID-19	Cluster analysis	Unsupervised	Resilience indicators like redundancy, collaboration, robustness	Healthcare	MCDM with PIV minimizes rank reversal in decision-making; cluster analysis groups resilience indicators; emphasizes redundancy, collaboration, and robustness during pandemics
(Stephan et al., 2022)	Analyzing COVID-19's impact on India's renewable energy shift and air quality through ML	Energy supply chain, particularly renewable vs. fossil fuels	COVID-19 pandemic effects on energy demand and supply chain	Several ML models	Supervised, Unsupervised	Pre-COVID and post-COVID energy data, air quality metrics, economic indicators	Renewable Energy	ML techniques for energy trend forecasting show rise in renewable energy post-COVID, reflecting economic slowdown & govt. support for climate action & energy transition
(Nguyen et al., 2023)	Using sentiment analysis on news to enhance demand forecasting for pharmaceuticals during	Pharmaceutical supply chain	Epidemic outbreaks, natural disasters, pharmaceutical scandals	DL	Semi-supervised, Unsupervised	Sentiment scores from news, structured medicine demand data	Pharmaceuticals	Combines NLP sentiment analysis with forecasting to boost predictability; shows impact of news on demand volatility; suggests blending AI with

	crises.							models for decision support
(Janjua et al., 2023)	Framework for detecting supply chain disruptions using Twitter data and NLP plus ML techniques	Social media data as a proxy for various supply chain components	Disruption events (e.g., natural disasters, strikes)	CRF, Bi-LSTM-CRF	Supervised	Semantic similarity, location characteristics, frequency of tweets	Cross-industry (applicable to any sector using social media data)	Uses social media for disruption analysis in real-time; applies NLP and fuzzy systems for risk assessment; emphasizes automation and objectivity benefits; encounters challenges in adapting to platforms beyond Twitter.
(Bodendorf et al., 2023)	Improving supply chain risk management with DL and causal inference to predict disruptions and assess impacts on delivery reliability	Automotive supply chain	Organizational and environmental factors causing supply disruptions	DL	Supervised	Supplier characteristics, delivery performance metrics, environmental and organizational data	Automotive	Combines DL with causal inference to understand and mitigate supply disruption risks, using internal and external datasets for risk management insights
(Badakhshan & Ball, 2023)	Develop SC digital twin framework with ML and simulation for optimizing inventory and cash policies during disruptions in flows.	Inventory, cash flow, supply chain performance	Demand increase, capacity reduction, credit purchase increase	DT	Supervised	Inventory policies, cash conversion cycle (CCC), disruption scenarios	General Supply Chain	Demonstrates ML integration with digital twins for SC management; central planning benefits; reduced disruptions; improved cash cycles for SC members.
(Cho & Hong, 2023)	Exploring ML tech to enhance healthcare ops with AI & CNN for malaria diagnosis.	Healthcare operations, diagnostic processes	N/A (Focus is on healthcare operations rather than supply chain)	CNN	Supervised	Microscopic image data, diagnostic accuracy metrics	Healthcare	Demonstrates CNN effectiveness in improving diagnostics, cutting costs; ML potential to automate healthcare diagnostics in limited settings
(Cuong et al., 2023)	Predicting cargo flow at ports with a hybrid model of DWT and LSTM.	Port throughput systems, maritime logistics	Supply chain disruptions, market volatility	LSTM	Supervised	Time-series data, seasonal and trend decomposition, nonlinear dynamic behavior	Maritime logistics	Enhanced prediction accuracy for port throughput during disruptions; uses robust hybrid model for insights into dynamics and strategic planning in port management
(Zdolsek Draksler et al., 2023)	Assess process optimization potential in postal logistics via new digital technologies, focusing on real-time optimization of cross-border deliveries	Postal delivery systems, cross-border logistics	Supply chain disruptions, intraday changes	Cognitive Advisor (AI/ML framework)	Supervised	Delivery event data, simulation scenarios, KPI improvement metrics	Postal logistics	AI shows promise in optimizing real-time operations. It cuts costs, boosts flexibility, and enhances customer satisfaction. It aids in transitioning to Logistics 4.0, improving resilience to disruptions.
(Shahzad et al., 2023)	Predict US GDP responses to supply chain disruptions, energy prices, and economic policy uncertainty using DL and ANN	Global supply chain, economic policy, energy prices	Russia-Ukraine conflict, COVID-19 pandemic, economic recessions	DL, NN	Supervised	Supply chain performance indicators, Google Trends, energy prices, economic uncertainty	Economic forecasting	AI used to forecast GDP trends during disruptions using Google Trends; aids policymakers in crafting resilience strategies. Recommends bolstering fiscal policy, adjusting FED rates gradually, and global collaboration to reduce economic shocks. Proposes further study on sector analysis, decarbonization effects, and advanced ANN models.
(Y. Yang et al., 2023)	Create and assess production change plans for PPE manufacturing in COVID-19, emphasizing process switching strategies	Personal Protective Equipment (PPE)	COVID-19 pandemic	NN	Not specified	Demand trends, production capacity, profit, stockout cost, inventory cost	PPE manufacturing	Advocates early-stage process switching for inventory and edge. Suggests switching to high-value products later, expanding capacity for low-value products in later stages. Emphasizes production strategy for resilient supply

								chain.
(Badakhshan & Ball, 2024)	A hybrid modeling framework integrates simulation, optimization, and ML for updating supply chain master plans during disruptions.	Production, storage, distribution	Demand increase, lead time extension	DT, Hybrid	Supervised	Inventory levels, service level targets, total cost minimization	General Supply Chain	Hybrid frameworks > single-method. Increase inventory downstream for better service during disruptions. Develop SC digital twins for real-time adaptation. Plan for service and cost efficiency.
(Corsini et al., 2024)	Develop digital twin model to optimize replenishment parameters in production-distribution systems during disruption.	Replenishment, inventory, supply chain resilience	Unpredictable delivery lead time increases	NN	Supervised	Forecasting smoothing factor, safety stock factor, proportional controller	Semiconductor	Demonstrates improvements in resilience metrics like fill rate and time-to-recover vs. static strategies. Stresses dynamic, data-driven approaches for SC responsiveness to disruptions. Suggests using DT systems in SC management for real-time adjustment to disruptions.
(Ashraf et al., 2024)	A hybrid DL method for disruption detection in a digital supply chain twin to improve resilience.	Disruption detection, real-time response	Various disruptions (demand surges, failures)	Deep Autoencoder, One-Class SVM, LSTM, Anomaly Detection	Supervised, Unsupervised	Disruption signals, echelon status, time-to-recovery	General Supply Chain	Trade-offs in model sensitivity vs. false alarms, real-time detection importance for resilience. Suggestions for anomaly detection and recovery enhancements, with potential future studies for real-world application and scalability.
(Camur et al., 2024)	Develop regression models for predicting product availability dates for logistics and inventory planning.	Inbound logistics, shipment planning	Uncertainty in product availability due to global disruptions	RF, GBM, NN, Linear regression, Lasso, Ridge, Elastic Net	Supervised	Latest Promise Date, Latest Need By Date, Supplier Code	Gas and steam turbines manufacturing	Tree models handle non-linear data well for predicting availability dates, aid logistics, cut costs, and enhance planning. Suggests integrating time series analysis for better predictive ability and managing supply chain dynamics.
(S. Yang et al., 2024)	For annual sales change rates prediction after natural disasters, using GNN to analyze inter-firm connections.	Inter-firm relations, sales forecasts, spatial impacts	Natural hazards (floods)	MLP, RF, CatBoost, LightGBM, XGBoost, GNN	Supervised	Internal factors (sales, employees), external factors (inter-firm relations, hazard damages)	General/Multiple Industries	Emphasizes inter-firm topology, geographical proximity. XAI aids in model interpretation, identifying key sales recovery factors post-hazard. Integrates data sources, AI for enhanced SCRM and policy development
(Yan et al., 2024)	Predict Vessel Service Time (VST) with a tree-based stacking regression to improve port efficiency.	VST prediction, berth scheduling	Port inefficiencies, supply chain disruptions	RF, XGBoost, LightGBM, Stacking, BPNN	Supervised	Vessel-specific characteristics, EDT, historical port data	Maritime/Port Operations	Significant reduction in VST error improves berth allocation and scheduling. Real-time data and weather integration suggested for accuracy. Challenges in data accessibility and operational data noted.

4.1. Key Components and Functionalities of the Supply Chain

The supply chain encompasses a network of interdependent entities working to source, produce, and distribute goods and services from suppliers to consumers. Understanding these essential components—from supplier selection and order allocations to inventory management and inter-firm relations—is crucial for the seamless operation of any business. The intricacies of these components determine the efficiency and resilience of the supply chain, making it vital to analyze and comprehend potential disruptions. Disruptions can arise from a wide range of sources, such as natural disasters, pandemics, economic recessions, and geopolitical conflicts, each bearing unique impacts on supply chain operations. Thoroughly analyzing disruptions from these diverse sources is essential to mitigate risks, maintain operational continuity, and enhance the durability of supply chain networks.

RQ1: What are the key components and functionalities of the supply chain, and why is it essential to analyze and understand disruptions within these components?

Addressing RQ1, many academic studies have identified and analyzed various components of supply chains alongside the disruptions that affect them. Cavalcante et al. (2019) explored supplier selection and order allocations, examining supplier disruptions and delivery delays. Handfield et al. (2020) focused on supply base risks in Low-Cost Countries (LCCs), highlighting human resource and safety risks and inflation. Brintrup et al. (2020) concentrated on first-tier supply chain components, specifically suppliers, affected by order delays. Nikolopoulos et al. (2021) delved into pandemic-driven excess demand and its impact on supply chain components, causing disruptions in demand fluctuations and supply interruptions.

Moreover, Aboutorab et al. (2022) studied operational data related to supply chain disruptions, identifying risks affecting supply chain operations. Zamiela et al. (2022) highlighted the medical supplies supply chain within the healthcare sector, noting disruptions caused by COVID-19. Stephan et al. (2022) analyzed the energy supply chain, differentiating impacts on renewable versus fossil fuel sectors due to the COVID-19 pandemic. In the pharmaceutical sector, Nguyen et al. (2023) addressed epidemic outbreaks, natural disasters, and pharmaceutical scandals as sources of supply chain disruptions. Janjua et al. (2023) used social media data to proxy various supply chain components and their susceptibility to disruptions like natural disasters and strikes. Bodendorf et al. (2023) scrutinized the automotive supply chain and examined organizational and environmental factors causing supply disruptions. Badakhshan and Ball (2023) studied inventory, cash flow, and supply chain performance issues arising from demand increases and capacity reductions. Healthcare operations were the focus of Cho and Hong (2023), albeit considering diagnostic processes rather than supply chain dynamics. Cuong et al. (2023) explored port throughput systems and maritime logistics in the context of market volatility and supply chain disruptions. Zdolsek Draksler et al. (2023) analyzed postal delivery and cross-border logistics systems. Lastly, Shahzad et al. (2023) considered global supply chain dynamics impacted by geopolitical conflicts and pandemics. Through these analyses, the critical necessity of dissecting supply chain disruptions within various components becomes evident, emphasizing the need to strengthen the resilience and responsiveness of supply chains in an ever-evolving global landscape. Fig. 3 illustrates a word cloud highlighting key terms associated with supply chain management. Prominent words such as "supply chain," "logistics," "inventory," "disruption," and "healthcare" indicate the primary focus areas and challenges within the field.

Fig. 3. Word cloud of key terms in supply chain management

4.2. ML Models for Predicting Supply Chain Disruptions

The application of ML models for predicting supply chain disruptions has garnered considerable attention due to the potential of these models to enhance decision-making processes and mitigate risks. ML models can analyze vast amounts of data and discern complex patterns often undetectable by traditional methods. The effectiveness of these models in supply chain prediction lies in their ability to utilize both historical and real-time data efficiently. Varied ML methodologies, ranging from classical statistical models to advanced DL techniques, have been employed across different studies to address the challenges inherent in supply chain disruption prediction.

RQ2: What are the most effective ML models for predicting supply chain disruptions?

Various research articles have explored diverse ML models, demonstrating their applicability and effectiveness in predicting supply chain disruptions. Cavalcante et al. (2019) utilized LR and KNN in their analysis, providing practical insights for supply chain management. Handfield et al. (2020) explored Machine-Based Learning alongside the ACH to discern patterns of supply chain disruptions, offering actionable strategies. On the other hand, Brintrup et al. (2020) employed various models, including RF, SVM, LR, KNN, and Linear Regression, showcasing the versatility of ML techniques in real-world scenarios. Nikolopoulos et al. (2021) advanced the field by integrating statistical and epidemiological models with ML and DL approaches, culminating in a novel hybrid forecasting method. Aboutorab et al. (2022) highlighted reinforcement learning's adaptability in the study. Additionally, as a testament to the collaborative nature of research in this field, Zamiela et al. (2022) utilized cluster analysis and MCDM with PIV for enhanced decision processes. Further demonstrating the power of collaboration in advancing supply chain management in recent studies, Nguyen et al. (2023) employed DL for sentiment analysis and a VARX model for time series data, while Bodendorf et al. (2023) focused on DL and causal inference frameworks. Cho and Hong (2023) explored the use of CNN. Cuong et al. (2023) combined LSTM networks with DWT for improved temporal analysis. Further exploration into neural network-based approaches is witnessed in studies by Yang et al. (2023), who implemented GNN, and by Ashraf et al. (2024), who experimented with Deep Autoencoders, One-Class SVM, and LSTM networks. Yang et al. (2024) integrate graph-based methods using GNN, while Corsini et al. (2024) combine ANN with Particle Swarm Optimization for enhanced predictive capabilities.

The diversity in model choices underscores the adaptability of ML techniques to various supply chain contexts. Each contributes valuable insights for mitigating potential disruptions across different industries. Figure 4 illustrates the counts of various ML models used in the reviewed studies.

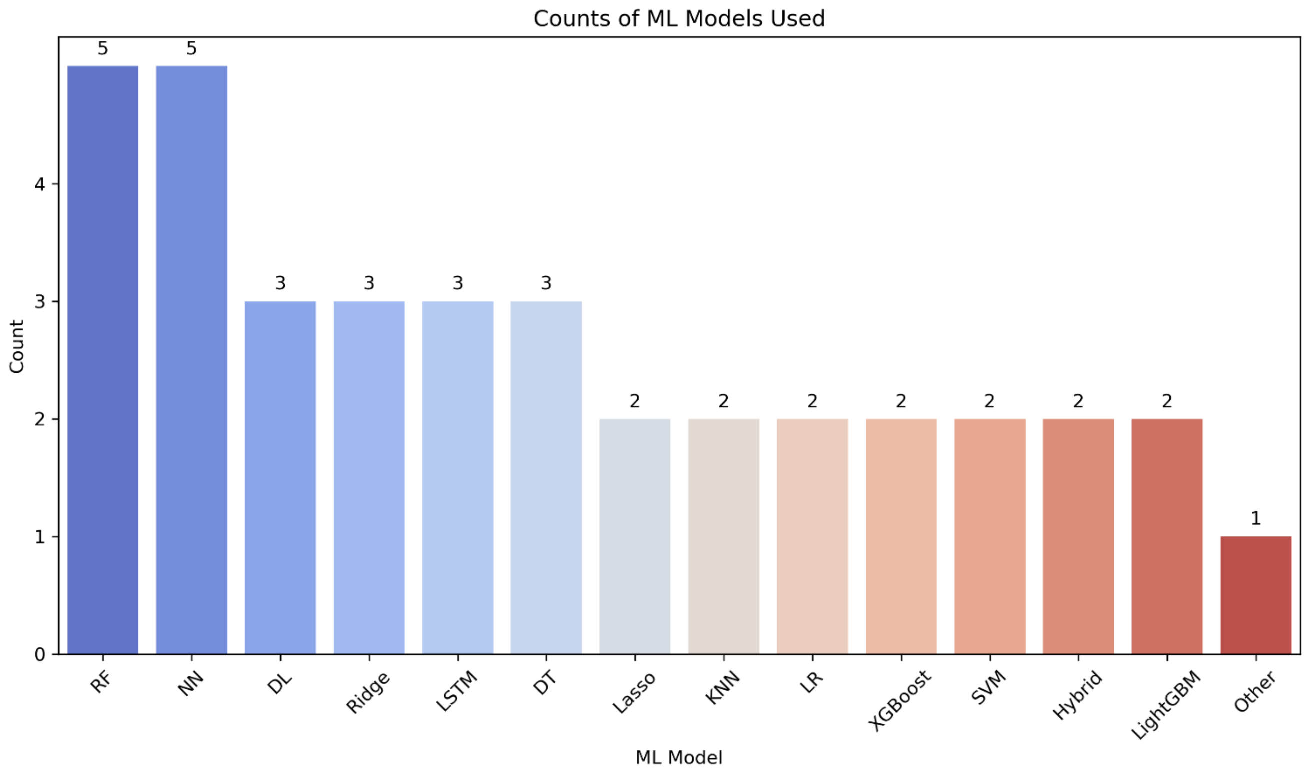

Fig. 4. Frequency of used models in reviewed papers

4.3. Comparative Efficiencies of Learning Methods in Identifying Disruptions

In the landscape of supply chain disruption detection, the application of supervised and unsupervised learning methodologies is pivotal. Both methodologies facilitate a proactive stance in supply chain management, with supervised learning leveraging historical data with known outcomes to train models that predict future disruptions, and unsupervised learning not relying on prior labeled data, making it valuable for identifying new patterns or anomalies in data, thus uncovering unforeseen disruptions. This proactive stance is often dictated by the availability of data and the complexity of the predictive task at hand.

RQ3: What are the comparative efficiencies of unsupervised vs. supervised learning methods in identifying supply chain disruptions?

Addressing RQ3, multiple studies illustrate the efficacy of supervised over unsupervised learning in specific contexts, often contingent upon the goal of the investigation and the intricacies of the data involved. Cavalcante et al. (2019) employed supervised learning to develop a hybrid simulation and ML technique to enhance supplier selection resilience. Similarly, Handfield et al. (2020) utilized supervised methods to assess long-term supply risks using newsfeed data in LCCs. This approach relied heavily on accurate data labelling for predictive accuracy. Brintrup et al. (2020) harnessed supervised learning for forecasting supply chain disruptions from historical data, focusing primarily on OEMs. In a comparable vein, Nikolopoulos et al. (2021) utilized supervised learning to develop predictive analytics for planning during the COVID-19 pandemic, leveraging historical data for precise forecasting. Conversely, the study by Zamiela et al. (2022) highlighted the potential of unsupervised learning by analyzing and ranking resilience indicators within the healthcare supply chain, aiming to tackle future disruptions like COVID-19. This approach underscored the strength of unsupervised methods in exploring uncharted disruptions without prior labelling. Stephan et al. (2022) adopted a blend of supervised and unsupervised methodologies to analyze COVID-19's impact on India's renewable energy shift, suggesting versatility in addressing multifaceted disruption scenarios. Aboutorab et al. (2022) explored Q-learning, a reinforcement learning method, to proactively identify risks, showcasing an alternative to traditional supervised and unsupervised approaches. Nguyen et al. (2023) implemented semi-supervised learning for sentiment analysis alongside unsupervised learning for time series, combining techniques to enhance demand forecasting for pharmaceuticals during crises. Janjua et al. (2023) employed a Bi-LSTM-CRF model for event annotation, facilitating nuanced disruptions detection using social media data. Further examples of supervised learning include Bodendorf et al. (2023), who implemented DL and causal inference to predict disruptions and assess impacts on delivery reliability, and Badakhshan and Ball (2023), who developed a digital twin framework integrating ML and simulation for inventory optimization. Studies by Cuong et al. (2023), Zdolsek Draksler et al. (2023), Shahzad et al. (2023), and others consistently demonstrate a preference for supervised methods in scenarios where data is abundant and meticulously labelled, allowing for refined predictive models that align with specific disruptions like economic policies or shifts in logistics. Notably, Ashraf et al. (2024) illustrated a hybrid approach that combines the strengths of both supervised and unsupervised methods for DL in disruption detection. This hybrid approach, by leveraging the precision of supervised learning and the adaptability of unsupervised methods, reinforces the potential advantages of integrating multiple methodologies to boost resilience in supply chain environments. It provides a versatile solution that can be adapted to various disruption scenarios, offering reassurance about its adaptability.
These studies collectively suggest that supervised learning is often preferred for its precision and reliability in forecasting disruptions using well-defined datasets; unsupervised and hybrid approaches can provide complementary benefits, especially in anticipating unforeseen disruptions where labelled data is limited or non-existent. Thus, a nuanced application of both approaches can optimize detection and response strategies within supply chain management. Fig. 5 represents the counts of different learning methods used, as depicted in a bar chart. The chart reveals that Supervised learning is the most frequently used method.

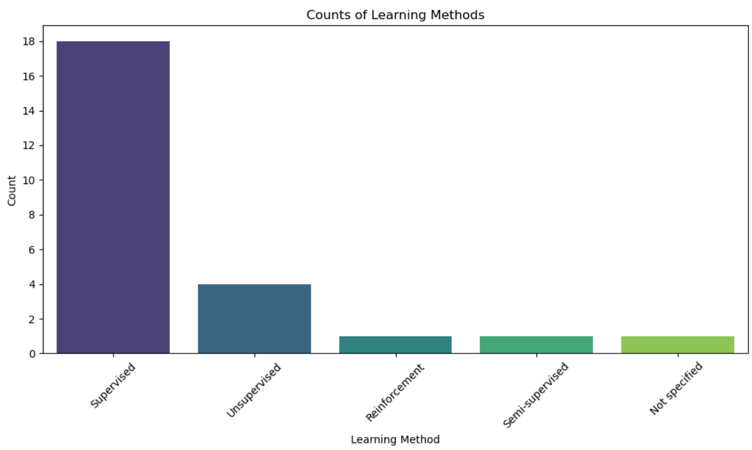

Fig. 5. Frequency of different learning methods

4.4. Significant Features for Predictive Models Across Industries

In developing predictive models for supply chain disruptions, identifying key features is essential for enhancing the accuracy and applicability of predictions within various industries. These features, often context-specific, serve as critical inputs that drive the performance of ML algorithms. They encompass a range of data points, including quantitative metrics such as delivery times and order quantities, qualitative indicators like resilience and collaboration, and advanced data like sentiment scores and semantic similarities. Recognizing these features allows for constructing more tailored and effective predictive models that can anticipate and mitigate potential supply chain disruptions, ultimately contributing to more resilient industrial operations.

RQ4: What features are most significant for the predictive models in various industries when predicting supply chain disruptions?

In response to RQ4, an examination of various studies reveals diverse features that significantly enhance predictive capabilities across different industrial contexts. Cavalcante et al. (2019) underscored the importance of delivery time and order quantity for supplier selection resilience. Handfield et al. (2020) identified risk impact and probability as crucial predictive indicators for assessing supply chain risk in low-cost countries. Brintrup et al. (2020) focused on engineered features, including agility, which proved vital for forecasting disruptions in supply chain operations. Nikolopoulos et al. (2021) highlighted the utility of country-specific COVID-19 data and Google trends in predictive analytics for pandemic-driven disruptions. Aboutorab et al. (2022) concentrated on a rich dataset comprising external and internal risk data, news articles, and environmental changes, underscoring their role in proactive disruption identification. Zamiela et al. (2022) emphasized resilience indicators, including redundancy, collaboration, and robustness, as central features for tackling future disruptions in healthcare supply chains. Stephan et al. (2022) integrated pre-COVID and post-COVID energy data, air quality metrics, and economic indicators into their models, demonstrating the importance of contextual environmental and economic data in evaluating renewable energy shifts. Nguyen et al. (2023) leveraged sentiment scores from news and structured medicine demand data to enhance demand forecasting during crises, while Janjua et al. (2023) incorporated semantic similarity, location characteristics, and tweet frequency as critical features for detecting supply chain disruptions through social media analysis. Bodendorf et al. (2023) identified supplier characteristics, delivery performance metrics, and environmental and organizational data as critical features for predicting supply disruptions in the automotive sector. Similarly, Badakhshan and Ball (2023) utilized inventory policies and cash conversion cycles as essential inputs in their digital twin framework for optimizing inventory and cash policies. Cho and Hong (2023) applied microscopic image data and diagnostic accuracy metrics to enhance healthcare operations through ML. Meanwhile, Cuong et al. (2023) leveraged time-series data, seasonal and trend decomposition, and nonlinear dynamic behavior to predict port cargo flows. Further, Zdolsek Draksler et al. (2023) emphasized delivery event data, simulation scenarios, and KPI improvement metrics in postal logistics optimization. Shahzad et al. (2023) incorporated supply chain performance indicators, Google Trends, energy prices, and economic uncertainty to predict the economic impact of disruptions. Yang et al. (2023) focused on demand trends, production capacity, and profitability metrics as primary features in PPE manufacturing during the COVID-19 pandemic. Subsequent studies by Badakhshan and Ball (2024) and Corsini et al. (2024) highlighted inventory levels, service level targets, and cost minimization as critical features for optimizing supply chain master plans and production distribution systems during disruptions. Ashraf et al. (2024) posited disruption signals, echelon status, and time-to-recovery as vital for enhancing resilience in digital supply chain twins. Camur et al. (2024) focused on supply chain features like the Latest Promise Date and Supplier Code. Meanwhile, Yang et al. (2024) integrated internal and external factors, including inter-firm relations and hazard damages, to assess the impact on supply chain operations. Lastly, Yan et al. (2024) underscored vessel-specific characteristics, estimated delivery times, and historical port data as crucial for predicting port efficiencies.
These studies collectively demonstrate the significance of selecting industry-specific features tailored to each sector's nuances and evolving demands, aligning predictive models closely with real-world supply chain challenges.

4.5. Industry Implementations of ML Solutions

ML solutions have become integral across various industries, revolutionizing the management of supply chain disruptions. Different sectors have drawn valuable lessons from implementing ML, demonstrating that tailored approaches are often the most beneficial. ML has provided predictive insights in healthcare and renewable energy that support strategic decision-making and policy formulation. However, it's within manufacturing and logistics that ML truly shines, improving operational efficiency and flexibility, and enabling more responsive supply chain strategies. These practical benefits illustrate the crucial role of understanding and adapting to industry-specific contexts, showcasing the extensive potential of ML to optimize operations and bolster resilience against disruptions.

RQ5: How are ML solutions implemented across different industries, and what lessons can we derive from their use?

The survey of ML implementations across sectors reveals critical insights into how industries leverage these technologies to meet unique challenges and opportunities. Digital manufacturing has seen ML combined with digital twins for enhanced supplier selection and risk mitigation. At the same time, the apparel sector uses ML to convert unstructured data into actionable risk assessments and sourcing decisions. In complex asset manufacturing, feature engineering and domain knowledge are emphasized to improve prediction accuracy. Cross-industry applications highlight the need for hybrid models and homogeneous databases for accurate forecasting, especially during pandemics. ML in healthcare and pharmaceuticals has improved decision-making processes by integrating data from multiple sources for better demand and risk management. The automotive industry benefits from DL and causal inference to mitigate supply risks, illustrating the integration of internal and external datasets. Across general supply chains, ML combined with digital twins has shown significant potential for strategic inventory management and disruption reduction. Overall, these implementations underscore the adaptability of ML solutions, emphasizing the necessity for tailored approaches and integration of complex data to maximize operational resilience across industries.

5. Discussion

The present study provides a comprehensive examination of the role of ML in predicting and mitigating supply chain disruptions, offering valuable insights into the evolving landscape of supply chain management. The integration of ML into supply chain operations represents a paradigm shift, enabling organizations to harness vast amounts of data for enhanced decision-making and risk management. The analysis of supply chain components and functionalities underscores the complexity and interdependence inherent in modern supply networks. The ability to anticipate and respond to disruptions is contingent upon a deep understanding of these components and the external factors that influence them. The literature reviewed highlights the necessity for adaptive and resilient supply chain strategies to accommodate global markets' unpredictable nature. This aligns with the broader discourse on supply chain resilience, which advocates for a holistic approach to risk management that integrates technological, organizational, and strategic dimensions. The exploration of ML models for predicting supply chain disruptions reveals various methodologies, each with distinct advantages and limitations. The adaptability of ML techniques, ranging from supervised learning to DL, underscores their potential to transform supply chain management. The effectiveness of these models largely depends on the quality and relevance of the data inputs and the ability to interpret complex patterns and relationships. This study contributes to the ongoing dialogue on optimizing ML models, advocating for a nuanced approach considering the specificities of different industries and operational contexts. Identifying significant features for predictive models across industries highlights the importance of context-specific data in enhancing model accuracy and applicability. Integrating quantitative metrics, qualitative indicators, and advanced data points such as sentiment scores reflects the multifaceted nature of supply chain disruptions. These features improve predictive capabilities and provide actionable insights for practitioners, enabling more informed decision-making and strategic planning. The emphasis on industry-specific features aligns with the need for tailored solutions that address unique operational challenges and opportunities.

Implementing ML solutions across various industries demonstrates the transformative potential of these technologies in enhancing supply chain resilience. The case studies reviewed illustrate the diverse applications of ML, from improving operational efficiency in manufacturing to optimizing resource allocation in healthcare. The lessons derived from these implementations emphasize the importance of integrating ML with existing systems and processes, fostering a culture of innovation and adaptability. The cross-industry applications of ML highlight the potential for collaborative approaches that leverage shared knowledge and resources, ultimately contributing to more resilient and sustainable supply chain operations.

6. Conclusion

This study elucidates the critical role of Machine Learning (ML) in advancing supply chain resilience and efficiency. The importance of this study lies in its comprehensive analysis of ML applications, providing a foundation for academic research and practical implementations in supply chain management. The integration of ML into supply chain management represents a significant opportunity for organizations to enhance their predictive capabilities and mitigate the impact of disruptions. The findings underscore the importance of a comprehensive understanding of supply chain components and functionalities and the need for adaptive strategies to accommodate global markets' dynamic nature. Context is crucial, as ML models must be tailored to the specific operational environments and industry requirements to maximize their effectiveness. The diverse array of ML models explored in this study highlights the potential for these technologies to transform supply chain management. The effectiveness of ML models is contingent upon the quality and relevance of data inputs and the ability to interpret complex patterns and relationships. This study advocates for a nuanced approach to ML model optimization, considering the specificities of different industries and operational contexts. Identifying significant features for predictive models underscores the importance of context-specific data in enhancing model accuracy and applicability. Integrating quantitative metrics, qualitative indicators, and advanced data points reflects the multifaceted nature of supply chain disruptions. These features provide actionable insights for practitioners, enabling more informed decision-making and strategic planning. Implementing ML solutions across various industries demonstrates the transformative potential of these technologies in enhancing supply chain resilience. The lessons derived from these implementations emphasize the importance of integrating ML with existing systems and processes, fostering a culture of innovation and adaptability. The cross-industry applications of ML highlight the potential for collaborative approaches that leverage shared knowledge and resources. The study's implications include the potential for ML to revolutionize supply chain strategies, offering enhanced predictive capabilities and operational efficiencies. Future research should focus on refining ML models, exploring novel data sources, and fostering interdisciplinary collaborations to enhance supply chain resilience further. However, the limitations of this study include the variability in data quality across industries and the challenges in standardizing ML applications due to diverse operational contexts. As supply chains evolve in response to global challenges, the integration of ML will be instrumental in shaping resilient and sustainable operations. This study provides a roadmap for future research and practical applications, contributing to the ongoing discourse on supply chain resilience and the role of technology in shaping the future of supply chain management.

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