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The Significance of Machine Learning to Optimize Complex Supply Chain Processes

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Abstract

In today's complex and volatile global environment, supply chain management (SCM) faces significant challenges related to uncertainty, disruptions, and data complexity. Traditional SCM approaches often fall short in achieving agility and predictive accuracy, prompting a shift toward data-driven methods such as machine learning (ML). This study explores the role of ML in enhancing efficiency, responsiveness, and resilience across key supply chain domains, including design, supplier selection, procurement, inventory control, ordering strategies, coordination, and demand management. Through predictive analytics, real-time optimization, and automated decision-making, ML enables organizations to improve demand forecasting, optimize logistics, and strengthen risk management, resulting in reduced costs and improved service levels. Additionally, ML supports sustainable and resilient supply chain design by optimizing transportation routes, minimizing waste, and lowering carbon emissions. Despite its transformative potential, the adoption of ML in SCM faces barriers such as fragmented data systems, limited inter-organizational collaboration, process redesign challenges, and computational scalability constraints. Overcoming these challenges requires robust digital infrastructure, collaborative frameworks, and adaptive organizational strategies. Ultimately, the integration of ML represents a paradigm shift toward intelligent, proactive, and sustainable supply chains that can thrive in uncertain and competitive markets.

Keywords: supply chain, Machine learning, Optimisation, Procurement, Inventory, Ordering, Coordination, Collaboration**,** Demand Management, Scalability.

1. Introduction,

In today's dynamic and competitive global market, supply chains have become increasingly complex, requiring more advanced tools to ensure efficiency, resilience, and responsiveness. Traditional approaches to supply chain management often struggle to cope with massive datasets, rapidly shifting customer demands, and unpredictable disruptions such as pandemics or geopolitical tensions. As a result, organizations are turning to Machine Learning (ML), a branch of artificial intelligence, to leverage data-driven insights and enhance decision-making across supply chain processes **(Choi et al., 2018).**

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Machine learning enables organizations to analyze large volumes of structured and unstructured data, revealing hidden patterns and correlations that improve forecasting accuracy and operational efficiency. In supply chain contexts, ML techniques are applied to demand forecasting, inventory optimization, supplier selection, and risk management. For instance, predictive models can help organizations anticipate demand fluctuations, while reinforcement learning can optimize logistics networks in real time **(Wuest et al., 2016).** By doing so, companies can reduce costs, minimize stockouts, and improve service levels.

Beyond operational optimization, ML contributes to building more resilient and adaptive supply chains. With the increasing risks posed by global disruptions, ML algorithms can monitor and analyze risk indicators, detect anomalies, and suggest proactive mitigation strategies. This capability not only enhances visibility but also supports sustainability efforts by optimizing transportation routes, reducing waste, and lowering carbon emissions (Min, 2019). As digital transformation accelerates, the role of machine learning in shaping the future of supply chain management is expected to become more vital, bridging the gap between complexity and agility **(Hazen et al., 2016).**

a. Problem Statement

One of the most pressing issues in supply chain management is the lack of accuracy and adaptability in traditional forecasting and planning methods. Global disruptions—such as the COVID-19 pandemic, geopolitical conflicts, and raw material shortages—have further highlighted the vulnerability of supply chains. Conventional tools are often insufficient to anticipate rapid fluctuations in demand, supply bottlenecks, or risks associated with uncertain environments. This creates inefficiencies, including overstocking, stockouts, high operational costs, and reduced customer satisfaction. Machine learning offers the ability to learn from dynamic data, predict potential risks, and automate decision-making, which can significantly improve supply chain resilience and performance **(Min, 2019).**

b. Objectives of Supply Chain

The primary objectives of supply chain management are to ensure the smooth flow of goods, services, and information from suppliers to end customers while minimizing costs and maximizing customer satisfaction. Effective supply chains aim to:

- Optimize demand forecasting and inventory management.
- Improve responsiveness to market fluctuations and disruptions.
- Enhance visibility and traceability across the supply chain.
- Foster collaboration among stakeholders, including suppliers, manufacturers, and retailers.

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- Support sustainability by reducing waste and optimizing transportation routes.

Machine learning directly contributes to achieving these objectives by offering predictive insights, real-time optimization, and automation. Through its applications, ML empowers organizations to balance efficiency with agility, positioning supply chains to thrive in uncertain and competitive environments **(Hazen et al., 2016; Wuest et al., 2016).**

2. Background

The field of supply chain management is continuously evolving, presenting a range of complex challenges that demand strategic attention and innovation. In this dynamic environment, machine learning (ML) is increasingly transforming supply chain operations by enabling smarter, faster, and more resilient decision-making. This section explores the key challenges facing modern supply chains and examines how ML technologies are being applied to effectively address them.

a. Supply Chain Management Challenges

Modern supply chains are increasingly complex, globalized, and dynamic. Organizations face several challenges, such as fluctuating customer demands, shortened product life cycles, and volatile global markets. Additionally, disruptions caused by geopolitical tensions, pandemics, and natural disasters highlight the vulnerability of traditional supply chain systems. These challenges often lead to inefficiencies, including delays in deliveries, increased operational costs, and decreased customer satisfaction **(Ivanov & Dolgui, 2020).**

Another significant challenge is the lack of visibility and real-time data integration across supply chain networks. Many organizations still rely on fragmented systems and outdated forecasting methods that fail to capture the complexity of current supply chain operations. As a result, decision-making becomes reactive rather than proactive, reducing the ability to anticipate risks and respond effectively to unexpected changes **(Christopher, 2016).** To remain competitive, organizations require advanced tools that enhance transparency, accuracy, and resilience across their supply chains.

b. Machine Learning and Supply Chain

Machine learning (ML) has emerged as powerful technologies capable of addressing many of these supply chain challenges. AI broadly refers to computational systems that mimic human intelligence, while ML is a subset of AI focused on algorithms that improve their performance by learning from data. The ML algorithms examine extensive, intricate, and real-time data sets (such as historical sales) to uncover patterns and forecast results with a level of accuracy that significantly surpasses conventional techniques. In supply chain contexts, these technologies enable predictive analytics, optimization, and automation, allowing organizations to make faster and more accurate decisions **(Jordan & Mitchell, 2015).**

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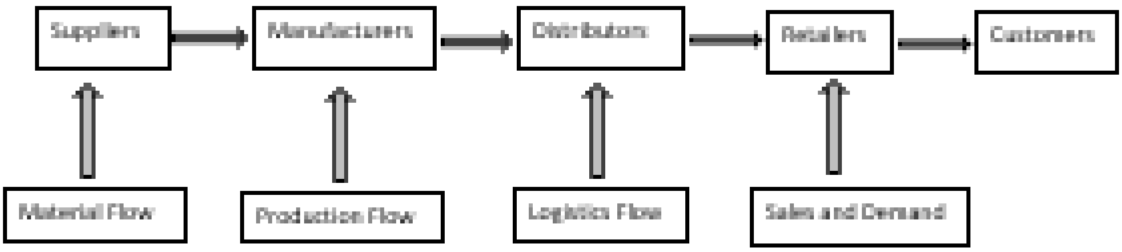
For example, ML algorithms can enhance demand forecasting by analyzing large datasets of historical sales, seasonal trends, and external factors such as weather or economic indicators. AI-powered systems can optimize logistics by determining the most efficient delivery routes, reducing transportation costs, and improving sustainability. Furthermore, real-time anomaly detection helps identify risks such as supplier delays or quality issues before they escalate into major disruptions **(Min, 2019).** By integrating machine learning and AI into supply chain management, companies can achieve greater efficiency, adaptability, and resilience in the face of uncertainty.



Information and Financial Feedback Loop (enabled by ML)

Figure 1: General Supply Chain Process

This figure illustrates the overall structure of a typical supply chain, highlighting the major stages—suppliers, manufacturers, distributors, retailers, and customers—and the flow of materials, information, and finances between them. Machine learning enhances visibility and decision-making across all stages by enabling real-time data analysis and predictive insights.

As shown in Figure 1, the supply chain consists of multiple interconnected stages that manage the flow of materials, information, and finances. Machine learning supports this process by integrating real-time data across suppliers, manufacturers, and retailers, enabling predictive analytics and optimization at each stage.

3. Supply Chain Design

Supply chain design refers to the strategic process of structuring supply chain networks to ensure efficiency, responsiveness, and long-term sustainability. It involves determining the optimal configuration of facilities, such as manufacturing plants, warehouses, and distribution centres, as well as decisions regarding sourcing, transportation, and inventory management. Effective supply chain design ensures that materials and products flow seamlessly from suppliers to end customers while balancing cost efficiency with service quality **(Chopra & Meindl, 2019).**

A key aspect of supply chain design is aligning the network structure with organizational goals and market demands. For instance, companies pursuing cost leadership may centralize production to achieve economies of scale, whereas firms focusing on responsiveness may adopt

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decentralized networks to reduce lead times and improve flexibility. Furthermore, supply chain design must consider global factors, such as tariffs, trade regulations, and geopolitical risks, which significantly influence sourcing and distribution strategies **(Christopher, 2016).**

The integration of advanced technologies, particularly machine learning (ML) and artificial intelligence (AI), has transformed supply chain design by enabling data-driven decision-making. Predictive analytics can optimize facility locations, supplier selection, and logistics routes by evaluating massive datasets that include market demand, transportation costs, and risk factors. Simulation models enhanced by ML allow organizations to test different network configurations and anticipate the impact of disruptions, thus improving resilience and adaptability **(Ivanov, 2021).**

In addition, sustainable supply chain design has gained prominence due to increasing environmental concerns and regulatory pressures. Organizations are now expected to incorporate sustainability metrics, such as carbon emissions, renewable energy use, and waste reduction, into their supply chain strategies. ML algorithms can support this goal by identifying energy-efficient transportation options and optimizing production schedules to minimize environmental impact **(Carter et al., 2019).** Therefore, effective supply chain design must not only achieve cost and service objectives but also support resilience and sustainability in an increasingly volatile global landscape.

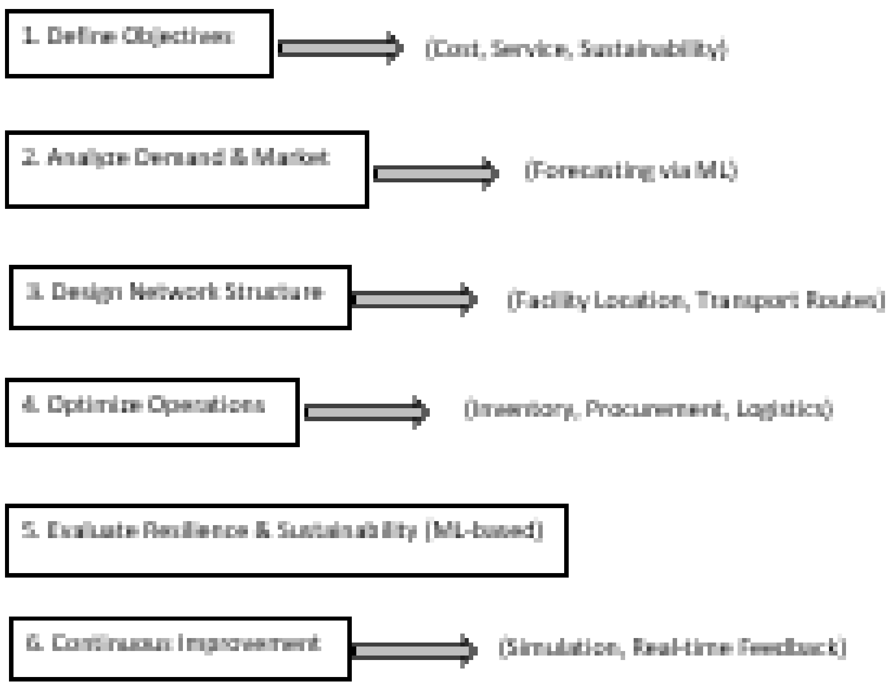

Figure 2: Supply Chain Design Process

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This figure demonstrates the main steps in designing an effective supply chain network, emphasizing how data and machine learning contribute to optimization and sustainability decisions.

Figure 2 outlines the process of supply chain design, which involves defining strategic objectives, analyzing market and demand data, and configuring the network structure. Machine learning contributes at every stage by providing predictive insights, scenario simulations, and sustainability evaluations, resulting in a more adaptive and resilient supply chain.

4. Supplier Selection Strategy and Procurement Strategy

The supplier selection strategy and procurement strategy are fundamental components of effective supply chain management, working together to ensure efficient sourcing, cost optimization, quality assurance, and risk mitigation. The supplier selection strategy focuses on identifying and evaluating potential partners capable of meeting the organization's operational and strategic objectives. It involves assessing suppliers based on criteria such as reliability, cost efficiency, quality standards, and sustainability practices. Meanwhile, the procurement strategy defines the organization's overall approach to acquiring the goods and services required to maintain optimal inventory levels and support production or service delivery. In essence, the procurement strategy determines what materials or services are needed, while the supplier selection strategy determines who is best suited to provide them. Together, these strategies enhance supply chain performance, foster long-term partnerships, and contribute to achieving competitive advantage.

a. Supplier Selection Strategy

Supplier selection is a critical element of supply chain management, as suppliers significantly influence the cost, quality, and reliability of products and services. The choice of suppliers affects not only operational efficiency but also long-term competitiveness. Effective supplier selection requires evaluating multiple criteria such as cost, quality, delivery performance, financial stability, and sustainability practices **(Ho et al., 2010).**

Traditional approaches to supplier selection often rely on weighted scoring models, where different attributes are ranked according to organizational priorities. However, with growing supply chain complexity, organizations are increasingly adopting data-driven and multi-criteria decision-making (MCDM) methods, such as the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and fuzzy logic-based models. These methods provide structured frameworks for balancing trade-offs among conflicting objectives, such as cost versus sustainability or flexibility versus efficiency **(Govindan et al., 2015).**

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In recent years, machine learning (ML) has also been integrated into supplier selection processes. ML algorithms can analyze large datasets on supplier performance, past delivery records, and risk indicators to support predictive decision-making. For example, predictive analytics can identify suppliers more likely to experience delays or quality failures, enabling proactive risk management **(Kaur & Singh, 2021).**

b. Procurement Strategy

Procurement strategy refers to the systematic process of acquiring goods and services that meet organizational objectives while optimizing cost, quality, and value. A well-designed procurement strategy ensures alignment with business goals, market conditions, and risk management practices. Organizations can adopt different procurement approaches, including centralized, decentralized, or hybrid models, depending on their size, industry, and global presence **(Monczka et al., 2016).**

Modern procurement strategies extend beyond cost savings to emphasize supplier collaboration, innovation, and sustainability. Strategic sourcing involves building long-term partnerships with suppliers, negotiating favorable terms, and ensuring supply continuity. Furthermore, digital transformation has reshaped procurement through e-procurement systems, blockchain for transparency, and AI-driven tools for spend analysis and contract management **(Tiwari et al., 2018).**

Machine learning enhances procurement strategy by enabling demand forecasting, spend classification, and automated supplier risk assessments. By leveraging predictive models, organizations can identify cost-saving opportunities, negotiate better contracts, and mitigate procurement risks. For instance, anomaly detection algorithms can flag irregular pricing trends or fraudulent activities, improving the overall integrity of procurement processes **(Min, 2019).**

Together, supplier selection and procurement strategies form the foundation of supply chain competitiveness. When integrated with advanced technologies such as machine learning, they contribute to building resilient, cost-effective, and sustainable supply chain networks.

5. Inventory and Ordering Strategy

Inventory and ordering strategies are critical components of supply chain management, as they directly affect service levels, operational costs, and overall efficiency. The primary goal of inventory management is to ensure that the right products are available in the right quantities at the right time, while minimizing excess stock and associated carrying costs. Ordering strategies complement this by determining when and how much to order, balancing trade-offs between demand uncertainty, lead times, and storage capacities **(Silver et al., 2016).**

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a. Inventory Strategy

Inventory strategies generally fall into two categories: push-based and pull-based systems. Push-based strategies rely on demand forecasts to drive production and replenishment decisions, whereas pull-based systems depend on actual customer demand signals. Hybrid models, such as just-in-time (JIT) and vendor-managed inventory (VMI), have been widely adopted to reduce stock levels and improve responsiveness. JIT aims to minimize inventory by synchronizing production with demand, while VMI shifts replenishment responsibilities to suppliers, enhancing collaboration across the supply chain **(Christopher, 2016).**

Recent advancements in machine learning (ML) have transformed inventory strategies by improving demand forecasting accuracy. ML models can analyze large datasets—such as historical sales, seasonal trends, and macroeconomic indicators—to predict demand fluctuations more effectively than traditional methods. This reduces the risk of stockouts and overstocks, thereby lowering costs and improving customer satisfaction **(Carbonneau et al., 2008).**

b. Ordering Strategy

Ordering strategies are concerned with determining the optimal order quantity and timing. The Economic Order Quantity (EOQ) model remains a foundational approach, providing a balance between ordering costs and holding costs. For environments with uncertain demand, more advanced strategies such as the (Q, R) model (continuous review) or the (S, S) model (periodic review) are often applied. These models help organizations decide when to place an order (reorder point) and how much to order, ensuring efficiency under uncertainty **(Zipkin, 2000).**

Machine learning enhances ordering strategies by enabling adaptive decision-making. Predictive models can dynamically adjust reorder points and safety stock levels based on real-time demand and supply data. Reinforcement learning techniques are increasingly being explored to optimize ordering policies by simulating various scenarios and learning from outcomes **(Feng et al., 2021).** Moreover, anomaly detection algorithms can identify unusual demand spikes or supply delays, allowing managers to act proactively.

In today's volatile markets, integrating machine learning into inventory and ordering strategies provides organizations with agility, resilience, and cost efficiency. This shift from static models to data-driven and adaptive strategies represents a major step toward building more intelligent and responsive supply chains.

c. Definition of the (Q, R) and (s, S) Inventory Models

(Q, R) Model (Continuous Review System): In the continuous review (Q, R) model, inventory levels are continuously monitored. When the inventory position (on-hand + on-order – backorders) drops to a predetermined reorder point (R), a fixed quantity Q is ordered. The

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values of Q and R are calculated to balance ordering costs, holding costs, and service levels. This model is most effective in environments with stable demand and reliable lead times, and it supports quick responses to inventory depletion.

Formulaic Representation:

Order when inventory $\leq$ R

Order quantity = Q

Example:

If R = 500 units and Q = 1,000 units, a new order of 1,000 units is placed every time stock falls to 500.

(S, S) Model (Periodic Review System): In the periodic review (S, S) model, inventory is reviewed at regular time intervals (e.g., weekly or monthly) rather than continuously. If the inventory level at the time of review is below the threshold s (reorder level), an order is placed to raise the inventory up to the target level S. The size of each order varies depending on the current inventory level. This model is suitable for systems with batch ordering, variable demand, or limited ability to track inventory continuously.

Formulaic Representation:

If inventory < s → Order = S – current inventory

Example:

If s = 300 and S = 1,200, and current stock is 200, the order quantity will be 1,000 units.

6. Supply Chain Coordination Strategy

Supply chain coordination strategy refers to the alignment of decisions and actions among supply chain partners to improve overall efficiency, reduce costs, and enhance customer satisfaction. Lack of coordination often results in inefficiencies such as the bullwhip effect, where small fluctuations in demand at the customer level cause increasingly larger variations upstream in the supply chain. This leads to excess inventory, production inefficiencies, and poor service levels **(Lee et al., 1997).**

a. Importance of Coordination

Effective coordination ensures that information, materials, and financial flows across suppliers, manufacturers, distributors, and retailers are harmonized. Coordinated supply chains can better manage demand variability, reduce lead times, and enhance responsiveness to disruptions. Strategies such as information sharing, joint forecasting, collaborative planning, and synchronized replenishment are essential for achieving seamless coordination **(Simatupang & Sridharan, 2005).**

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b. Traditional Coordination Mechanisms

Historically, supply chain coordination has been achieved through contractual agreements such as buy-back contracts, revenue-sharing agreements, and quantity-flexibility contracts. These mechanisms align incentives among supply chain partners and reduce risks of opportunistic behavior. For example, revenue-sharing contracts encourage retailers to share sales data with manufacturers, thus improving demand forecasts and reducing inefficiencies **(Cachon, 2003).**

c. Technology-Driven Coordination

Advancements in digital technologies have revolutionized coordination strategies. Enterprise Resource Planning (ERP) systems, cloud-based platforms, and blockchain have enabled greater visibility, transparency, and trust among partners. More recently, machine learning (ML) and artificial intelligence (AI) have provided predictive capabilities, enabling supply chains to anticipate disruptions, optimize collaboration, and adapt in real time **(Ivanov et al., 2019).** For instance, ML-driven collaborative forecasting allows multiple stakeholders to integrate their data and generate more accurate predictions of customer demand, reducing the likelihood of stock imbalances.

d. Towards Resilient and Sustainable Coordination

Beyond efficiency, modern coordination strategies also focus on building resilient and sustainable supply chains. Coordinated efforts in sustainability—such as green procurement, circular economy practices, and optimized transportation—require strong collaboration between partners. ML and AI tools support this by analyzing carbon footprints, optimizing logistics routes, and facilitating sustainable supplier selection **(Shen et al., 2020).** Thus, supply chain coordination is no longer limited to cost minimization but extends to resilience, adaptability, and environmental responsibility.

7. Demand Management Strategy

Demand management strategy is a critical aspect of supply chain management that focuses on aligning customer demand with the firm's supply capabilities. It involves forecasting, planning, and influencing demand in order to balance resources, reduce uncertainty, and improve customer satisfaction. Effective demand management ensures that organizations can respond to fluctuations in demand without incurring excessive costs or service disruptions **(Mentzer et al., 2007).**

a. Importance of Demand Management

Uncertainty in demand is one of the primary sources of inefficiency in supply chains. Poorly managed demand often results in the bullwhip effect, leading to either stockouts or excess

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inventory across the network **(Lee et al., 1997).** A well-designed demand management strategy helps mitigate these risks by integrating forecasting with sales and operations planning (S&OP). It also facilitates collaboration between supply chain partners, ensuring that production, inventory, and distribution decisions are informed by accurate demand signals **(Stank et al., 2011).**

b. Traditional Approaches to Demand Management

Historically, demand management relied on statistical forecasting methods, such as moving averages, exponential smoothing, and regression models. These methods use historical data to estimate future demand, but they often struggle with volatile markets and complex consumer behaviors. Companies also employed demand-shaping strategies such as promotions, pricing, and product substitution to influence customer behavior and align it with supply availability **(Chopra & Meindl, 2019).**

c. Machine Learning and Data-Driven Demand Management

Recent advancements in machine learning (ML) and artificial intelligence (AI) have significantly improved demand management strategies. ML algorithms can capture nonlinear relationships in large datasets, incorporating diverse factors such as weather, economic indicators, social media trends, and competitor activity into demand forecasts. Compared with traditional statistical methods, ML offers higher accuracy and adaptability in dynamic markets **(Carbonneau et al., 2008).**

For example, deep learning models have been successfully applied to forecast short-term retail demand with high precision, while reinforcement learning is being explored to optimize demand-shaping strategies such as dynamic pricing and promotions **(Choi et al., 2018).** Moreover, real-time analytics enable organizations to adjust forecasts and inventory policies continuously, creating agile and customer-responsive supply chains.

d. Towards Collaborative and Sustainable Demand Management

Modern demand management extends beyond forecasting and shaping to include collaboration across the supply chain. Joint forecasting, collaborative planning, and information sharing among suppliers, manufacturers, and retailers improve forecast accuracy and reduce demand uncertainty **(Danese & Kalchschmidt, 2011).** In addition, sustainability has become an important consideration, with organizations increasingly seeking to balance demand fulfillment with environmental and social goals. Data-driven demand management strategies help optimize production and distribution in ways that minimize waste, energy consumption, and carbon emissions.

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8. Challenges in Implementing Machine Learning in Supply Chain

Although machine learning (ML) and artificial intelligence (AI) hold great potential for transforming supply chain management, their implementation faces significant challenges. These challenges can be broadly grouped into issues of connectivity, collaboration, process design, and computational scalability.

a. Connection Challenges

One of the key barriers to successful ML adoption in supply chains is the lack of seamless connectivity across systems and stakeholders. Many supply chain networks still rely on fragmented legacy systems that are not designed to integrate large-scale, real-time data flows. This disconnect hinders the visibility required for predictive and prescriptive analytics. Furthermore, data quality and standardization remain persistent issues; inconsistent data formats across suppliers, distributors, and retailers reduce the effectiveness of ML models **(Waller & Fawcett, 2013).**

b. Collaboration Challenges

Collaboration among supply chain partners is essential for achieving the full benefits of ML-driven strategies, but it is often constrained by trust and information-sharing concerns. Organizations may be reluctant to share sensitive operational data with partners due to competitive pressures, fear of data misuse, or lack of contractual clarity **(Simatupang & Sridharan, 2005).** Without collaborative data sharing, ML models may be trained on incomplete datasets, limiting their predictive accuracy and effectiveness in managing demand, risks, and disruptions.

c. Process Design Challenges

Integrating ML into supply chain operations also requires redesigning traditional processes. Many organizations struggle with aligning new data-driven insights with existing workflows, decision-making structures, and performance metrics. Resistance to change from employees, lack of skilled personnel, and unclear governance models often slow down adoption **(Choi et al., 2018).** Moreover, supply chains need to develop hybrid decision-making approaches that balance human expertise with automated ML-driven recommendations.

d. Computational Scalability Challenges

Finally, computational scalability is a major concern in applying ML to global supply chains. Supply chains generate massive amounts of structured and unstructured data, such as IoT sensor data, logistics tracking, and social media signals. Training ML models on these large datasets requires significant computational power, storage, and advanced infrastructure. Small and medium-sized enterprises (SMEs) often face difficulties in accessing such resources, which may limit widespread adoption **(Jordan & Mitchell, 2015).** In addition, as supply chain

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models grow more complex, ensuring real-time analytics while maintaining cost-effectiveness becomes increasingly challenging.

Overcoming these challenges requires investment in digital infrastructure, fostering collaborative ecosystems, redesigning processes for agility, and leveraging scalable cloud-based and edge computing solutions. Addressing these issues will determine the success of machine learning in creating efficient, resilient, and sustainable supply chains.

9. Conclusion

The integration of machine learning (ML) into supply chain management offers transformative potential, enabling organizations to move from reactive decision-making toward proactive and predictive strategies. Across key areas such as supply chain design, supplier selection, procurement, inventory management, ordering policies, coordination, and demand management, ML provides enhanced forecasting accuracy, real-time optimization, and adaptive decision support. These capabilities not only reduce inefficiencies and costs but also improve resilience and customer satisfaction in an increasingly uncertain global environment **(Choi et al., 2018; Min, 2019).**

However, the adoption of ML is not without challenges. Issues such as fragmented system connectivity, limited collaboration among stakeholders, difficulties in redesigning processes, and computational scalability constraints continue to hinder widespread implementation **(Jordan & Mitchell, 2015; Waller & Fawcett, 2013).** Addressing these barriers requires investments in digital infrastructure, the development of collaborative ecosystems, and organizational change management strategies that align people, processes, and technology.

Looking forward, the role of ML in supply chain management is expected to expand as organizations increasingly pursue resilient and sustainable supply chains. By integrating advanced analytics, real-time data, and collaborative platforms, supply chains can evolve into intelligent networks capable of anticipating disruptions, minimizing environmental impact, and supporting long-term competitiveness. Thus, while challenges remain, the strategic use of machine learning is not just an operational tool but a critical enabler of future-ready supply chains **(Ivanov, 2021).**

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