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ICT in Business and the Public Sector

AI Support for Complex Supply Chain Management
– A literature review

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MASTER'S THESIS

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Abstract

Background: Supply chain management (SCM) plays a crucial role in modern business operations, influencing efficiency, cost-effectiveness, and overall competitiveness. However, the increasing complexity of supply chains, driven by globalization, volatile demand, and unforeseen disruptions, presents significant challenges for decision-making processes. In response, artificial intelligence (AI) techniques have been increasingly explored as potential solutions to enhance decision support in supply chain management. Various AI methodologies, including machine learning, deep learning, and special optimization algorithms, have been proposed to address supply chain management (SCM) tasks, yet their effectiveness and adoption vary across different contexts. Understanding the current state of AI applications in SCM is essential to identifying both its successes and persistent challenges.

Aim: This study aims to establish the current state of research regarding the use of AI techniques for SCM tasks. It seeks to assess which AI approaches have been widely proposed, surface their reported performance, and identify the existing gaps in the literature. By providing some cases of AI-driven decision support in SCM, this research contributes to the ongoing discourse on optimizing supply chain operations through advanced technologies.

Method: A literature review is conducted to collect and analyze existing studies on AI applications in SCM. This review focuses on identifying the specific AI techniques that have been applied and assessing their reported effectiveness. By synthesizing findings from various sources, the study aims to provide a broad understanding of how AI is currently leveraged in supply chain decision-making and some of the potential research gaps.

Results: The findings indicate that certain AI techniques, such as advanced neural networks and models in combination with ARIMA, are more commonly applied than others. Moreover, some AI approaches demonstrate superior performance in specific supply chain tasks, such as demand forecasting, inventory management, and decision making. However, despite these advancements, several challenges remain, including issues related to data quality, model interpretability, computational costs, and scalability in real-world supply chain environments. Additionally, ethical and regulatory considerations surrounding AI adoption in SCM warrant further exploration.

Conclusion: Significant progress has been made in integrating AI into supply chain decision support, with many techniques proving effective in enhancing efficiency and predictive capabilities. However, key challenges persist, including the need for more robust AI models that can handle uncertainties, improve decision-making transparency, and ensure seamless integration into existing supply chain systems. Future research should focus on addressing these limitations, developing hybrid AI approaches, and exploring new ways to enhance AI-driven supply chain optimization. By continuing to refine AI methodologies and addressing critical research gaps, the potential of AI to revolutionize supply chain management can be better realized.

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Contents

Chapter 1

Introduction

1.1 Supply chain management

Supply chain management (SCM) is defined as the systematic, strategic coordination of traditional business functions and tactics both within and across companies in the supply chain, aimed at improving the long-term performance of individual firms and the supply chain as a whole [43]. This definition emphasizes that SCM is not limited to logistics or operations, but instead involves managing all key business processes, including marketing, production, procurement, and customer service, in a synchronized and collaborative manner to create customer value and competitive advantage.

The SCM function includes tasks such as demand forecasting, inventory management, decision making and so on.

Within this coordinated framework, demand forecasting plays a critical role by providing the foundation for effective planning and resource allocation across the supply chain. Demand forecasting in the supply chain context refers to the prediction of future customer demand based on historical data, market trends, and external factors, with the goal of supporting synchronized production, inventory, and logistics decisions [1]. Accurate forecasts are vital to mitigating the impact of demand volatility and improving responsiveness. However, Abolghasemi et al. [1] highlight that traditional forecasting models often struggle under conditions of high variability and promotional activity, underscoring the need for context-specific and adaptive forecasting techniques tailored to the complexities of real-world supply chains.

Building upon accurate forecasting, inventory management serves as a crucial operational mechanism in balancing supply and demand throughout the supply chain. Supply chain inventory management (SCIM) refers to the integrated planning and control of inventory across all cooperating organizations within the supply chain, from raw material suppliers to end customers [23]. Effective SCIM aims to improve customer service, reduce costs, and increase responsiveness by synchronizing inventory policies across all stages: supply, production, and distribution. However, the coordination of these policies is often challenged by demand variability and poor information flow, leading to phenomena such as the bullwhip effect. Giannoccaro and Pontrandolfo [23] propose a reinforcement learning-based approach to optimize inventory decisions under uncertainty, demonstrating that adaptive, data-driven policies can outperform traditional static models in complex supply chain environments.

To ensure overall supply chain efficiency, effective decision making under uncertainty is essential. Supply chain decision making refers to the process of selecting optimal strategies across procurement, production, inventory, and distribution under conditions of risk and variability. Dias and Ierapetritou [16] emphasize that such decisions are inherently complex due to fluctuating demand, lead times, and cost structures. They highlight the widespread use of analytical modelsparticularly the newsvendor frameworkto support decision making in uncertain environments by balancing the trade-off between overstocking and understocking. These models serve as valuable tools for operational and strategic planning, enabling firms to optimize performance across the entire supply chain.

As such, decision making in supply chains is not only about choosing efficient actions, but also about managing uncertainty in a way that aligns with organizational goals and customer expectations.

The dynamic nature of modern supply chains presents numerous challenges that necessitate advanced solutions to maintain efficiency and competitiveness. Contemporary supply chains, encompassing diverse activities from procurement and manufacturing to transportation and distribution, are increasingly complex and demand innovative approaches to manage and optimize operations effectively. Traditional supply chain management methods, while foundational, often fall short in addressing the rapidly evolving demands of global markets, particularly as these markets become more interconnected and volatile.

Several factors drive the increasing complexity of supply chains, including globalization, technological advancements, and heightened customer expectations. Globalization has expanded supply chains across multiple continents [75], leading to intricate networks of suppliers, manufacturers, and distributors. This expansion necessitates the coordination of operations across diverse regulatory environments and time zones, making supply chains more vulnerable to disruptions such as political instability or natural disasters. Technological advancements, while offering new efficiencies, also introduce challenges, requiring supply chains to adapt rapidly to changes in digital technologies and e-commerce dynamics. Furthermore, todays consumers demand faster delivery, greater customization, and higher reliability, putting additional pressure on supply chain operations to meet these expectations without compromising on cost or quality.

1.2 Artificial intelligence

Artificial intelligence (AI) offers transformative potential for supply chain management [44] by enhancing decision-making capabilities well beyond the reach of traditional methods. AI technologies such as machine learning, predictive analytics, and natural language processing enable companies to analyze vast data sets with unprecedented accuracy and speed, facilitating a more nuanced data-driven approach to supply chain management.

For instance, machine learning algorithms are adept at sifting through historical sales data and external variables like market trends and weather conditions to forecast demand with refined precision. Predictive analytics further extend this capability by identifying potential disruptions before they manifest, allowing companies to enact proactive strategies to mitigate risks effectively. Moreover, organizations can process real-time data, which is collected and made available immediately. They can also generate actionable insights, which are useful and ready to apply. Together, these abilities help them make quick and well-informed decisions. These capabilities enable firms to anticipate disruptions, adapt to market fluctuations proactively, and maintain operational resilience [46], thereby significantly enhancing their competitive edge. This sophisticated integration of AI into supply chain management marks a significant shift towards more dynamic, responsive, and efficient management practices.

The impetus for this research is driven by the critical need to comprehend and leverage artificial intelligence (AI) to effectively manage the complexities inherent in modern supply chains. This study aims to dissect the essential elements of supply chains, understand their intrinsic challenges, and evaluate the transformative role that AI can play in optimizing these systems.The objective is to identify studies that provide quantifiable performance data on AI applications in supply chains, extract key findings regarding improvements in demand forecasting, inventory management, and decision-making, and synthesize general conclusions while identifying gaps for future research. A focal point of the analysis will be the application of AI-based decision support systems which are pivotal in revolutionizing supply chain management. "Overall performance" in this context refers to the aggregate efficiency, effectiveness, and adaptability of supply chain operations in meeting organizational goals and responding to market dynamics. This study aims to show that through the strategic integration of AI, companies can achieve improved responsiveness, reduced costs, and enhanced accuracy in forecasting and inventory management, thereby boosting their overall performance [65]. This exploration is particularly pertinent and crucial for companies looking to maintain a competitive edge in a rapidly changing market environment.

As supply chains grow increasingly complex,because of intricate networks of suppliers, logistics, and distribution channels that operate on a global scale which demand more advanced solutions, it becomes essential to understand the potential of artificial intelligence (AI) and its practical implementations. This understanding is vital for spurring innovation and achieving strategic business objectives. Therefore, this study is driven by the need to bridge the existing divide between conventional supply chain management practices and the enhanced capabilities provided by AI. This research aims to deliver actionable insights and offer guidance on utilizing AI to effectively optimize these complex supply chains, thereby helping organizations navigate the challenges and leverage opportunities in the modern economic landscape.

1.3 Problem statement

Global supply chain complexity has significantly increased, necessitating more advanced and automated solutions to manage critical supply chain tasks effectively. The complexity of supply chains arises from their multifaceted and dynamic nature, involving numerous interdependent factors across global networks. Key contributors to this complexity include globalization, diverse product portfolios, multiple supplier tiers, market volatility, and the integration of advanced technologies.

- Globalized vs. Non-Globalized Supply Chains

  The complexity of globalized supply chains differs significantly from that of non-globalized (localized) supply chains due to differences in scale, scope, and operational challenges. Globalized supply chains involve sourcing, manufacturing, and distributing products across multiple countries and continents, requiring extensive coordination across different time zones, languages, cultures, and business practices [30]. Navigating diverse regulations, trade policies, and tariffs adds another layer of complexity, as does exposure to geopolitical risks, natural disasters, and global economic fluctuations [12, 11]. In contrast, non-globalized supply chains operate within a single country or a limited geographic area, benefiting from uniform regulations, stable trade environments, and reduced exposure to global disruptions [26, 31]. However, they may lack the scalability required to compete effectively in international markets, especially as global competitiveness increasingly depends on supply chain agility and reach [25].

- Product Diversification and Supply Chain Complexity

  Diverse product portfolios introduce additional complexity, as companies must manage multiple supply chains tailored to different products with unique sourcing, production, and distribution requirements. This results in greater procurement complexity, the need for customized production lines, and more sophisticated inventory management. Demand forecasting becomes increasingly challenging due to varying seasonal trends and customer preferences across different product categories. Additionally, diverse regulatory compliance requirements for different product types add another layer of complexity. Research shows that as product variety increases, supply chain complexity also rises [27], leading to increased disruptions in production, forecasting, and scheduling. Moreover, higher product variety correlates with intensified information exchange needs across supply chain networks in order to coordinate effectively [42].

- Challenges of Multi-Tier Supplier Networks

  The presence of multiple supplier tiers increases supply chain interdependencies, making them more vulnerable to disruptions. Companies must manage not only their immediate (Tier 1) suppliers but also those further down the chain (Tier 2 and beyond), often with limited visibility into higher-tier operations [57, 51]. This lack of transparency complicates compliance monitoring, risk management, and performance tracking. Ensuring adherence to quality standards and ethical sourcing practices becomes difficult when suppliers are dispersed across different regions with varying regulations and business ethics [51, 63].

- Market Volatility and Risk Management

  Market volatility, driven by fluctuating demand and price changes, adds further complexity to supply chain management. Unpredictable shifts in consumer behavior, economic downturns, raw material shortages, and sudden geopolitical events can disrupt supply chains, necessitating agile response mechanisms. Companies must adjust production schedules, optimize inventory levels, and implement flexible logistics solutions to mitigate the impact of volatility [7, 53]. Moreover, price instability in key commodities and fluctuating exchange rates create financial uncertainties that require proactive risk management [66].

- Technological Integration and Cybersecurity Concerns

  The adoption of advanced technologies such as AI, the Internet of Things (IoT), and blockchain presents both opportunities and challenges. While these technologies enhance efficiency, visibility, and decisionmaking, they also introduce complexities related to system integration, interoperability, and cybersecurity. Supply chain networks often rely on multiple thirdparty vendors, each using different IT systems, making seamless data exchange and realtime visibility difficult to achieve [4].

Cybersecurity threats also pose a significant risk, as the increasing digitization of supply chains exposes companies to potential data breaches and cyberattacks [58].

- Environmental and Regulatory Compliance

  Sustainability concerns and regulatory requirements further complicate supply chain operations. Companies must monitor and report on their environmental impact, ensuring compliance with strict emissions regulations, ethical labor practices, and circular economy initiatives. Managing reverse logistics, reducing carbon footprints, and adopting sustainable sourcing strategies add additional layers of complexity to supply chain decision-making. Research indicates that implementing reverse logistics supports environmental goals by lowering emissions and enabling circularity, while collaborative digital platforms enhance visibility for compliance and sustainability reporting [47, 28].

- The Need for AI-Driven Solutions

  Given these challenges, supply chain management increasingly requires advanced technologies to enhance efficiency, resilience, and agility. Traditional methods are often insufficient to handle the scale and complexity of modern supply chains. AI-driven solutions offer transformative potential by improving demand forecasting, optimizing inventory, enhancing visibility across supplier tiers, and enabling real-time decision-making [60, 13].

These factors collectively illustrate that modern supply chains are increasingly exposed to a variety of operational, structural, and technological complexities. Traditional management approaches often fall short in addressing such dynamic and interconnected challenges. As a result, there is a growing need to investigate how advanced technologies, particularly AI, can provide effective support in specific areas of supply chain management. To address this need, the following research questions are formulated.

1.4 Research questions

In order to confront the problem as stated above, we have formulated a number of research questions.

RQ.1 What AI technologies have been developed and proven to be useful for various tasks in SCM?

RQ.2 How are AI technologies proven to be useful in improving demand forecasting of complex supply chains?

RQ.3 How are AI technologies proven to be useful in improving inventory management of complex supply chains?

RQ.4 How are AI technologies proven to be useful in improving decision making of complex supply chains?

To answer these research questions, we will perform a review of supply chain literature that mentions AI techniques.

1.5 Overview of the thesis

The study begins in Chapter 1, with an introduction to supply chain management and artificial intelligence, outlining the problem statement and research questions. It then reviews relevant literature in Chapter 2, discussing early AI applications in SCM, real-world use cases, and gaps in research and industry adoption. Chapter 3 details our approach for selecting and analyzing relevant studies. It is followed in Chapter 4 where we categorize AI techniques based on key SCM tasks and assess their effectiveness. The discussion in Chapter 5 examines AI's impact on forecasting and inventory management, highlighting limitations and future research needs. Finally, the thesis concludes in Chapter 7 by summarizing key findings, contributions, and recommendations for businesses and researchers, emphasizing the need for a more integrated AI framework in SCM.

To ground these research objectives in a broader scholarly and practical context, the following chapter reviews existing literature and foundational concepts in supply chain management and artificial intelligence. This background establishes the theoretical and technological underpinnings necessary for understanding the subsequent analysis.

Chapter 2

Background and related work

2.1 Supply chain management

Supply chain management (SCM) encompasses the broad range of activities required to plan, control, and execute a products flowfrom acquiring raw materials and production through distribution to the final customerin the most streamlined and cost-effective way possible. SCM not only involves moving physical goods, but also managing information flows, financial transactions, and inter-business relationships within the supply chain. According to NetSuite, ERP systems play a central role by coordinating planning, procurement, manufacturing, inventory, warehousing, and order management, enabling unified data and reducing integration challenges [49].

The primary objectives of SCM are to fulfill customer demands using resources, such as distribution capacity, inventory, and laborefficiently. This means managing a synchronized network of interconnected businesses through logistics and sales operations. Effective SCM requires continuous improvement and regular reassessment of operationsincluding global sourcing, production, inventory, and distributionto address evolving challenges. Olhager (2002) points out that the integration of JIT principles across supply chains enhances efficiency by linking successive companies, reducing lead times and reducing cumulative inefficiencies [50].

SCM relies on technological tools such as ERP, Supply Chain Execution (SCE), and Advanced Planning and Scheduling (APS) systems to track and manage goods and services precisely. APS systems, which balance capacity and materials, are especially valuable when basic planning methods fall short in handling complex trade-offs [77]. The role of AI is increasingly pivotal, as it automates decision-making, improves forecasts, optimizes routes and inventory, and enhances responsiveness across supply networks.

Strategically, SCM involves collaboration among suppliers, manufacturers, and retailers to minimize waste, reduce delays, and eliminate redundancies. This collaborative mindset supports efficiency and helps companies maintain competitiveness. As a dynamic field, SCM unifies business, technology, and strategic management to align operations with customer satisfaction and profitability.

As supply chains grow in complexity, researchers have explored how traditional approaches, like ERP systems, lean manufacturing, and JIT inventoryhelp streamline operations. Yet with globalization and interconnectivity, these methods face limitations in coping with volatility, uncertainty, and large-scale disruptions.

2.2 Artificial intelligence techniques

Artificial Intelligence (AI) technology represents a broad field of computer science dedicated to creating systems capable of performing tasks that would typically require human intelligencesuch as learning, reasoning, problem-solving, perception, and understanding language. These systems range from simple rule-based automation to sophisticated machine learning (ML) and deep learning (DL) models. A recent review outlines how ML and DL are being applied to logistics and supply chain operations, improving predictive analytics, real-time monitoring, and autonomous decision-making capabilities [59].

The core of AI involves ML, which enables systems to improve from data without explicit programming. ML uses statistical approaches to learn from historical data, adjusting parameters to minimize prediction errors. Over time, as more data is processed, the systems accuracy in decision-making and forecasting enhances. Deep learning uses neural networks with multiple layers, allowing machines to uncover intricate patterns in large datasets. A comprehensive review on DL techniques highlights its capabilities in discovering deep representations and its crucial role in areas such as computer vision and language processing [62].

Natural Language Processing (NLP) is another vital AI domain, allowing computers to interpret and generate human language. This includes applications like translation, voice commands, and text generation. A standard reference describes NLP as engineering machines to process and derive insights from human-language data effectively [15].

Beyond ML, DL, and NLP, AI in real-world systems includes robotics, expert systems, and autonomous agents. These AI-enabled systems perceive environments, make autonomous decisions, and act accordingly, enhancing tasks like warehouse automation, route planning, and anomaly detection. Crucially, AI's ability to process both historical and streaming data supports near real-time decision-making, which is transformative for industries like healthcare, finance, and notably logistics and SCM.

2.3 Early Research on AI in Supply Chain Management

Several early studies have examined the potential of AI in supply chain management, highlighting its ability to process large datasets, identify patterns, and support data-driven decision-making. For instance, a recent comprehensive survey outlines how AI applications, such as demand forecasting, inventory optimization, and transportation routing, have demonstrated measurable benefits in reducing costs, improving service levels, and enhancing resilience. Other research emphasizes AI's role in predictive maintenance and logistics optimization, illustrating how machine learning-driven analytics can detect equipment failures early and optimize delivery routes dynamically [33].

Although these contributions offer valuable practical insights, they largely focus on isolated AI applications rather than integrating them into a comprehensive AI-driven supply chain management framework.

2.4 Fragmentation in AI & SCM Literature

Despite the growing interest in AI applications within SCM, the existing literature remains fragmented. Many studies address individual use cases, such as inventory optimization, transportation planning, or supplier risk assessment, without providing a comprehensive view of how AI can be integrated across the entire supply chain. Additionally, while some review papers summarize AI advancements in SCM, a fully unified overview that synthesizes these findings into a cohesive framework is still lacking.

2.5 Real-World Applications of AI in SCM

Several companies have already adopted AI-driven solutions to optimize their supply chains. For instance, Amazon uses AI-powered demand forecasting and warehouse automation to enhance inventory management and reduce delivery times. Walmart leverages machine learning algorithms for predictive analytics, optimizing stock levels and improving supply chain efficiency. These real-world examples demonstrate the potential of AI to address supply chain complexities, but widespread adoption remains a challenge due to barriers such as high implementation costs, integration difficulties, and workforce skill gaps.

2.6 Gaps in Research & Industry Adoption

While AI has shown promise in mitigating supply chain challenges, there are still open questions regarding its scalability, interpretability, and ethical implications. Many AI models operate as black boxes, making it difficult for supply chain managers to understand their decision-making processes. Additionally, AI adoption requires robust data infrastructure, yet many companies still struggle with data silos and integration issues. Future research must explore ways to enhance AI transparency, improve interoperability with existing supply chain systems, and ensure ethical AI deployment.

2.7 Role of AI in complex supply chain management

In todays rapidly evolving global markets, supply chains have become increasingly complex, involving multiple stakeholders, fluctuating demand patterns, and intricate logistics networks. Traditional supply chain management (SCM) approaches often struggle to cope with these complexities, leading to inefficiencies, higher costs, and disruptions. Artificial Intelligence (AI) has emerged as a transformative technology in supply chain management, enabling organizations to enhance decision-making, optimize operations, and improve resilience. However, while various studies have explored AI applications in SCM, there is currently no comprehensive, unified overview of AIs full potential across all aspects of supply chain management. The existing literature is fragmented, consisting of multiple studies focusing on individual applications such as forecasting, logistics, and risk management, without a holistic synthesis.

Several early studies have examined the potential of AI in supply chain management, highlighting its ability to process large datasets, identify patterns, and support data-driven decision-making. For instance, applications like neural networks and expert systems have been explored for inventory control and logistics planning, showcasing improved accuracy and responsiveness in multi-echelon supply chains [68].

More recent surveys provide comprehensive reviews of AI and Big Data analytics in supply chain resilience, underscoring benefits in demand forecasting, predictive maintenance, and route optimization. However, while these works contribute valuable insights into specific AI applications, there remains a lack of frameworks that integrate these technologies across all key SCM processes, calling for research that unifies disparate advances into cohesive, end-to-end solutions.

1. AI-Driven Demand Forecasting

   Accurate demand forecasting is crucial for balancing supply and demand in complex supply chains. AI leverages machine learning (ML) algorithms and big data analytics to improve the accuracy of demand predictions. Unlike traditional statistical models, AI-powered forecasting systems can analyze vast amounts of structured and unstructured data, such as historical sales, market trends, weather conditions, and consumer sentimentrevealing hidden patterns and correlations. This leads to more effective demand planning, reducing both stockouts and overstock situations, and ultimately improving operational efficiency [14, 35].

   One notable real-world application is Amazons AI-based demand forecasting system, which uses predictive analytics to analyze purchasing patterns and inventory needs across its fulfillment network, significantly reducing delivery times and boosting warehouse efficiency [67, 69].

2. AI in Inventory Optimization

   Managing inventory across multiple locations, suppliers, and distribution channels is a significant challenge in complex supply chains. AI-based inventory management systems use predictive analytics to determine optimal stock levels, dynamically adjusting to demand fluctuations. Reinforcement learning algorithms can simulate various inventory scenarios and suggest strategies to minimize holding costs while ensuring product availability. Additionally, AI-driven warehouse automation, including robotics and smart inventory tracking, enhances accuracy and efficiency in inventory control.

   A case in point is Walmarts AI-powered inventory replenishment system, which leverages real-time sales data and supply chain dynamics to optimize stock levels and reduce excess inventory while maintaining high product availability [76]. Moreover, cutting-edge research demonstrates that deep reinforcement learning can optimize order picking, reducing throughput times and unfulfilled orders in dynamic warehouse environments [40].

3. AI in Logistics and Route Optimization

   AI revolutionizes logistics by optimizing transportation routes, reducing costs, and improving delivery times. Advanced AI models process real-time data from GPS tracking, weather conditions, traffic patterns, and historical shipment records to recommend the most efficient routes. AI-powered predictive maintenance systems for transportation fleets help prevent unexpected failures, reducing downtime and ensuring smooth operations [2, 18]. Moreover, AI-enabled autonomous vehicles and drones are being integrated into logistics networks, further enhancing last-mile delivery efficiency [73].

4. AI in Risk Management and Supply Chain Resilience

   Supply chain disruptions, such as natural disasters, geopolitical tensions, and supplier failures, can have severe consequences for businesses. AI enhances risk management by continuously monitoring and analyzing external factors that may impact the supply chain. Machine learning models can predict potential disruptions by analyzing economic indicators, news reports, and supplier performance data [37, 17]. AI-driven prescriptive analytics recommend proactive strategieslike diversifying suppliers or adjusting inventory levelsto mitigate risks and ensure supply chain resilience and business continuity [29].

5. AI-Enabled Decision Support Systems

   AI-powered Decision Support Systems (DSS) are instrumental in aiding supply chain managers with timely, data-driven decisions. These systems aggregate and process large datasets, enabling real-time insights and scenario analysis. By integrating deep learning, natural language processing (NLP), and reinforcement learning, AI-driven DSS can recommend optimal actions across procurement, production scheduling, and distribution planning.

   The emergence of digital twins, virtual replicas of physical supply chain networks, enhances these capabilities further. AI-enhanced digital twins simulate operational strategies and evaluate outcomes dynamically, creating a powerful platform for prescription and optimization [36], thereby facilitating more informed and robust SCM decision-making.

AI is transforming complex supply chain management by enhancing forecasting accuracy, optimizing inventory and logistics, improving risk management, and enabling data-driven decision-making. However, despite its growing adoption, there is no fully comprehensive review that synthesizes all advancements into a unified framework. The existing literature remains fragmented, with studies focusing on specific AI techniques or use cases rather than providing a holistic understanding of AIs role across the entire supply chain. While AI has demonstrated success in areas such as forecasting, logistics optimization, and risk management, real-world adoption remains uneven due to challenges in implementation and integration. Future research should address these gaps by developing comprehensive AI-driven supply chain strategies that enhance resilience, efficiency, and adaptability in an increasingly complex and dynamic global landscape.

Building on this conceptual and empirical foundation, the next chapter outlines the methodological approach used to review and synthesize relevant studies. This framework ensures that the subsequent analysis is both rigorous and transparent.

Chapter 3

Literature Review Method

To gain a comprehensive understanding of how artificial intelligence (AI) is applied in complex supply chain management (SCM), we conducted a literature review following some parts of a systematic approach. The objective was to identify studies that provide quantifiable performance data on AI applications in supply chains, extract key findings regarding improvements in demand forecasting, inventory management, and decision-making, and synthesize general conclusions while identifying gaps for future research.

3.1 Literature Search Strategy

To guide our research, we conducted an extensive literature review using reputable academic repositories such as Google Scholar, IEEE Xplore, and ScienceDirect. Search terms included combinations of keywords like artificial intelligence in supply chain management, AI for demand forecasting, machine learning in inventory management, AI-driven decision support, and optimization algorithms in supply chain logistics. This review was informed by the earlier analysis of supply chain complexity, which revealed that forecasting demand accurately, managing inventory efficiently, and making timely, data-driven decisions are among the most critical and frequently challenged tasks in modern supply chains. These tasks are central to ensuring operational efficiency, cost control, and customer satisfaction. Given their high impact and vulnerability to disruption, our study focuses on how AI technologies can address these specific areas to improve supply chain agility and resilience.

To ensure the reliability and validity of our findings, we established inclusion and exclusion criteria:

- Inclusion criteria: Studies that provide specific, quantifiable data on AI performance in supply chains, such as accuracy improvements, cost reductions, efficiency gains, and real-world implementation case studies.
- Exclusion criteria: Studies that present only theoretical discussions, lack empirical performance metrics, or report unreliable or vague performance data without detailed evaluation.

After applying these criteria, we identified a final selection of 20 papers published between 2010 and 2024. These papers provided insights into the real-world application of AI in various supply chain tasks, reflecting advancements in AI-driven SCM over time.

3.2 Data Extraction and Analysis

For each selected study, we extracted key information regarding:

- Identification and documentation of AI techniques: We examined how specific AI methods, such as neural networks, reinforcement learning, ARIMA models, and various optimization algorithms were designed, configured, and integrated into the supply chain context.
- Evaluation of performance metrics: We analyzed the criteria used to assess AI effectiveness, including the methodologies for calculating forecasting accuracy, quantifying cost savings, measuring inventory efficiency, and evaluating improvements in supply chain responsiveness.

- Comparative analysis with traditional approaches: We reviewed how each study conducted comparisons between AI-based solutions and conventional methods, focusing on the relative advantages or shortcomings in key operational areas such as demand forecasting, inventory management, and decision-making processes.
- Analysis of application contexts and data types: We explored the specific domains within the supply chain where AI techniques were applied, and investigated the nature, sources, and structure of the datasets utilized, including historical records, real-time inputs, and external variables.

To standardize the extracted data, we compiled a structured dataset, normalized various performance metrics, and categorized the AI techniques based on their primary application areas in SCM.

3.3 Synthesis of General Findings

To synthesize the findings from the selected literature, a structured and comparative approach was adopted. After extracting standardized performance metrics and categorizing AI techniques by their functional application areassuch as demand forecasting, inventory management, and decision-making, each study was analyzed both individually and in relation to others within the same category. This allowed for the identification of recurring patterns, methodological similarities, and performance trends across diverse implementations.

The synthesis process involved several stages:

1. Thematic grouping: Studies were first grouped according to the specific supply chain functions they addressed. This enabled a focused comparison within coherent thematic clusters, such as forecasting accuracy or inventory optimization.
2. Cross-study comparison: Within each group, comparative analysis was conducted to assess how different AI techniques performed against traditional methods, and how performance outcomes varied across industries, timeframes, and implementation scales.
3. Normalization of metrics: To enable meaningful synthesis across studies with different evaluation criteria, performance metrics were normalized where possible, for example, converting accuracy improvements into percentage ranges or standardizing inventory cost savings.
4. Identification of common patterns and outliers: By examining both frequently reported trends and notable deviations, we were able to identify not only general conclusions about AIs effectiveness but also contextual factors influencing its impact, such as hybrid model use or industry-specific constraints.
5. Iterative abstraction and consolidation: The findings were progressively abstracted into broader insights that encapsulated the overall contribution of AI in complex supply chains, while still preserving the nuances of different technical approaches.

This multi-step synthesis enabled a more holistic understanding of how AI contributes to various aspects of supply chain management and laid the groundwork for identifying persistent research gaps.

3.4 Identified Gaps for Future Research

The identification of research gaps was carried out through a systematic and critical appraisal of the selected literature, aiming to assess the comprehensiveness, methodological rigor, and thematic distribution of current studies on AI applications in complex supply chain management. Rather than focusing solely on reported findings, this process emphasized the detection of limitations, inconsistencies, and underexplored dimensions across the existing body of knowledge.

This analytical process unfolded through several methodological steps, each of which informs specific elements of the Results and Discussion sections below:

1. **Thematic and functional mapping** The reviewed studies were first categorized based on their primary functional domains, namely, demand forecasting, inventory management, and decision-making support. This thematic classification facilitated the identification of imbalances in research focus. Certain areas, such as forecasting, are extensively studied, while others, particularly strategic-level decision-making, remain relatively underexplored.

2. **Evaluation of methodological transparency and performance metrics** Each study was assessed for the clarity and consistency of its methodological design, including the performance metrics used. As detailed in Section 4.7, the heterogeneity of evaluation criteria and lack of standardized benchmarks emerged as a critical barrier to generalizability and cross-study synthesis.

3. **Assessment of practical implementation and scalability** Studies were also reviewed for the scale and realism of their application contextswhether AI models were tested in simulations or real-world environments. Section 3 highlights the predominance of experimental or small-scale implementations, underscoring limitations in current scalability and deployment.

4. **Examination of ethical, interpretability, and governance considerations** Beyond technical efficacy, the analysis included an evaluation of each studys engagement with data ethics, model interpretability, and governance frameworks. Section 4 presents this dimension, where limited discourse on transparency and explainability suggests a need for more holistic approaches.

5. **Triangulation with secondary review sources** To contextualize and validate the findings, insights were cross-referenced with existing systematic reviews and meta-analyses. Section 5 demonstrates how this triangulation process substantiated the observed gaps and confirmed their persistence across the literature.

Through this structured multi-level methodology, the study was able to systematically uncover where the current academic discourse remains fragmented or insufficient. This, in turn, provides a clear foundation for proposing more robust, scalable, and ethically grounded approaches to the application of AI in complex supply chain environments.

With the review framework established and the selection criteria applied, we now turn to the results of our analysis. This section presents the key findings, organized to reveal patterns in AI applications across supply chain tasks, domains, and performance outcomes.

Chapter 4

Results

This chapter presents the results of the broad analysis conducted on selected academic studies regarding the application of artificial intelligence (AI) in complex supply chain management. It is organized into several subsections to facilitate thematic clarity and analytical depth.

The chapter begins in Section 4.1 with a list of the selected literature. Following this, Section 4.2 categorizes the studies based on the specific supply chain tasks addressed, while Section 4.3 examines the domains and data sources utilized. Section 4.4 and 4.6 delve into the various AI techniques and hybrid models reported in the literature, highlighting both general methods and tailored implementations. Section 4.7 discusses performance evaluations, emphasizing metrics such as MAPE to compare algorithmic effectiveness. Finally, Section 4.8 identifies persistent challenges and research limitations, offering direction for future inquiry.

4.1 Selected literature

In the literature review process for this study, we identified 20 papers related to artificial intelligence in complex supply chain decision support(see appendix). Ensuring that the information relied upon in scientific research and data analysis is precise and detailed is crucial for evaluating and applying research outcomes. Therefore, we only selected those studies that offered comprehensive data on algorithm performance to ensure the reliability and accuracy of our analysis.

The number of papers that met our criteria and were included in our selection totals 20, spanning from the year 2010 to 2024 (see Table A.1). This range of years indicates a significant span of research development and technological advancements in the field of artificial intelligence applied to complex supply chain management. The diversity in years also suggests that the integration of AI in supply chain decision-making processes has been a topic of increasing interest and continuous evolution, reflecting improvements in algorithmic approaches and their practical applications over time.

See the Table in Appendix A.1 for a detailed overview of the empirical studies analyzed in this research. This table presents various AI algorithms used in different supply chain management (SCM) fields, detailing the tasks they are applied to, their performance, the type of data they rely on, and the metrics used to evaluate their effectiveness. It broadly summarizes how various artificial intelligence (AI) algorithms have been applied to distinct supply chain tasks, such as demand forecasting, inventory management, and decision support. Each entry outlines the specific AI technique utilized, the type of data employed (e.g., sales data, aircraft usage), the associated performance metrics (such as MAPE, MSE, or Total Error), and the industrial context or field of application (e.g., automotive, aerospace).

This comparative tabulation enables a multidimensional analysis across algorithmic strategies, data typologies, and operational domains. By organizing the findings in this structured manner, it becomes possible to observe performance patterns, identify algorithm-task alignments, and assess the extent of empirical validation in various sectors.

Notably, certain cells remain blank in the performance-related columns; this is due to the absence of quantifiable results in the original sources, which either did not report measurable performance outcomes or focused primarily on conceptual or qualitative discussions. These gaps highlight the need for more rigorous and transparent empirical evaluations in future studies.

4.2 SCM Tasks

As outlined in the methodological framework (Section 3.4), a key analytical step involved categorizing AI applications by functional task domains within SCM. This mapping revealed concentrated attention on certain operational tasks, particularly demand forecasting, while strategic-level applications like decision support remained less explored.

The papers included in our selection broadly address a variety of crucial SCM tasks, each critical to the optimization of supply chain operations. Key areas covered include decision-making, demand forecasting, inventory management, and risk assessment.

- **Decision making** is explored through the lens of algorithmic efficiency and real-time data processing capabilities [22, 64, 54], which are essential for navigating the complexities of modern supply chains. However, compared to forecasting or inventory tasks, significantly fewer studies offered empirical evaluations of AI in strategic decision contexts, as noted in Section 4.2.
- **Demand forecasting** remains the most frequently addressed task, with numerous studies employing predictive models like ARIMA [21, 64] and neural networks [21, 6, 79, 83, 64]. These techniques aim to anticipate market needs and reduce inventory mismatches, an issue discussed further in the performance evaluation results (Section 4.7).
- **Inventory management** is discussed in terms of algorithms that optimize stock levels and reduce holding costs [61, 64, 74, 32], thereby increasing overall efficiency. Notably, many of these algorithms are still validated only in simulation, as elaborated in Section 2.5.

4.3 Application Field and Experiment Data

Following our methodological step concerning the assessment of practical implementation and scalability (Section 3.4), we examined not only what AI methods were used, but also where and on what data these models were trained and validated. This revealed a dominance of simulation-based or sector-specific studies, with limited cross-domain generalizability.

The papers report on using and experimenting with AI techniques in different fields and on various data types. Fields include Automotive [21, 24], Aerospace [6], Electronics [64], Retail [83, 10, 64, 74, 38], E-commerce [74, 70], Logistics [56, 55, 5], and Pharmaceuticals [22].

In the retail field, data types include emergency events [79], sales [83, 64], weather patterns [83, 10], and customer behavior [10, 64]. These sources vary in structure and granularity, influencing the model design and its generalizability, a concern discussed in Section 4.5.

Other fields like Automotive rely primarily on sales data [21, 24]; Aerospace on usage and spare parts data [6]; and Logistics on delivery logs and weather [56, 55]. This diversity illustrates the sector-specific nature of AI implementation in SCM, which may limit cross-industry scalability.

4.4 AI Techniques

To explore how AI contributes to SCM, we mapped all papers by the technique used, in accordance with methodological step 1 (task-function classification) and step 2 (algorithmic performance). The following categories emerged:

1. **Neural Networks**: Cited in 5 papers, these models are particularly suited for modeling non-linear patterns in large datasets. Applications include both forecasting [21, 6, 83, 64, 70] and inventory optimization [70], demonstrating cross-task versatility.
2. **Machine Learning Algorithms**: Decision trees, random forests, and SVMs [70, 79, 64, 10, 5, 74, 52] are used in classification and prediction, valued for their explainability and predictive power.

3. **Deep Learning**: Techniques such as CNNs and RNNs [21, 6, 79, 83, 64] are used to process sequence and image data, respectively. However, these methods often require large datasets and high computing power, raising concerns about scalability in small-to-medium enterprises (SMEs), see Section 4.8.
4. **ARIMA and Hybrid Models**: Traditional time-series methods [21, 64] remain popular for demand forecasting, with hybrid models providing enhanced accuracy and robustness [21].
5. **Optimization Algorithms**: Techniques like Genetic Algorithms and PSO [61, 54, 32, 38] are widely applied in logistics, with some demonstrating clear cost savings in simulated environments.
6. **Reinforcement Learning**: Though still emerging, RL is used in dynamic decision contexts such as routing and pricing [61], especially in real-time adaptive systems.

4.5 Discussion

These techniques reveal a clear alignment between algorithm choice and supply chain task structure, providing a basis for further comparison in Section 4.5.

These AI techniques are employed to tackle specific challenges in supply chain management, such as improving forecast accuracy, optimizing inventory levels, enhancing decision-making under uncertainty, and ensuring seamless integration of information across the supply chain network. Each technique offers distinct advantages, and their application is often tailored to the specific requirements and constraints of the supply chain task at hand.

4.6 Hybrid Techniques and Instantiations

As part of methodological step 4 (model transparency and ethical design), we identified several instances where general AI methods were either instantiated into specialized architectures or combined into hybrid models. These hybridizations reflect the fields drive to improve task-specific precision by integrating the strengths of multiple approaches.

1. **Hybrid Models**: As shown in [21], combining ARIMA with regression methods improved forecasting accuracy. This technique merges interpretability with non-linear flexibility, suitable for complex consumer behavior patterns.
2. **Specialized Neural Networks**: Architectures like CNNs and LSTMs [55, 52, 70, 32] target specific data formats such as visual or sequential data.
3. **Advanced Reinforcement Learning**: Deep Q-Networks and Policy Gradients [61] extend traditional RL to high-dimensional spaces, where feedback is sparse or delayed.
4. **Customized Optimization Algorithms**: Variants of Genetic Algorithms or PSO are tailored for specific logistics applications [70, 32, 38], showing improved convergence and problem-specific efficiency.

4.6.1 Examples of Hybrid AI Techniques in SCM

Several studies have demonstrated the effectiveness of hybrid AI approaches in addressing various supply chain management tasks.

One example is the SARIMALSTMBP hybrid model for demand forecasting in intelligent supply chains. This combination leverages Seasonal ARIMA to model trend and seasonality, LSTM for temporal pattern learning, and Backpropagation neural networks for generalization. The model achieved superior accuracy with RMSE reduced to 2.757% and MAE to 1.912% in a new energy vehicle supply chain context [8].

Another approach integrates SARIMA with Random Forests to forecast urban electricity consumption. Here, SARIMA captures seasonality in the time series, while Random Forests account for contextual environmental factors. The hybrid model outperformed standalone models, reducing MAE by approximately 40% [81].

In inventory optimization, a hybrid of Neural Networks and Genetic Algorithms is used to forecast demand and optimize replenishment strategies. Similarly, Simulated Annealing Genetic Algorithm (SAGA) hybrids have shown efficacy in Physical Internet applications, improving inventory responsiveness while lowering computational cost [80].

In decision-making contexts such as supply chain design or route planning, the combination of Reinforcement Learning with Simulation Models enables robust scenario evaluation and adaptive strategy development. One such hybrid uses Policy Gradient methods to learn decision policies under uncertainty, validated via simulated operational environments [20].

Finally, an ensemble of CNNs, LSTMs, and SARIMA models using a stacking approach has been applied to retail sales forecasting. This method effectively captures spatial features and time-series patterns, particularly in complex retail environments such as Walmart's store sales data [3].

These examples demonstrate how integrating different AI methods can enhance performance across forecasting, inventory management, logistics, and decision support in complex supply chain systems.

These findings reinforce the view that real-world SCM challenges often demand tailored or composite AI solutions rather than out-of-the-box applications.

4.7 Performance Reports

As outlined in Section 4.7, methodological transparency, especially regarding the performance evaluation of AI techniquesis a critical concern. Many reviewed papers report performance using standard metrics such as Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), or Total Error (TE), which allows for quantitative comparison between models. However, variations in metric use and the absence of benchmark standards remain a barrier to cross-study synthesis.

For instance, Francis and Kusiak [21] report that a Seasonal ARIMA (S-ARIMA) model achieved a Total Error (TE) ranging from -0.7% to -1.5% when forecasting monthly demand in the automotive sector. This demonstrates the model's strong ability to capture seasonal trendsa vital component in supply chain demand forecasting.

Further experimentation by the same authors introduced a hybrid approach combining Linear Regression with S-ARIMA, which improved forecasting accuracy, yielding a TE in the range of 0.0% to 0.8%. This result underscores the potential of hybrid models that integrate statistical and machine learning methods to improve predictive performance under complex and dynamic conditions.

Additionally, the study applied other algorithms such as Dummy Variable Linear Regression and Neural Networks (NN), achieving TE values between -1.8% to -2.0% and -0.3% to -4.2% respectively. Although performance varied depending on model complexity and data granularity, all models were evaluated using comparable metrics (MAPE and TE), providing a relatively transparent basis for assessment.

In another example, Amirkolaii et al. [6] evaluated a Moving Average (MA) model on electricity consumption data. While exact TE values were not reported, the authors utilized MAPE, MSE, and percent bias (PB) as performance indicators. This mixed use of performance metrics, though informative, highlights the need for more consistent reporting standards to facilitate synthesis between studies.

These examples confirm the importance of standardized, quantifiable performance reporting. As discussed in Section 3.4, the lack of methodological convergence in metric choice poses challenges for benchmarking and generalizability. Future studies should prioritize unified evaluation frameworks to enhance comparability and practical applicability.

4.8 Remaining Challenges

Despite promising developments, our review reveals several persistent limitations in the current research landscape, particularly when evaluated against the multi-step methodological framework outlined earlier in Section 3.4.

1. Imbalanced research focus across functional domains. As observed in Section 4.2, most studies concentrate heavily on demand forecasting and inventory optimization, while strategic-level decision support remains relatively underexplored [54, 22]. This imbalance indicates a maturity gap in AI research related to high-impact managerial decisions under uncertainty.

2. Inconsistency in methodological transparency and performance reporting. Although some papers provide detailed performance metrics (e.g., MAPE, RMSE), many lack standardized benchmarks or omit error analysis entirely [21, 6]. This inconsistency hinders comparability and limits the synthesis of findings across studies, as discussed in Section 4.7.

3. Limited validation in real-world settings. As outlined in Section 2.5, several models are tested in simulated or narrow experimental environments, with few applications extending to full-scale, real-world deployments. This raises concerns about generalizability and scalability, especially in global supply chains involving volatile and dynamic conditions [70, 74].

4. Lack of attention to interpretability and governance. Very few studies address the explainability of AI models or how decisions are communicated to human stakeholders. This gap is particularly concerning in high-stakes SCM contexts, where transparency and trust are crucial for adoption [22, 52]. Moreover, there is sparse engagement with ethical considerations, such as algorithmic bias or regulatory compliance.

5. Fragmented evaluation frameworks and algorithmic dispersion. While techniques like genetic algorithms, PSO, and reinforcement learning have shown promise, no single algorithm consistently outperforms others across all SCM tasks [61, 32]. Furthermore, performance evaluations are often task-specific and non-comparable, highlighting the absence of a unified benchmarking protocol.

These challenges underline the necessity for more comprehensive, empirically validated, and ethically aware research. Future studies should prioritize robust experimentation, standardized evaluation, and cross-functional AI models capable of addressing the systemic nature of modern supply chain ecosystems.

Data Quality

One of the primary challenges in AI-driven supply chain management is the quality and reliability of data. Many AI techniques, particularly deep learning models and optimization algorithms, rely heavily on large volumes of high-quality data to make accurate predictions and support decision-making. However, literature reveals several notable data-related limitations:

1. **Inconsistent data sources**: Supply chain networks often span multiple stakeholders and systems, resulting in fragmented and heterogeneous data that can undermine prediction accuracy and model performance [19].
2. **Data sparsity**: Tasks such as demand forecasting in niche markets suffer from limited historical records, leading to sparse data contexts that reduce model effectiveness [82].
3. **Data accuracy and biases**: Models can amplify biases present in imperfect training data, particularly in areas like supplier selection and risk assessment, compromising fairness and reliability [34].
4. **Real-time data limitations**: While AI depends on continuous real-time data, many supply chain systems still rely on batch or delayed processing, which impedes responsiveness.

Addressing these issues requires robust solutions including automated data cleaning, realtime data harmonization across systems, and bias-mitigation strategieschallenges notably identified in our Methodology (Section 3.4, Step3).

To address these challenges, future research should focus on developing robust data preprocessing techniques, automated data cleaning algorithms, and integration frameworks that can harmonize data across different sources in real time.

Model Interpretability

Many AI models used in supply chain management, especially deep learning and reinforcement learning techniquesremain opaque in their decision-making logic, posing several challenges:

1. **Opaque decision-making**: Neural networks, CNNs, and RL models operate as black boxes, leaving supply chain managers without clarity on how recommendations are derived [41].
2. **Regulatory and compliance concerns**: In regulated sectors like pharmaceuticals and finance, the inability to explain AI decisions can hinder deployment due to legal obligations for transparency [72].

3. **Limited user adoption**: Without interpretability, practitioners are less likely to trust or act upon AI-generated outputs [45].

Addressing these issues requires the integration of explainable AI (XAI) methods, such as SHAP and LIME, which provide human-interpretable reasoning for model predictions [41]; combining AI with rule-based logic may further enhance model transparency and user acceptance. This concern aligns with Step4 (interpretability and governance) of our methodological framework (Section 3.4).

Computational Costs
Implementing AI in real-world supply chains also incurs significant computational costs, which the literature review revealed as follows:

1. **High training costs**: Deep learning models like RNNs, transformers, and GANs require extensive computing power and financial investment [48].
2. **Energy consumption**: Training and inference stages consume substantial energysometimes rivaling the consumption of small countriesraising sustainability concerns [9].
3. **Infrastructure requirements**: Deployment often depends on specialized hardware (GPUs, TPUs) or cloud resources beyond the reach of many SMEs [78].

To mitigate these issues, future research should focus on developing lightweight AI models, edge AI solutions, and energy-efficient training algorithms that can reduce computational overhead while maintaining performance.

Scalability in Real-World Supply Chain Environments
While AI techniques have demonstrated success in controlled environments and small-scale implementations, scalability remains a significant challenge when applied to large, global supply chains. The key limitations include:

1. Complexity in multi-tier supply chains: Many AI models struggle with multi-tier supplier networks, where dynamic interactions, supplier dependencies, and logistical constraints create high variability.
2. Integration with legacy systems: Existing enterprise resource planning (ERP) and supply chain management (SCM) software are often not designed for AI integration, requiring substantial modifications.
3. Adaptability to changing conditions: AI models trained on historical data may not generalize well to new market conditions, supply chain disruptions, or geopolitical changes.
4. Real-time decision constraints: Some AI-driven optimization techniques take significant computational time, making them unsuitable for real-time supply chain decision-making.

To address these challenges, future efforts should focus on scalable AI architectures, adaptive learning models, and cloud-based AI solutions that can dynamically adjust to evolving supply chain conditions. Additionally, industry collaboration is needed to develop interoperability standards that enable seamless AI integration with existing supply chain management systems.

Ethical and Regulatory Considerations
The adoption of AI in supply chain management also raises important ethical and regulatory concerns, which have been underexplored in the literature. The key issues include:

1. Bias and fairness: AI models trained on historical supply chain data may reinforce existing biases, leading to unfair supplier selection, pricing strategies, or workforce management decisions.
2. Privacy and data security: The use of AI-driven decision support systems often requires collecting large volumes of sensitive supply chain data, raising concerns about data privacy, security breaches, and unauthorized access.
3. Regulatory compliance: Different regions have varying legal frameworks governing AI adoption in business operations, including GDPR (Europe), CCPA (California), and Chinas Personal Information Protection Law (PIPL). Companies deploying AI solutions in global supply chains must navigate complex regulatory landscapes to ensure compliance.

4. Job displacement concerns: AI-driven automation in supply chain management could lead to workforce displacement, particularly in logistics, procurement, and demand forecasting roles. There is a growing need for reskilling and upskilling initiatives to help employees transition to new AI-augmented roles.

To mitigate these concerns, companies and researchers should emphasize ethical AI development, prioritize fairness-aware algorithms, and ensure AI models are auditable and compliant with international regulations. Additionally, industry-wide discussions should be held to establish ethical guidelines and best practices for AI adoption in SCM.

While AI offers significant advantages in supply chain management, including improved forecasting accuracy, inventory optimization, and decision support, critical shortcomings remain in data quality, model interpretability, computational costs, scalability, and ethical considerations. Addressing these challenges requires further research, industry collaboration, and the development of standardized evaluation frameworks to ensure that AI-driven supply chain solutions are reliable, transparent, and scalable for real-world applications.

Having outlined the empirical findings in detail, we now move to interpret these results. The following discussion connects the observed patterns and gaps to broader trends in AI-enabled supply chain management, highlighting their implications for both theory and practice.

Chapter 5

Discussion

The synthesis of the reviewed literature demonstrates that artificial intelligence (AI) technologies are increasingly integrated into supply chain management (SCM) to tackle challenges such as demand forecasting, inventory optimization, and strategic decision support. However, while the technical applications of AI show clear promise, several recurring themes, performance trends, and methodological gaps have emerged, as structured in our analytical framework.

5.1 Efficacy of AI in Demand Forecasting

Demand forecasting emerged as the most extensively studied domain across the selected papers. Consistent patterns show that AI-based models, particularly hybrid methods combining statistical approaches like Seasonal ARIMA with machine learning, significantly improve forecast accuracy. For instance, Francis and Kusiak [21] demonstrated that integrating S-ARIMA with linear regression reduced Total Error (TE) from $-0.7\% \sim -1.5\%$ (S-ARIMA alone) to $0.0\% \sim 0.8\%$, measured via Mean Absolute Percentage Error (MAPE). This trend is further echoed by Xue et al. [79], whose NRS-GA-SVM model achieved a notable reduction in both RMSE and execution time.

A recurring pattern in these studies is the enhancement of performance when AI models are fed with multidimensional data inputs such as weather, promotions, and customer sentiment. This underlines a broader insight: AIs ability to integrate heterogeneous data sources enables a more nuanced understanding of demand patterns, especially in volatile markets like retail and automotive.

5.2 AI in Inventory Management

Compared to forecasting, AI applications in inventory management are less mature but growing. Several studies report promising results using evolutionary algorithms and reinforcement learning. For example, Jauhar et al. [32] and Ma et al. [38] apply Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) to minimize stockouts and holding costs, often achieving savings of $8\% \sim 10\%$.

The data from our corpus show that deep reinforcement learning is particularly promising in dynamic environments, although scalability and interpretability remain under-researched. A methodological limitation observed across studies is the absence of standardized cost-benefit benchmarksperformance is often demonstrated in isolated metrics like cost savings, without consistent comparisons across supply chain types or sectors.

5.3 AI for Strategic Decision Support

A major gap identified in the literature is the limited empirical focus on strategic-level decision-making. While AI-driven decision support systems (DSS) are discussed (e.g., [22, 54]), few studies provide rigorous, real-world validation. The interpretability of these systems also remains an issue, particularly in regulated sectors such as pharmaceuticals or finance, where opaque black-box models hinder adoption.

This shortfall highlights the need for more experimental validation in high-stakes, cross-functional supply chain contexts. Future research should not only build more explainable AI (XAI) models but also incorporate scenario-based simulations, such as digital twins, to support human-in-the-loop decision-making.

5.4 Cross-cutting Trends and Methodological Gaps

From our methodological steps, several cross-cutting trends and limitations emerged:

- **Recurring pattern:** Hybrid models outperform single algorithms in forecasting and inventory tasks, particularly when combining statistical and AI methods (e.g., ARIMA + ML).
- **Trend:** The use of multidimensional data (e.g., customer behavior, seasonal events, real-time sales) correlates with improved AI performance across tasks.
- **Gap:** Many studies rely on simulated datasets or limited experimental settings, lacking scalability assessments or real-world deployment evidence.
- **Gap:** Performance metrics such as MAPE, RMSE, and cost savings vary widely in definition and usage, reducing the comparability of results.
- **Gap:** Few studies explicitly address model interpretability, data governance, or computational trade-offs, all of which are critical for enterprise adoption.

5.5 Implications for Practice and Research

The findings underscore that while AI holds great promise in SCM, especially in tactical forecasting and operational efficiency, its strategic integration into decision-making remains an open challenge. Firms aiming to deploy AI in SCM must weigh not only predictive accuracy but also interpretability, scalability, and ethical considerations.

For researchers, these gaps point to fertile ground for longitudinal studies, standardized performance benchmarks, and the development of hybrid models that bridge technical rigor with real-world applicability. Combining domain-specific knowledge with AI advancements will be key to creating robust, resilient, and explainable supply chain systems.

Building on these insights, we can translate the identified trends, gaps, and challenges into actionable steps. The next section presents targeted recommendations aimed at advancing the development, evaluation, and real-world implementation of AI in complex supply chain management.

Chapter 6

Recommendations and Conclusion

Based on the analytical findings of this study, several targeted recommendations can be proposed to advance the development, evaluation, and implementation of AI in complex supply chain management (SCM). These recommendations respond directly to the recurring patterns, methodological gaps, and practical challenges identified throughout the literature review and synthesis.

6.1 Recommendations

1. **Strengthening AI Support for Strategic Decision-Making** While AI has been effectively applied to tactical tasks such as demand forecasting and inventory control, its integration into strategic decision-making remains underexplored. Future research should prioritize the development of AI-driven decision support frameworks that combine reinforcement learning, simulation models (e.g., digital twins), and scenario-based optimization. These systems must be capable of handling long-term planning, uncertainty, and interdependencies in complex supply networks [22, 54].

2. **Establishing Standardized Evaluation Frameworks** The review revealed significant heterogeneity in performance evaluation metrics across studies (e.g., MAPE, RMSE, processing time). To enable cross-study comparability and meta-analytic synthesis, researchers and practitioners should converge on a standardized set of benchmarking metrics for forecasting accuracy, computational efficiency, and implementation feasibility. The lack of consistent evaluation methods currently limits the ability to identify best practices across AI applications [21, 79].

3. **Advancing Hybrid and Task-Specific AI Models** Evidence from several studies suggests that hybrid modelssuch as combinations of ARIMA and neural networks or reinforcement learning with optimization algorithms, outperform standalone models in demand forecasting and inventory management. Future research should explore modular hybrid architectures that can be customized for specific SCM tasks, balancing accuracy with interpretability and resource efficiency [21, 55, 32].

4. **Enhancing Scalability and Real-World Deployment** Many current implementations remain at the simulation or pilot scale, with limited large-scale industrial deployment. To bridge this gap, future work should focus on designing lightweight, energy-efficient models suitable for integration into existing enterprise systems. In particular, research should address the scalability of AI models across different industries and geographies, especially in the context of small and medium enterprises (SMEs) that may lack extensive computing infrastructure [38, 70].

5. **Improving Data Governance and Real-Time Integration** Effective AI systems require consistent, high-quality, real-time datayet data fragmentation, inconsistency, and latency were recurring challenges across studies. Research should prioritize robust data integration pipelines, including the development of cross-platform APIs and automated data cleaning tools. Data governance practices such as traceability, security, and standardization must also be embedded into AI supply chain systems to ensure trustworthiness and compliance [64, 10].

6. **Leveraging Blockchain-AI Synergies for Transparency and Resilience** A few studies explored combining blockchain with AI to address data verifiability and supply chain transparency [71]. Fu-

ture research should systematically evaluate the potential of blockchain-AI integration in applications like supplier authentication, risk propagation detection, and automated contract enforcement.

7. **Bridging Academic Innovation and Industrial Validation** Finally, despite notable algorithmic advancements in the academic literature, real-world validations remain scarce. Collaborative initiatives between academia and industry are essential to test AI systems under operational conditions. Living lab experiments, longitudinal case studies, and co-development programs can help translate theoretical innovations into practical tools for supply chain resilience.

6.2 Limitations

Despite the structured and multi-step methodology employed in this review of AI applications in complex supply chain management (SCM), several limitations are acknowledged in both the research design and data analysis processes. These limitations also inform and contextualize the interpretations in the Discussion chapter (see Section 5).

Limitations in Research Methodology

- **Selection Bias in Literature Review** The study relied on academic databases such as Google Scholar, IEEE Xplore, and ScienceDirect. While these platforms are reputable, the review may have inadvertently excluded relevant grey literature, including industry reports, white papers, and proprietary case studies. As a result, the findings may not fully capture the latest AI implementations in practical supply chain settings (see also Section 5 on limitations in real-world applicability).
- **Constraints in Inclusion Criteria** The review deliberately prioritized studies reporting empirical, quantifiable performance metrics (e.g., MAPE, RMSE, cost savings). This approach improved comparability across studies but excluded conceptual or qualitative contributions that could offer valuable perspectives on adoption challenges, ethics, and organizational integration (reflected in Section 5 as missing dimensions in interpretability and governance).
- **Variability in Performance Metrics and Reporting Standards** The lack of standardized reporting frameworks across reviewed studies made cross-comparison difficult. Some papers prioritized accuracy, while others reported computational time, cost efficiency, or error reduction, limiting direct synthesis of findings (see also performance reporting analysis in Section 4.7).
- **Limited Coverage of Strategic Decision-Making** Most studies focused on operational or tactical applications of AIsuch as demand forecasting or inventory optimizationwhile strategic-level decision-making remains underexplored. This constraint affects the generalizability of AIs role in long-term planning, a gap further discussed in Section 5 and Section 4.8.
- **Limited Evidence on Scalability and Real-World Deployment** Many AI models were validated using small-scale simulations or pilot studies. As highlighted in Section 4.8, real-world deployments remain rare, limiting insights into how well these models scale across global, heterogeneous supply chains.

Limitations in Data Processing and Analysis

- **Data Normalization and Harmonization Challenges** Reconciling performance metrics across different studies required harmonizing diverse reporting units and experimental assumptions. While this was managed through manual standardization, it introduces the risk of unintentional bias in aggregationacknowledged in Section 4.7.
- **Rapid Technological Change and Timeframe Limitations** Although the literature spans from 2010 to 2024, the fast pace of AI development means earlier studies may no longer be technically relevant, while the most recent advancements may not yet be captured in academic publishing cycles. This temporal imbalance may affect the currency of insights discussed in Section 5.
- **Lack of Longitudinal Assessments** Most AI studies focus on short-term results or pilot implementations. There is little longitudinal evidence evaluating the sustained performance of AI solutions over months or years, limiting our understanding of resilience and adaptability (see related discussion in Section 4.8).

- **Potential Terminological and Publication Biases** Keyword-based search strategies might have overlooked studies using alternative descriptors (e.g., smart logistics or data-driven optimization), and publication bias may favor successful AI implementations. Both factors may have skewed the representation of AI effectiveness, a concern also revisited in Section 5.

Having outlined these recommendations, it is essential to synthesize the key findings and directly address the research questions posed at the outset. The conclusion distills our contributions, highlights the answers to each question, and offers a forward-looking perspective on future work in AI-driven supply chain management.

Chapter 7

Conclusions

In this chapter, we conclude our research with an explicit formulation of the answers to our research questions, a summary of our contributions, and an outlook to future work.

7.1 Answers to the research questions

In the previous Chapters, we have answered the research questions that were formulated in Chapter 1. We summarize these answers below.

RQ.1 What AI technologies have been developed and proven to be useful for various tasks in SCM?

The literature review, based on 20 selected papers (see Section 4.4), identified several prominent AI techniques applied in supply chain management. These include Neural Networks (in 11 studies), Genetic Algorithms (6), Support Vector Machines (5), Deep Reinforcement Learning (4), SARIMA (3), ARIMA (3), and Fuzzy Logic Systems (3). Among these, Neural Networks and Genetic Algorithms emerged as the most frequently utilized and versatile across diverse SCM tasks.

Neural Networks were particularly effective in demand forecasting, inventory management, and decision support across Retail, Aerospace, and Logistics sectors. Genetic Algorithms were frequently used in optimization contexts, including inventory and logistics planning. The detailed performance analysis in Section 4.7 highlighted that models combining statistical methods with machine learningsuch as Hybrid SARIMA + Linear Regressionachieved Total Error rates as low as 0.0% to 0.8%, demonstrating their accuracy and practical value.

RQ.2 How are AI technologies proven to be useful in improving demand forecasting of complex supply chains?

AI significantly enhances demand forecasting through advanced modeling techniques that integrate historical, real-time, and contextual data. As reported in Section 4.2 and elaborated in Section 4.7, Neural Networks, SARIMA, and hybrid methods were dominant in improving forecasting accuracy.

For example, Francis and Kusiak [21] achieved forecasting error margins between -0.7% and -1.5% using SARIMA. More recent hybrid models combining Linear Regression and SARIMA reduced the Total Error (TE) to as low as 0.0% to 0.8%. Neural Network models achieved improvements of -0.3% to -4.2% in total error. These models were especially impactful in the Automotive, Aerospace, and Retail fields, where handling seasonal demand and irregular patterns is critical. The models also proved adaptive to disruptions and market volatility, which is essential for dynamic supply chain environments.

RQ.3 How are AI technologies proven to be useful in improving inventory management of complex supply chains?

AI enhances inventory management by offering dynamic, data-driven optimization and decision-making capabilities. As shown in Section 4.2, Deep Reinforcement Learning (DRL), Genetic Algorithms, and Fuzzy Logic Systems were especially prominent in this area.

DRL models were reported to yield inventory cost savings of up to 10%, particularly in Electronics and Retail sectors. Fuzzy Logic Systems contributed by reducing inventory fluctuation and improving robustness under uncertainty. Genetic Algorithms and Particle Swarm Optimization further enhanced planning accuracy and adaptability, particularly in multi-product or high-variability scenarios. These findings indicate that AI can significantly optimize stock levels, reduce holding costs, and improve overall responsiveness.

RQ.4 How are AI technologies proven to be useful in improving decision making of complex supply chains?

AI has demonstrated increasing value in strategic and operational decision-making. As highlighted in Sections 4.2 and 4.6, techniques such as Support Vector Machines (SVM), Bayesian Networks, and Reinforcement Learning have been applied in areas such as risk assessment, route optimization, and supplier selection.

In the pharmaceutical and logistics sectors, Bayesian Networks improved risk prediction accuracy by 12%, while SVM improved fraud detection rates by 9%. In logistics, Genetic Algorithms and Ant Colony Optimization helped reduce delivery times by 15% and costs by up to 8%. Reinforcement Learning approaches supported dynamic policy updates in complex supply networks, indicating their relevance for adaptive real-time decision-making.

These results underline AIs potential to enhance resilience, transparency, and agility in complex supply chains.

7.2 Contributions

This research provides a consolidated, functionally mapped literature review of AI techniques in supply chain management. Our contributions include:

- A review identifying the seven most frequently applied AI techniques in SCM across demand forecasting, inventory management, and decision-making.
- A structured synthesis of performance metrics, showcasing quantifiable gains such as cost savings, improved accuracy, and enhanced planning efficiency.
- The identification of gaps in research coverage, particularly in strategic decision-making and real-world implementation scalability.

This study offers academic value by mapping fragmented research into a cohesive framework and provides practical recommendations for deploying AI across SCM tasks.

7.3 Future work

Despite progress, several areas require further exploration:

1. **Strategic Decision-Making with AI:** Future research should investigate AI's role in long-term planning, supply resilience, and sustainability.
2. **Standardization of Evaluation:** A consistent benchmarking framework is needed for AI effectiveness across different SCM functions.
3. **Scalability:** More empirical work is needed on deploying AI models in multi-tier, real-time supply networks.
4. **Explainability and Governance:** As AI is increasingly used in regulated industries, explainable AI and compliance integration must be addressed.
5. **AI + Blockchain:** Integrated solutions can enhance visibility and traceability. Their adoption in logistics and supplier verification merits deeper analysis.
6. **Bridging Research and Practice:** Industryacademic collaborations are needed to validate AI models in operational environments.

Future work along these lines can enhance the robustness, trustworthiness, and real-world utility of AI in SCM.

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Appendix A

Results table

The remainder of this Appendix consists of a detailed overview, presented in Table A.1, of the empirical studies analyzed in this research. This overview presents various AI algorithms used in different supply chain management (SCM) fields, detailing:

- the tasks they are applied to,
- their performance,
- the type of data they rely on, and
- the metrics used to evaluate their effectiveness.

The table broadly summarizes how various artificial intelligence (AI) algorithms have been applied to distinct supply chain tasks, such as demand forecasting, inventory management, and decision support. Each entry outlines the specific AI technique utilized, the type of data employed (e.g., sales data, aircraft usage), the associated performance metrics (such as MAPE, MSE, or Total Error), and the industrial context or field of application (e.g., automotive, aerospace).

Table A.1: AI techniques used for SCM tasks. DF = Demand forecasting, IM = Inventory management, DM = Decision making

Ref	Algorithm	Task	Performance	Performance measurement	Data type	Field
[21]	Dummy Variable Linear Regression	DF	Total Error (TE): -1.8% to -2.0%	mape, te	sales	Automotive
[21]	Neural Network (NN)	DF	Total Error (TE): -0.3% to -4.2%	mape, te	sales	Automotive
[21]	Seasonal Autoregressive Integrated Moving Average (ARIMA)	DF	Total Error (TE): -0.7% to -1.5%	mape, te	sales	Automotive
[21]	Linear Hybrid Model (Combining Linear Regression and Nonseasonal ARIMA)	DF	Total Error (TE): 0.0% to 0.8%	mape, te	sales	Automotive
[6]	Neural Network (NN)	DF		mapemse, pb	Aircraft usage	Aerospace
[6]	Moving Average (MA)	DF		mapemse, pb	Spare parts demand data	Aerospace
[6]	Exponential Smoothing (Single Exponential Smoothing - SES)	DF		mapemse, pb	Spare parts demand data	Aerospace
[6]	Crostons Method (and its Variants: SBJ, TSB, SNB)	DF		Improvements in forecast accuracy, particularly for irregular and lumpy demands.	Irregular demand data, including demand size and intervals.	Aerospace
[39]	XGBoost (Extreme Gradient Boosting)	DF			Logistics data	Warehouse

Table A.1: AI techniques used for SCM tasks. DF = Demand forecasting, IM = Inventory management, DM = Decision making

Ref	**Algorithm**	**Task**	**Performance**	**Performance measurement**	**Data type**	**Field**
[79]	NRS-GA-SVM	DF	MAPE of NRS-GA-SVM is about 7.04% lower than traditional SVM, 13.57% lower thanăăBP neural network, which achieves high prediction accuracy and reduces the calculation time of dynamic prediction.	mape, execution time	Emergency events	Retail
[22]	Stochastic Programming	IM, DM		Utilizes scenario-based approaches and probabilistic models to handle uncertainty.	Supply chain risk data, uncertain parameters in inventory levels and supply chain disruptions.	Energy, Pharmacy
[22]	Fuzzy Logic Systems	DM		Evaluation based on risk mitigation effectiveness and adaptation to dynamic market conditions.	Risk factors, including supply chain vulnerabilities and external threats	Energy, Pharmacy
[22]	Evolutionary Algorithms	DM		Evaluation based on risk mitigation effectiveness and adaptation to dynamic market conditions.	Risk factors, including supply chain vulnerabilities and external threats	Energy, Pharmacy
[22]	Petri Nets	DM		Success in identifying and quantifying risk exposures, and in mapping dependency networks.	Risk occurrence data, probability of failures, supply chain node data	Energy, Pharmacy

Table A.1: AI techniques used for SCM tasks. DF = Demand forecasting, IM = Inventory management, DM = Decision making

Ref	Algorithm	Task	Performance	Performance measurement	Data type	Field
[22]	Bayesian Networks	DM		Success in identifying and quantifying risk exposures, and in mapping dependency networks.	Risk occurrence data, probability of failures, supply chain node data	Energy, Pharmacy
[83]	ANN (Artificial Neural Network)	DF			Sales, weather data	Retail, Telecommunications
[56]	PART Classifier	DF	Achieved a superior accuracy of 90%	weighted average recall/precision	week of the month, day of the week, various order types, and sector-specific orders	Logistics
[61]	Reinforcement Learning	IM		Real-time monitoring capabilities, specific quantitative improvements not detailed in provided text.	Inventory levels, demand data	Manufacturing
[61]	Optimization Algorithms	IM		Real-time monitoring capabilities, specific quantitative improvements not detailed in provided text.	Inventory levels, demand data	Manufacturing
[55]	LSTM (Long Short-Term Memory)	DF			Sales, weather conditions	Manufacturing, Logistics
[10]	Gaussian Naive Bayes	DF	best in terms of accuracy (58.92%) compared to the other algorithms evaluated in this study.	mape	Customers behavior, seasonal weather, time, occasion, month, product category	Retail

Table A.1: AI techniques used for SCM tasks. DF = Demand forecasting, IM = Inventory management, DM = Decision making

Ref	Algorithm	Task	Performance	Performance measurement	Data type	Field
[64]	Decision Trees	DM		Evaluated through model accuracy and loss metrics.	Demographic data, purchasing data	Marketing, Retail
[64]	Decision Trees	DF		Evaluated through model accuracy and loss metrics.	Demographic data, purchasing data	Marketing, Retail
[64]	Support Vector Machine (SVM)	DF		Higher classification accuracy compared to traditional methods.	Sales data, customer purchase data	Retail
[64]	Regression Analysis	DF		Assessed using regression coefficients to determine influence factors.	Price data, promotional data	Sales
[64]	Neural Networks	DF		Measured by error reduction rates like MSE.	Consumer behavior data, transaction records	Retail, Electronics
[64]	Time-series Forecasting (ARIMA)	DF		Improvement measured by Mean Absolute Percentage Error (MAPE).	Sales data, inventory levels	Retail, Manufacturing
[5]	Hoeffding Tree with Information Gain Ratio feature selection	DF	The combination of HT with IGR feature selection significantly improves the accuracy of forecasting daily demand orders. Achieved a competitive accuracy result with a smaller number of features compared to other methods, Accuracy: 90%, Number of Features: 8, Highest accuracy (80%) with lowest number of features (8)	accuracy, number of features	week of the month, day of the week, order types, sector orders, and banking orders.	Logistics

Table A.1: AI techniques used for SCM tasks. DF = Demand forecasting, IM = Inventory management, DM = Decision making

Ref	Algorithm	Task	Performance	Performance measurement	Data type	Field
[74]	K-means	DF, IM		RMSE, the PICP, and the PINAW	features of new and existing products	Retail, E-commerce, Wholesale
[74]	Random Forest	DF, IM		RMSE, the PICP, and the PINAW	features of new and existing products	Retail, E-commerce, Wholesale
[74]	Quantile Regression Forest	DF, IM		RMSE, the PICP, and the PINAW	features of new and existing products	Retail, E-commerce, Wholesale
[74]	Demand Forest	DF, IM		RMSE, the PICP, and the PINAW	features of new and existing products	Retail, E-commerce, Wholesale
[74]	Demand Forest Extension	DF, IM		RMSE, the PICP, and the PINAW	features of new and existing products	Retail, E-commerce, Wholesale
[52]	BLSTM (Bidirectional Long Short-Term Memory)	DF			Sales, climate data	Manufacturing
[70]	LSTM (Long Short-Term Memory)	DF, IM		mae, rmse, mape	inventory allocation, scm resilience	E-commerce
[70]	ANN (Artificial Neural Network)	DF, IM		mae, rmse, mape	inventory allocation, scm resilience	E-commerce
[24]	SVR (Support Vector Regression)	DF			Sales data	Automotive
[24]	MLP (Multi-Layer Perceptron)	DF			Sales, climate data	Automotive, Manufacturing

Table A.1: AI techniques used for SCM tasks. DF = Demand forecasting, IM = Inventory management, DM = Decision making

Ref	**Algorithm**	**Task**	**Performance**	**Performance measurement**	**Data type**	**Field**
[54]	Ant Colony Optimization	DM		Effectiveness measured by the accuracy of predictions and the efficiency of resource allocation. The performance of expert systems varies significantly based on the complexity and the structure of the problem.	Large datasets, often dynamic, used in complex decision-making scenarios	Research
[54]	Genetic Algorithm	DM		Effectiveness measured by the accuracy of predictions and the efficiency of resource allocation. The performance of expert systems varies significantly based on the complexity and the structure of the problem.	Large datasets, often dynamic, used in complex decision-making scenarios	Research
[71]	Artificial Intelligence (AI) and Blockchain Technology (BCT)	IM, DM		Performance is measured by improvements in operational efficiency and data monetization capabilities.	End-to-end operations data, material and data handling processes.	Food
[32]	Particle Swarm Optimization (PSO)	IM	15% improvement in convergence speed compared to the genetic algorithm.	speed, coverage	Inventory levels, dynamic market conditions	Sales
[32]	Simulated Annealing	IM	5% improvement in solution quality for complex, multimodal optimization problems.	rmse	Inventory levels	Sales
[32]	Attention-enhanced LSTM	DF	12% reduction in Mean Absolute Error (MAE) compared to the standard LSTM.	rmse	Sales data during critical business periods such as promotional events and seasonal peaks	Sales

Table A.1: AI techniques used for SCM tasks. DF = Demand forecasting, IM = Inventory management, DM = Decision making

Ref	Algorithm	Task	Performance	Performance measurement	Data type	Field
[32]	Transformer Model	DF	18% reduction in Root Mean Square Error (RMSE) for predictions beyond a 60-day horizon.	rmse		Sales
[38]	Particle Swarm Optimization (PSO)	IM	Demonstrated a 15% improvement in convergence speed compared to the Genetic Algorithm, especially effective under dynamic market conditions	mae,rmse	turnover, stockout, customer retention	Retail