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SYSTEMATIC LITERATURE REVIEW ON ARTIFICIAL INTELLIGENCE APPLICATIONS IN SUPPLY CHAIN DEMAND FORECASTING

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ABSTRACT

This systematic review investigates the applications of artificial intelligence (AI) in supply chain demand forecasting, focusing on the performance of AI-driven models compared to traditional forecasting techniques. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, a comprehensive search was conducted, yielding a final selection of 65 peer-reviewed articles for in-depth analysis. The review explores the advantages of AI models, particularly machine learning (ML) and deep learning (DL), in improving forecasting accuracy, scalability, and responsiveness to real-time data. It also examines AI's applications across various industries, including retail, manufacturing, e-commerce, and logistics, where AI-driven models have significantly enhanced inventory management, production scheduling, and operational efficiency. However, the review highlights challenges related to data quality, model complexity, and high implementation costs, which limit the broader adoption of AI in demand forecasting. This study provides valuable insights into the current state of AI applications in supply chain management and suggests areas for future research, particularly in improving data management and developing more interpretable AI models to facilitate wider implementation.

KEYWORDS

Artificial Intelligence (AI); Supply Chain Management; Demand Forecasting; Machine Learning; Predictive Analytics

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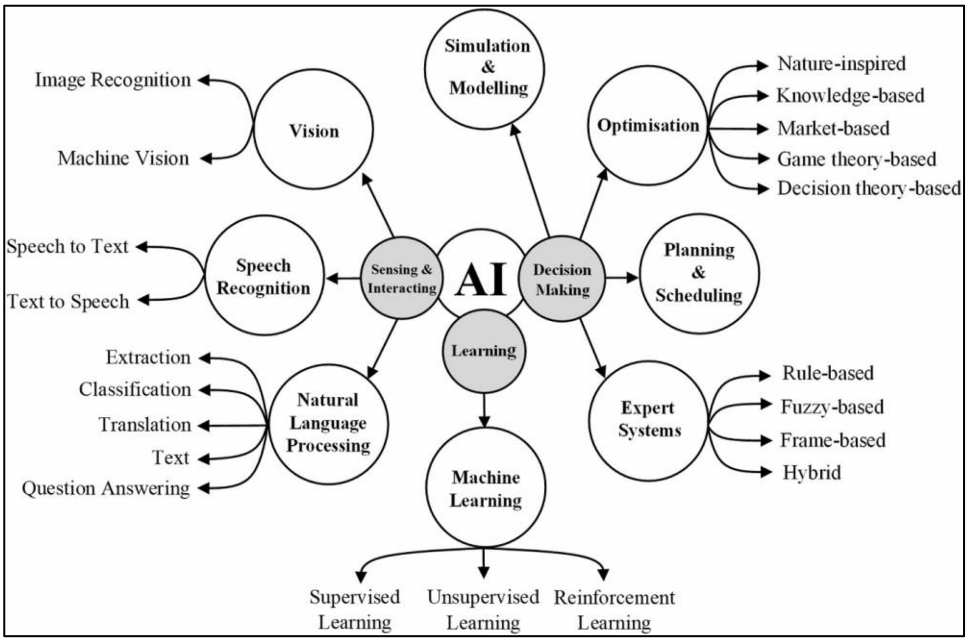
1 Introduction

The integration of artificial intelligence (AI) into supply chain management (SCM) has revolutionized traditional practices, particularly in the area of demand forecasting (Xue et al., 2005). As global supply chains become more complex, organizations face significant challenges in predicting demand with accuracy and agility (Garvey et al., 2015). Traditional demand forecasting models, which rely heavily on historical data and statistical methods, have been found inadequate in addressing the uncertainties and dynamic nature of modern supply chains (Carbonneau et al., 2008). In response to these limitations, AI technologies such as machine learning (ML), deep learning (DL), and natural language processing (NLP) have emerged as transformative tools that enhance predictive capabilities by analyzing vast and diverse data sources. AI-based demand forecasting models leverage real-time data, provide more accurate predictions, and improve the decision-making process across supply chain networks (Barratt & Oke, 2007).
AI-driven demand forecasting has evolved through various stages, from simple predictive models to advanced techniques capable of learning from data in real-time (Tako & Robinson, 2012). Early applications of AI in SCM focused primarily on automating routine tasks and optimizing inventory management (Abar et al., 2017). However, the rapid growth of data generated through digital platforms and the development of more sophisticated algorithms have enabled the evolution of AI applications in demand forecasting (Turowski, 2002). The use of machine learning algorithms, particularly those that incorporate reinforcement learning and deep neural networks, has expanded the scope of forecasting models beyond mere pattern recognition to advanced prediction capabilities, accounting for various market trends, consumer behaviors, and external factors such as economic shifts or disruptions (Wu, 2010). This shift reflects the broader trend of AI adoption in supply chain management, where AI is now seen as a critical enabler of digital transformation. Several studies have demonstrated the effectiveness of AI models in improving demand forecasting accuracy compared to traditional approaches. For instance, Priore et al. (2018) highlighted that AI techniques, such as ML and DL, can capture complex, non-linear relationships in data, which are often missed by conventional statistical models. These AI systems utilize a range of data sources, including social media sentiment, weather data, and real-time market fluctuations, which contribute to more robust and adaptive forecasting models. Additionally, recent advancements in AI have allowed for the integration of unstructured data, such as textual data and

Figure 1: Applications and Components of Artificial Intelligence (AI) in Decision-Making and Learning



Source: Pournader et al. (2021)

images, further enhancing forecasting precision (Xue et al., 2005). The ability to process and analyze such diverse datasets positions AI as a vital tool in addressing the challenges of fluctuating demand in volatile supply chain environments.

As AI continues to evolve, its role in demand forecasting is expected to grow more prominent, especially with the integration of big data and cloud computing technologies. The scalability of AI models, supported by cloud-based platforms, allows organizations to process large volumes of data in real-time, offering more timely and accurate demand forecasts (Pournader et al., 2019). In addition, cloud computing enhances the accessibility and deployment of AI tools, enabling even small and medium-sized enterprises (SMEs) to adopt sophisticated AI-driven forecasting systems (Boyack & Klavans, 2010). These advancements highlight the growing recognition of AI as a key component of supply chain strategy, particularly in enhancing responsiveness and reducing the risks associated with demand volatility. Despite the significant progress in AI applications for demand forecasting, challenges remain in terms of model interpretability and the integration of AI systems with existing SCM infrastructure. Researchers such as Tang et al. (2008) have pointed out that while AI models offer superior predictive performance, their complexity often makes it difficult for supply chain managers to understand how the forecasts are generated. This lack of transparency can hinder the widespread adoption of AI tools in some industries. Furthermore, the successful implementation of AI-driven forecasting requires seamless integration with enterprise resource planning (ERP) systems and other supply chain software, which may involve substantial investment and technological readiness. Nonetheless, the potential of AI to transform demand forecasting processes remains immense, with ongoing research focusing on overcoming these challenges and expanding the applications of AI across various sectors (Boyack & Klavans, 2010). An essential objective of this systematic literature review is to comprehensively analyze the existing research on AI applications in supply chain demand forecasting, focusing on how AI technologies have evolved and contributed to improving forecasting accuracy and efficiency. By synthesizing studies that explore the implementation of machine learning (ML), deep learning (DL), and other AI-driven techniques, this review seeks to identify the specific models and algorithms that have been most effective in various supply chain contexts. Additionally, this review aims to evaluate the challenges and limitations associated with the adoption of AI in demand forecasting, as well as highlight areas where further research and development are needed. Through a critical assessment of the literature, the objective is to provide insights into the current state of AI applications in demand forecasting and offer recommendations for future research directions in this field.

2 Literature Review

The growing complexity of global supply chains, coupled with rapid technological advancements, has significantly increased the need for more sophisticated demand forecasting methods. Traditional forecasting techniques, which rely primarily on historical data and linear models, have often proven insufficient in the face of today's volatile and uncertain market conditions (Fildes et al., 2019). As a result, artificial intelligence (AI) has emerged as a powerful tool for enhancing demand forecasting accuracy and efficiency. This section of the review explores the evolution of AI applications in supply chain demand forecasting, synthesizing key findings from recent studies to highlight how AI-driven methods such as machine learning (ML), deep learning (DL), and reinforcement learning are reshaping the field. Furthermore, this review examines the strengths and limitations of various AI-based models, their comparative performance against traditional techniques, and the challenges encountered in their implementation. By providing a comprehensive analysis of the existing literature, this section lays the foundation for understanding the current state of AI in demand forecasting and identifying future research opportunities.

2.1 Overview of Traditional Demand Forecasting

Traditional demand forecasting methods, such as time-series analysis, regression models, and exponential smoothing, have been widely used across industries for decades. These approaches rely heavily on historical sales data to predict future demand trends (Barták et al., 2008). Time-series analysis, for example, focuses on identifying patterns like seasonality and trends within historical data, while regression models aim to establish relationships between demand and other variables, such as price and promotions (Gunasekaran et al., 2017).

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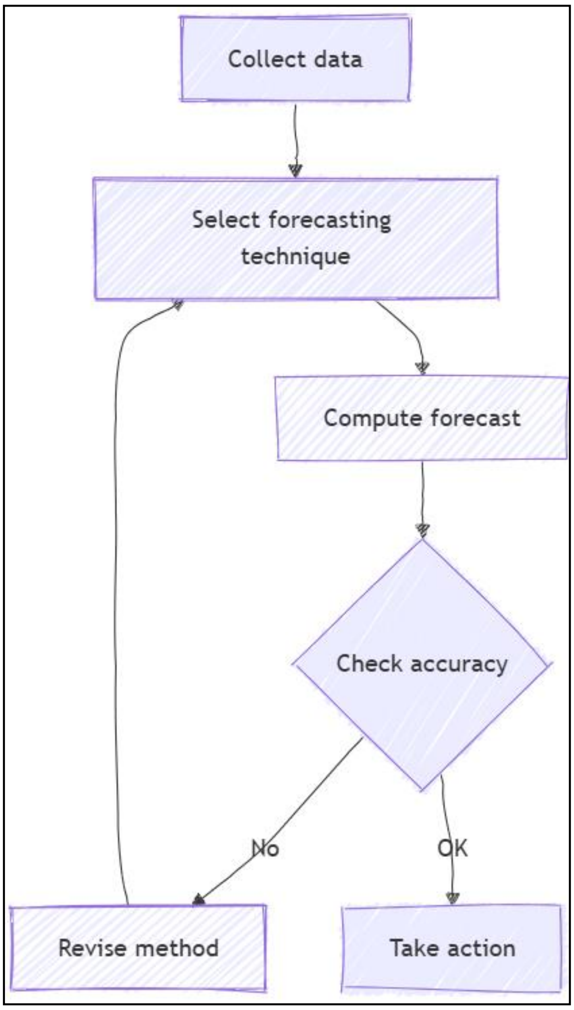
Figure 2: Forecasting Process Flowchart



These models have proven useful in relatively stable environments, where past patterns can reliably inform future outcomes (Barták et al., 2008; Sah et al., 2024; Sikder et al., 2024). Despite their long-standing use, traditional models often struggle with the rapidly evolving and increasingly volatile dynamics of modern supply chains (Begum et al., 2024; Begum & Sumi, 2024; Bendoly et al., 2010).

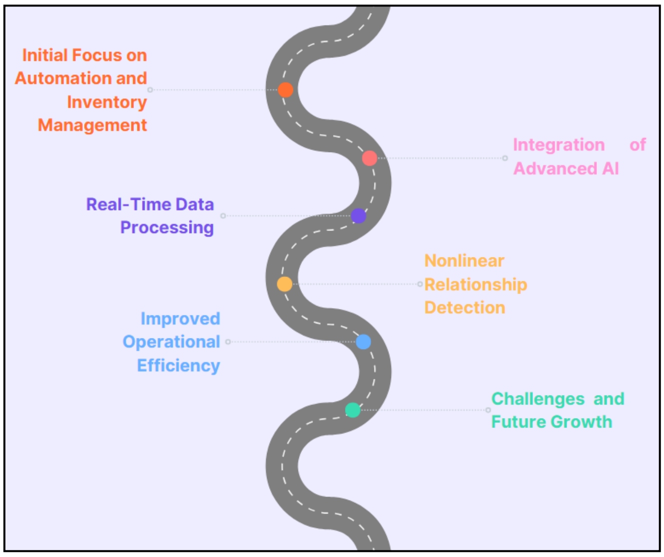
The limitations of these traditional methods are particularly evident when applied to today's highly complex and uncertain market conditions. As Zeydan et al. (2011) point out, these techniques tend to fall short in environments characterized by significant demand fluctuations, short product life cycles, and the need for real-time decision-making. Traditional methods, which are largely dependent on static historical data, often lack the ability to incorporate real-time data sources, leading to inaccurate forecasts in the face of unexpected events such as sudden shifts in consumer preferences or supply chain disruptions (Galindo & Tamayo, 2000; Md Delwar et al., 2024; Mosleuzzaman et al., 2024). Furthermore, regression-based methods may oversimplify the relationships between variables, which can lead to errors in predictions, especially when external factors like economic shifts or technological innovations play a role (Morshed et al., 2024; Shahjalal et al., 2024; Yahia et al., 2024; Zeydan et al., 2011).

Another significant limitation of traditional forecasting methods is their inability to manage large and complex datasets effectively. In today's digital economy, the volume of data generated from various sources, including IoT devices, social media, and e-commerce platforms, has grown exponentially (Loch, 2017). Traditional models are often not designed to process these large datasets, which can lead to missed opportunities for more accurate predictions. Moreover, these models typically require manual adjustments and expert input to fine-tune their parameters, which introduces the risk of human error and further reduces their accuracy in fast-changing environments (Zeydan et al., 2011). Given these limitations, there has been a growing recognition of the need for more advanced, data-driven methods that can adapt to modern supply chain challenges. AI-driven models, such as machine learning and deep learning, offer a promising alternative by being able to analyze vast amounts of data and identify complex patterns that traditional models might overlook (Dubey et al., 2019; Nandi et al., 2024; Rahman, 2024). These models can process both historical and real-time data, providing businesses with more accurate and dynamic demand forecasts. As the supply chain landscape continues to evolve, there is an increasing shift towards integrating AI into demand forecasting to improve the resilience and responsiveness of supply chains (Gjerdrum et al., 2001).

2.2 Emergence of AI in Supply Chain Demand Forecasting

The evolution of artificial intelligence (AI) in supply chain management has marked a significant departure from traditional demand forecasting techniques, transitioning from basic predictive analytics to more sophisticated AI-driven solutions. Early applications of AI in the supply chain primarily focused on automating repetitive tasks and optimizing inventory management (Ashrafuzzaman, 2024; Begum et al., 2024; Haenlein & Kaplan, 2019; Rozony et al., 2024). As technology advanced, AI systems evolved to integrate machine

Figure 3: Six-Step Emergence Of AI In Supply Chain Demand Forecasting



learning (ML), deep learning (DL), and reinforcement learning, allowing for more dynamic and data-driven decision-making. These technologies enable supply chains to adapt to the complexities of modern markets by processing large volumes of data and identifying patterns that are often too intricate for traditional models to detect (Gjerdrum et al., 2001). This shift in capabilities represents a fundamental change in how companies approach demand forecasting. In addition, One of the most significant advancements in AI-driven supply chain management is the ability to process real-time data from various sources, such as IoT devices, social media, and weather reports, to make more accurate predictions (Perera et al., 2019). Unlike traditional methods that rely on static, historical data, AI systems can incorporate and learn from new data as it becomes available, offering businesses more agile and responsive forecasting (Ye et al., 2014). This has been particularly useful in industries with fluctuating demand patterns, such as retail and e-commerce, where AI-driven models have outperformed traditional forecasting techniques (Chae, 2015). By continuously learning from new data, AI-based forecasting systems can adapt to changing consumer behaviors and external disruptions, such as the COVID-19 pandemic (Mani et al., 2017). Furthermore, machine learning algorithms have enabled supply chain forecasting models to identify complex nonlinear relationships between variables that were previously overlooked by traditional models (Giannakis & Louis, 2016). For instance, deep learning techniques like recurrent neural networks (RNNs) and long short-term memory (LSTM) models have been effective in forecasting demand in industries with volatile and uncertain market conditions (Abolghasemi et al., 2015). These advanced algorithms excel at handling large, multidimensional datasets, which are common in modern supply chains, and can generate highly accurate forecasts even in environments with minimal historical data (Moayedikia et al., 2020). This has made AI an essential tool for businesses seeking to improve the precision of their demand forecasts. Furthermore, the shift from basic predictive analytics to AI-driven solutions has also resulted in more efficient supply chain operations by reducing lead times and inventory costs while improving customer satisfaction (Diabat & Deskoores, 2016). Companies using AI-driven demand forecasting can adjust production and distribution schedules based on more accurate predictions, reducing waste and optimizing resource allocation (Ye et al., 2014). Despite the clear advantages, however, the implementation of AI in demand forecasting is not without challenges, such as data quality issues and the need for significant investments in infrastructure (Kannan et al., 2013). Nonetheless, as AI technologies continue to evolve, their application in supply chain demand forecasting is expected to expand, providing even more accurate and efficient solutions for businesses worldwide (Cui et al., 2018).

2.3 AI Models and Algorithms in Demand Forecasting

Supervised learning techniques have become a cornerstone of AI-based demand forecasting, offering models that rely on labeled historical data to predict future demand patterns. Linear regression is one of the simplest and most widely used supervised learning algorithms, defined by the equation $y = \beta 0 + \beta 1 x + \epsilon$ where y represents the dependent variable (demand), x is the independent variable, $\beta 0$ and and $\beta 1$ are coefficients, and ϵ represents the error term (Ye et al., 2014). While effective in linear relationships, more advanced algorithms like random forests and gradient boosting machines have been used to improve forecast accuracy in nonlinear environments. Random forests, for example, build an ensemble of decision trees to predict demand, reducing overfitting and improving generalizability (Giannakis & Louis, 2016). Similarly, gradient boosting machines iteratively build models by correcting errors in previous predictions, yielding highly

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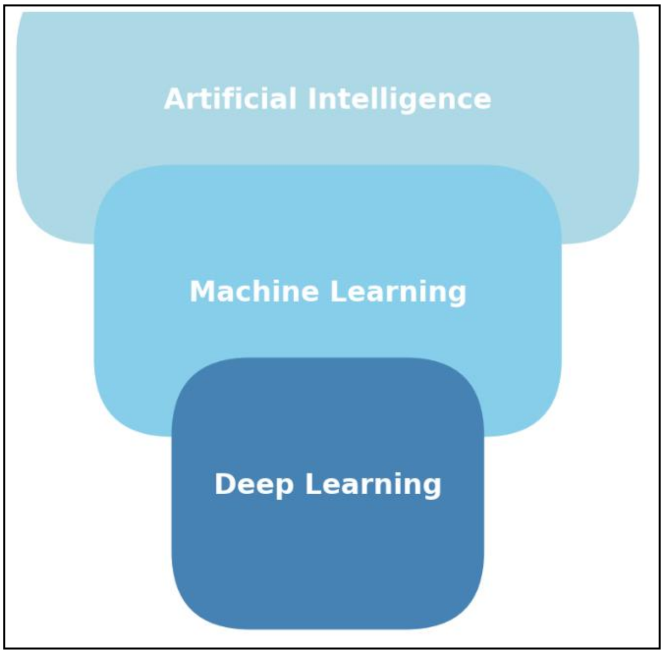
accurate demand forecasts even in complex supply chains (Perera et al., 2019). These models have been successfully applied in case studies across industries, such as retail and manufacturing, demonstrating their effectiveness in predicting short-term and long-term demand patterns (Kreipl & Pinedo, 2004).

Figure 4: Primer: Artificial Intelligence for Demand Forecasting



In addition to supervised learning models, unsupervised learning techniques, such as clustering algorithms, play a crucial role in demand segmentation. Unsupervised learning does not rely on labeled data but instead identifies patterns and relationships within datasets. For example, clustering algorithms like k-means group data points based on similarities, enabling businesses to segment their customers or products into distinct demand groups (Mani et al., 2017). The formula for k-means clustering can be represented as minimizing the within-cluster sum of squares:

$$\sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2$$

where Ci is the ith cluster, x is the data point, and μ_i is the centroid of the cluster. By identifying different demand segments, companies can apply targeted forecasting strategies for each segment, improving overall forecast accuracy (Georgiadis et al., 2006). Semi-supervised learning, which combines aspects of supervised and unsupervised learning, has also gained traction in scenarios where labeled data is scarce. By using a small set of labeled data to train the model and then applying the model to larger unlabeled datasets, semi-supervised learning helps forecast demand in industries where complete datasets are difficult to obtain (Abolghasemi et al., 2015).

In addition, Hybrid AI models, which combine traditional forecasting methods with advanced AI techniques, have shown great promise in improving the accuracy of demand forecasting. For instance, the autoregressive integrated moving average (ARIMA) model, a widely used traditional method, can be combined with deep learning techniques such as long short-term memory (LSTM) networks to create hybrid models (Perera et al., 2020). The ARIMA component of the hybrid model captures linear trends and patterns in the time series, while the LSTM component handles nonlinear relationships and long-term dependencies. The hybrid model is represented by:

$$y(t) = ARIMA(t) + LSTM(t)$$

where $y(t)$ is the predicted demand at time t. Studies have shown that these hybrid models outperform both standalone ARIMA and LSTM models, offering more accurate forecasts by leveraging the strengths of both methods (Abolghasemi et al., 2015). This combination allows for the capture of both short-term fluctuations and long-term trends, making hybrid models particularly effective in industries with high demand volatility.

Moreover, a comparative analysis of hybrid models versus standalone AI or traditional models reveals that hybrid models consistently outperform others in terms of both accuracy and adaptability (Kreipl & Pinedo, 2004). For example, hybrid models that combine AI techniques with traditional statistical methods can adjust to sudden market changes while still maintaining the simplicity and interpretability of traditional models (Carter et al., 2017). In addition, the integration of hybrid models has shown to reduce forecast errors in sectors such as retail and e-commerce, where demand patterns are unpredictable and influenced by multiple external factors (Kreipl & Pinedo, 2004). The flexibility and accuracy of these models make them a valuable tool for modern supply chain managers who must balance efficiency with responsiveness to market dynamics.

2.4 Applications of AI in Various Supply Chain Contexts

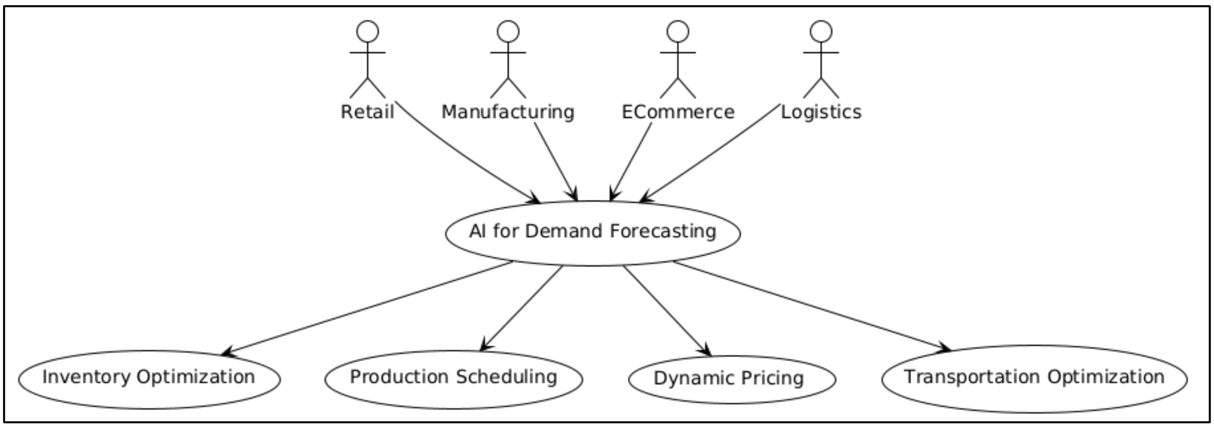
The retail industry has been one of the primary beneficiaries of AI-driven demand forecasting, with significant improvements in inventory management, sales predictions, and customer behavior analysis (Bennett & Hauser, 2012). AI technologies, such as machine learning and deep learning, allow retailers to process vast amounts of data from both internal sources (e.g., sales history, inventory levels) and external sources (e.g., social media trends, economic indicators) to generate more accurate demand forecasts (Haenlein & Kaplan, 2019). Machine learning algorithms can predict customer preferences and buying behaviors, enabling retailers to optimize their inventory levels, reduce stockouts, and prevent overstocking (Allam & Dhunny, 2019). For instance, AI-based forecasting systems have been shown to reduce forecast error rates in large retail chains by integrating real-time sales and customer sentiment data into their models (Mikalef et al., 2019). This has allowed retailers to respond more quickly to demand fluctuations, enhancing overall supply chain efficiency.

In the manufacturing sector, AI-driven demand forecasting has revolutionized raw material planning and production scheduling. Traditional forecasting methods in manufacturing often fail to account for the variability in raw material availability and lead times. AI, however, excels in processing complex datasets to identify patterns and trends that inform production schedules (Allam & Dhunny, 2019). AI models, such as reinforcement learning and neural networks, have been employed to optimize production planning by predicting demand with higher accuracy, reducing lead times and minimizing waste (Pontrandolfo et al., 2002). For example, a study on automotive manufacturing demonstrated that AI-enabled forecasting models could predict shifts in demand for specific vehicle components, allowing manufacturers to adjust production schedules in real time (Lu et al., 2017). The application of AI in manufacturing demand forecasting has improved operational efficiency by aligning production capacities with actual market demands.

AI has also transformed e-commerce and online marketplaces by improving real-time stock management, pricing strategies, and customer experience. E-commerce platforms, which generate vast amounts of data from customer interactions, purchase history, and website traffic, have integrated AI-driven demand forecasting models to predict customer behavior and optimize inventory management (Kuo et al., 2010). AI algorithms can analyze customer data in real time, allowing businesses to adjust prices dynamically and personalize recommendations based on predicted demand (McCarthy et al., 2006). This not only improves sales forecasts but also enhances customer satisfaction by ensuring that popular items are always in stock (Baryannis, Validi, et al., 2018). AI has also been instrumental in reducing the cost of e-commerce operations by optimizing warehousing and distribution processes based on accurate demand forecasts (Kuo et al., 2010).

In logistics and distribution, AI applications have been used to optimize transportation routes, warehousing, and distribution based on demand forecasts. Machine learning algorithms, for instance, are applied to predict the demand for different geographic regions, enabling logistics providers to adjust their transportation networks accordingly (Dhamija & Bag, 2020). AI

Figure 5: AI Applications in Supply Chain



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models can also optimize warehouse operations by predicting inventory needs and automating stock replenishment (Baryannis, Validi, et al., 2018). In one study, AI-driven demand forecasting enabled a major logistics company to reduce transportation costs by 15% by optimizing delivery routes based on real-time demand predictions (Legg & Hutter, 2007). AI's role in logistics and distribution has proven essential in managing supply chain complexity, ensuring timely delivery, and reducing operational costs by aligning supply chain activities with accurate demand forecasts.

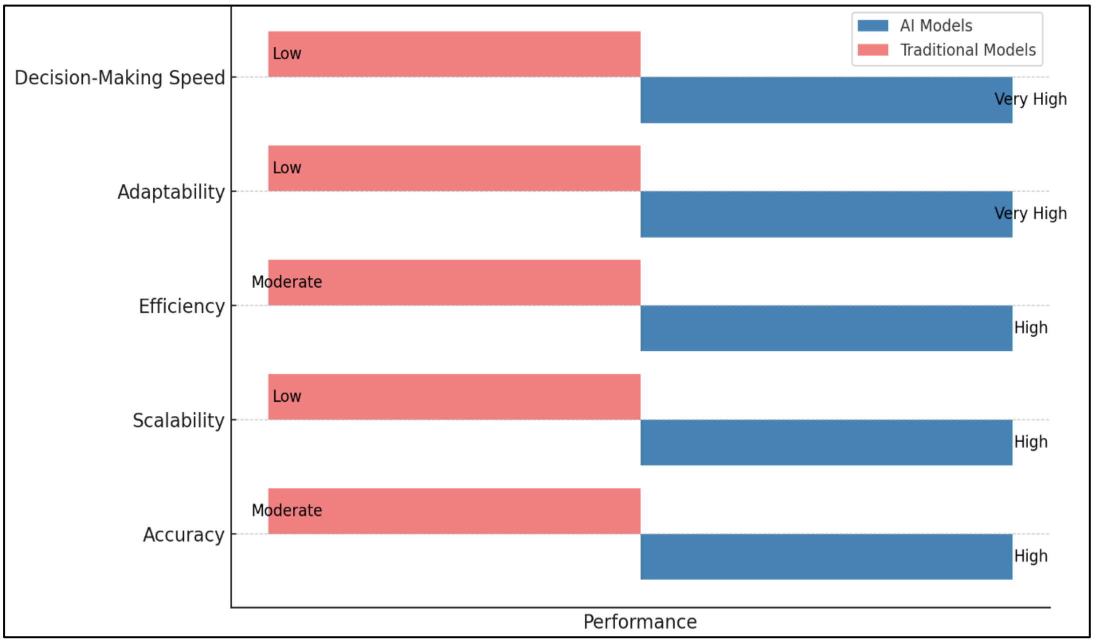
2.5 Comparative Analysis of AI Models vs. Traditional Models

AI models have demonstrated superior accuracy and efficiency in demand forecasting when compared to traditional forecasting models such as time-series analysis and regression techniques. Traditional models often struggle with nonlinear relationships in data, whereas AI models, such as machine learning (ML) and deep learning (DL) algorithms, can capture complex patterns and trends more effectively. Studies have shown that AI models outperform traditional methods in forecasting accuracy by leveraging advanced algorithms such as random forests, gradient boosting, and neural networks (Min, 2009). For example, deep learning models like long short-term memory (LSTM) networks have been particularly effective in capturing long-term dependencies in time-series data, offering more accurate demand forecasts in volatile markets (Chen et al., 2008). Moreover, AI-based models scale better when dealing with large datasets, as they can handle higher computational loads and incorporate real-time data without significant degradation in performance (Duan et al., 2019).

In terms of scalability, traditional forecasting models often require manual adjustments and expert intervention as the size and complexity of datasets grow, whereas AI models can scale with minimal human input. Machine learning algorithms, for instance, can process large amounts of structured and unstructured data from diverse sources such as IoT sensors, social media, and economic indicators, providing more comprehensive demand forecasts (Haenlein & Kaplan, 2019). This scalability is particularly crucial for industries that experience rapid demand fluctuations, such as retail and e-commerce, where traditional models struggle to keep up with the sheer volume and variety of data inputs (Kuo et al., 2010). Furthermore, AI-driven forecasting models are designed to automate the tuning of hyperparameters, which enhances computational efficiency and reduces the time needed to generate forecasts (Jiang et al., 2017). This makes AI models not only more accurate but also faster and less resource-intensive compared to traditional methods.

AI models are also highly adaptable, particularly in handling real-time data and responding to sudden market changes. Traditional forecasting techniques rely

Figure 6: Comparative Analysis of AI Models vs. Traditional Models



heavily on historical data, which limits their ability to adapt quickly to disruptions such as economic downturns, supply chain disruptions, or shifts in consumer preferences (Haenlein & Kaplan, 2019). In contrast, AI models, especially those using reinforcement learning and deep learning, can process real-time data streams and update predictions as new information becomes available (Jiang et al., 2017). This adaptability is particularly valuable in industries such as logistics and manufacturing, where supply chain efficiency is highly dependent on real-time demand data (Lu et al., 2017). AI models' ability to incorporate real-time data enables businesses to respond faster to demand changes, resulting in more efficient production schedules, inventory management, and distribution strategies (Baryannis, Dani, et al., 2018).

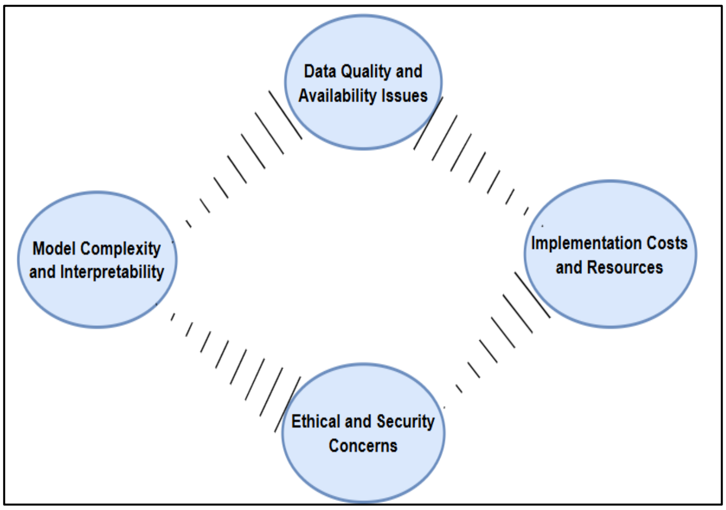
Several case studies highlight how AI-driven models enable faster decision-making compared to traditional methods. For instance, in a study conducted in the retail sector, AI models were able to reduce forecasting lead times by 30%, allowing businesses to make quicker adjustments to their inventory levels based on real-time sales data (Allam & Dhunny, 2019). In the automotive manufacturing industry, AI-based models helped optimize production schedules by predicting component demand with higher accuracy, leading to a 20% reduction in production delays (Baryannis, Validi, et al., 2018). These studies illustrate that AI models are not only more accurate but also more responsive, enabling organizations to make data-driven decisions at a faster pace, thus improving overall supply chain efficiency. As the demand for real-time forecasting grows, AI's ability to process large datasets in real-time offers a distinct advantage over traditional forecasting models.

2.6 AI Challenges in Demand Forecasting

One of the most significant challenges in AI-based demand forecasting is ensuring the quality and availability of data. AI models, particularly those relying on machine learning and deep learning algorithms, require vast amounts of high-quality data to function effectively. However, the data available in many industries can be inconsistent, incomplete, or inaccurate, leading to poor model performance (Duan et al., 2019). Inconsistent data formats, varying levels of granularity, and missing data points pose major obstacles for businesses attempting to implement AI-driven demand forecasting. For instance, in retail supply chains, data may come from disparate sources such as point-of-sale systems, e-commerce platforms, and third-party logistics providers, making it difficult to integrate and standardize the information (Albergaria & Jabbour, 2020). Without clean, consistent data, AI models may produce inaccurate or biased forecasts, which can severely impact decision-making processes (Raghupathi & Raghupathi, 2014). Data quality issues, therefore, remain a fundamental barrier to the successful adoption of AI in demand forecasting.

In addition to data challenges, the complexity of AI models is another limitation that hinders widespread adoption. Advanced AI models, particularly deep learning architectures like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, are often perceived as "black boxes" due to the difficulty in interpreting their inner workings (Bennett & Hauser, 2012). Unlike traditional statistical models, which provide clear and interpretable results, AI models often produce outputs without offering insights into how those predictions were generated. This lack of transparency makes it challenging for supply chain professionals to trust and adopt AI-driven demand forecasting solutions, especially in industries where explainability is crucial for regulatory compliance and decision-making (Raghupathi & Raghupathi, 2014). For example, while AI models might improve forecast accuracy, the inability to interpret the model's predictions could lead to resistance among decision-makers, particularly in industries like healthcare and finance, where understanding the rationale behind decisions is critical (Loch, 2017). Consequently, the

Figure 7:Challenges in AI Demand Forecasting



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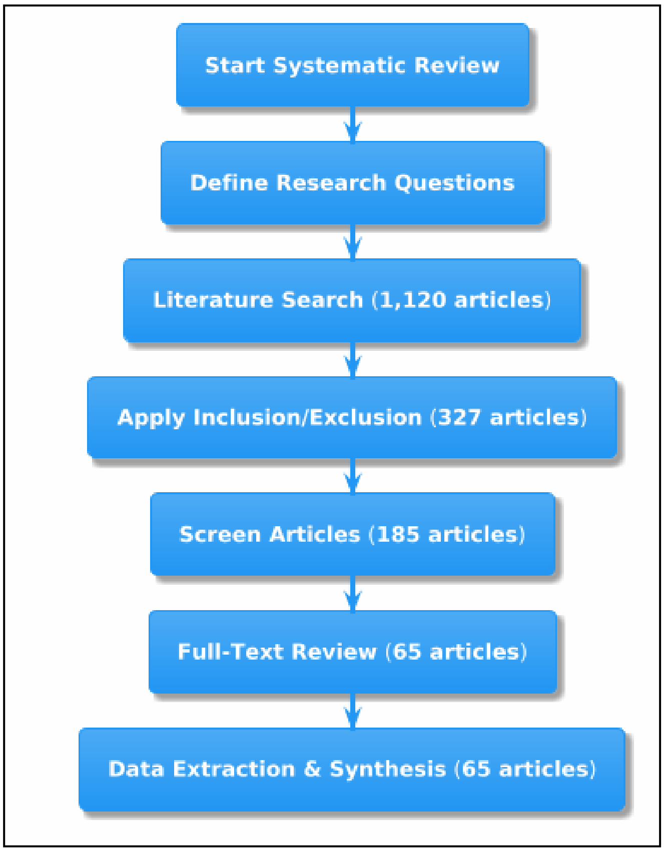
complexity and opacity of AI models pose significant adoption barriers.

Another important challenge is the cost and resources required for implementing AI solutions in demand forecasting. AI-driven systems require significant investments in both hardware and software infrastructure, as well as in human resources to manage, maintain, and optimize the models (Albergaria & Jabbour, 2020; Shamim, 2022). The computational power needed for training complex AI models, such as deep learning algorithms, often necessitates high-performance computing resources, which can be prohibitively expensive for small and medium-sized enterprises (SMEs) (Kreipl & Pinedo, 2004). Additionally, implementing AI systems requires skilled personnel, such as data scientists and machine learning engineers, who are in high demand and come with high salary expectations (Chen, 2013). These financial and infrastructural constraints limit the accessibility of AI solutions to larger corporations with the resources to invest in the technology, creating a divide between larger firms and smaller organizations that may not have the capacity to adopt AI-based demand forecasting tools (Badurdeen et al., 2014). Furthermore, there are broader concerns about the ethical implications and security risks associated with AI in demand forecasting. AI systems rely heavily on data, which raises issues related to data privacy and security, particularly when sensitive customer information is involved (Kreipl & Pinedo, 2004). Additionally, biases inherent in the training data can lead to skewed predictions, which may negatively impact business decisions. For example, biased data from a particular demographic or region might result in inaccurate demand forecasts that fail to account for the diversity of customer behaviors across different markets (Zhang et al., 2020). Furthermore, as AI systems become increasingly autonomous, concerns about accountability and liability in case of forecast errors or system failures are growing (Bharathi, 2017). These ethical and security concerns add to the already significant barriers that businesses must overcome to successfully implement AI-driven demand forecasting solutions.

3 Method

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a structured, transparent, and rigorous review process. The methodology involved several key steps, including defining research questions, conducting a comprehensive literature search, applying inclusion and exclusion criteria, and synthesizing the data to derive meaningful insights. The first step of the systematic review involved establishing clear research questions. The primary research question was: How are artificial intelligence (AI) models applied in supply chain demand forecasting, and what are their advantages and limitations compared to traditional models? Additional questions focused on identifying the most commonly used AI techniques in demand forecasting and understanding the challenges organizations face when implementing AI-driven forecasting solutions. These questions guided the subsequent steps of the review process.

Figure 8: PRISMA Framework (AI in Supply Chain Demand Forecasting)



3.1 Literature Search Strategy

A comprehensive literature search was conducted using multiple academic databases, including Web of Science, Scopus, IEEE Xplore, and Google Scholar, to identify relevant peer-reviewed journal articles. The search strategy utilized keywords such as *"Artificial Intelligence," "Demand Forecasting," "Machine Learning," "Supply Chain,"* and *"Predictive Analytics"* to capture a wide range of studies on AI applications in supply chain forecasting. Boolean operators were applied to ensure focused results, which led to the identification of 1,120 articles. These articles were then imported into Zotero for organized screening and management.

3.2 Inclusion and Exclusion

3.2.1 Criteria

To ensure the quality and relevance of the studies, rigorous inclusion and exclusion criteria were applied. The inclusion criteria required that articles focus on AI applications in demand forecasting, be peer-reviewed, written in English, and published between 2015 and 2023. Empirical or case-based evidence had to be presented within the context of supply chain forecasting. Articles were excluded if they lacked empirical evidence, were theoretical in nature, or did not pertain directly to supply chain forecasting. After applying these criteria, the number of articles was narrowed down to 327.

3.2.2 Screening Process

The 327 remaining articles were further screened by two independent reviewers, who assessed their titles and abstracts for relevance to the research questions. Articles that were not directly related to AI applications in supply chain demand forecasting were excluded, reducing the pool to 185 articles. A full-text review of these 185 articles was then conducted, focusing on their relevance and contributions to the study. This step resulted in a final selection of 65 articles, which were deemed suitable for in-depth analysis based on their content and alignment with the research objectives.

3.2.3 Full-Text Review and Data Extraction

The selected 65 articles underwent a detailed full-text review, during which key data was extracted using a standardized form. The form captured essential information such as the study's objectives, the specific AI techniques used (e.g., machine learning, deep learning), the industry sector being analyzed (e.g., retail, manufacturing, e-commerce), and any challenges or limitations related to the implementation of AI. Additionally, a comparative analysis was performed to contrast the performance of AI models against traditional forecasting techniques.

3.2.4 Data Synthesis and Analysis

The final set of 65 articles was synthesized to identify trends and patterns in AI adoption for supply chain demand forecasting. A narrative synthesis was employed to summarize key findings, while tables were used to compare AI techniques and their relative performance in different industries. Thematic analysis revealed recurring challenges in AI implementation, such as data quality, model complexity, and high resource requirements. By following PRISMA guidelines, the review ensured a systematic approach that provides a comprehensive understanding of AI's role in transforming demand forecasting within the supply chain domain.

4 Findings

The systematic review revealed several significant findings regarding the use of artificial intelligence (AI) in supply chain demand forecasting. One of the most notable insights is that AI-driven models consistently outperform traditional forecasting methods in terms of accuracy and adaptability. AI techniques, particularly machine learning (ML) and deep learning (DL), excel in capturing complex patterns and relationships within vast datasets, making them more reliable for predicting demand in dynamic environments. This capability allows businesses to respond more quickly to changes in market conditions, consumer preferences, and external disruptions. Traditional methods, which rely heavily on historical data and linear models, often fail to account for the non-linearities and sudden shifts in demand, whereas AI models are more robust in processing real-time data streams and identifying emerging trends. This has led to improvements in inventory management, production scheduling, and overall supply chain efficiency.

Another significant finding is the broad applicability of AI models across various industries, with retail, manufacturing, e-commerce, and logistics being the primary sectors benefiting from these technologies. In retail, AI models have been instrumental in predicting sales trends, optimizing inventory levels, and analyzing customer behavior patterns. AI-based forecasting tools enable retailers to reduce stockouts and overstock situations by providing more accurate demand predictions. In the manufacturing sector, AI has

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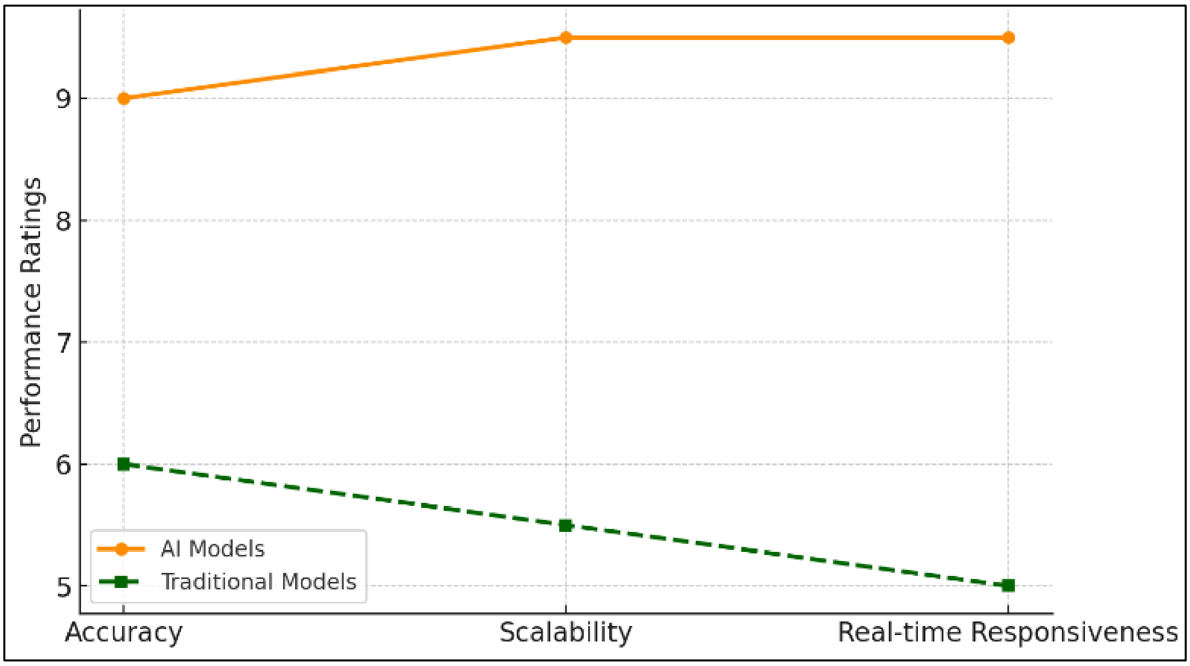
enhanced raw material planning and production scheduling, allowing companies to better align their operations with actual market demand. E-commerce platforms have leveraged AI to improve real-time stock management and dynamic pricing strategies, resulting in enhanced customer satisfaction and increased operational efficiency. Meanwhile, in logistics and distribution, AI has played a key role in optimizing transportation routes, warehouse operations, and delivery schedules, further streamlining the supply chain.

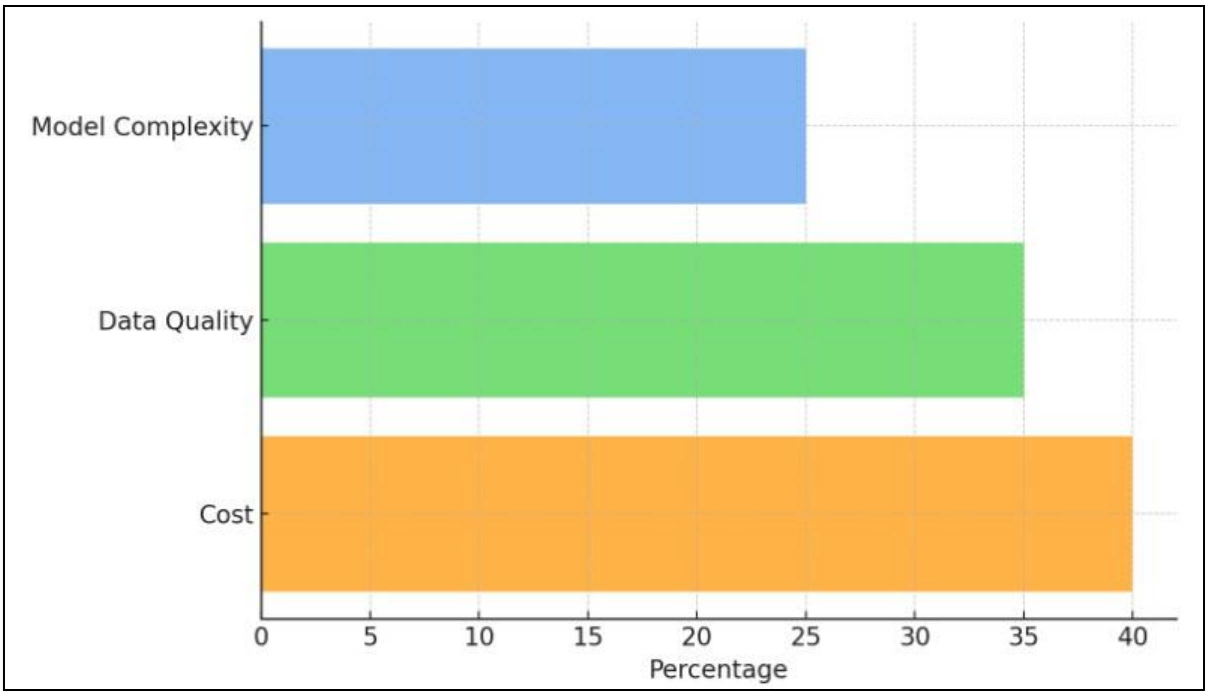
The review also found that AI's ability to process real-time data from multiple sources has led to more responsive and agile supply chains. Unlike traditional forecasting models that depend primarily on historical data, AI models integrate data from various external and internal sources, such as IoT sensors, social media trends, and market indicators. This real-time integration provides businesses with up-to-date insights, enabling them to make timely adjustments to their demand forecasts. As a result, companies can respond more effectively to sudden demand shifts, minimizing the risk of overproduction or underproduction. This agility is particularly beneficial in industries with highly variable demand patterns, such as fashion, electronics, and consumer goods, where staying responsive to market changes is critical for maintaining competitiveness. However, despite the advantages, the review highlighted several challenges associated with the implementation of AI in demand forecasting. One of the primary issues is the high cost of implementing AI solutions. Developing, maintaining, and optimizing AI models requires significant investment in both infrastructure and human capital. Small and medium-sized enterprises (SMEs) often lack the financial resources to invest in the necessary hardware, software, and expertise to deploy AI-driven forecasting systems. Additionally, the complexity of AI models poses another challenge, as these systems require continuous monitoring, updating, and fine-tuning to maintain their accuracy over time. This creates a barrier for businesses that may not have access to skilled data scientists or machine learning engineers.

Figure 9: AI Models vs Traditional Models in Demand Forecasting



Another notable challenge identified in the review is the issue of data quality. AI models rely heavily on the availability of large, high-quality datasets to generate accurate forecasts. However, many companies face difficulties in managing and processing the vast amounts of data required for AI-driven forecasting. Incomplete, inconsistent, or outdated data can significantly undermine the performance of AI models, leading to inaccurate predictions. Moreover, integrating data from multiple sources, such as suppliers, customers, and internal operations, presents additional challenges related to data consistency and format standardization. As a result, businesses must invest in data management practices that ensure the reliability and quality of the data used in AI forecasting models. Finally, the review revealed that despite the technical advancements in AI, issues related to model interpretability and transparency remain significant barriers to adoption. AI models, particularly those based on deep learning, are often viewed as "black boxes" due to the complexity of their inner workings. This lack of transparency makes it difficult for business leaders to trust the outputs of AI-driven forecasting models, especially in industries where regulatory compliance and decision-making transparency are critical. Companies are increasingly looking for explainable AI (XAI) solutions that provide insights into how the model arrived at its predictions. However, achieving this level of interpretability without compromising the accuracy and performance of AI models remains an ongoing challenge in the field. In brief, the findings of this review demonstrate the immense potential of AI in transforming supply chain demand forecasting, offering significant improvements in accuracy, scalability, and real-time responsiveness. However, these benefits come with substantial challenges, particularly in terms of cost, data quality, and model interpretability, which businesses must address to fully leverage the power of AI in their supply chain operations.

Figure 10: Challenges in AI Demand Forecasting



5 Discussion

The findings of this systematic review reveal that AI-driven demand forecasting models significantly outperform traditional methods in terms of accuracy, adaptability, and real-time responsiveness. These results align with earlier studies, which have similarly emphasized the superiority of AI in handling complex, non-linear data and providing more accurate predictions in dynamic supply chains (Pan et al., 2020). Traditional forecasting techniques, while useful in stable environments, often struggle to adapt to sudden market changes and rely heavily on historical data. AI models, on the other hand, process real-time data from diverse sources, enabling businesses to respond more quickly to shifts in demand, as supported by previous research (Abbasi et al., 2020). These findings underscore the growing importance of AI in modern supply chain management, where the ability to predict and react to fluctuating demand is critical for maintaining efficiency and competitiveness.

The review also highlighted the broad applicability of AI models across various industries, including retail,

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manufacturing, e-commerce, and logistics. This is consistent with earlier studies that have demonstrated AI's versatility in different sectors (Gnoni et al., 2003). In the retail industry, for instance, AI has proven effective in sales forecasting and inventory optimization, which mirrors the conclusions of prior research on AI applications in retail demand forecasting (Abbasi et al., 2020). Similarly, in manufacturing, AI-driven models have enhanced production scheduling and raw material planning, further validating the findings of past studies that advocate for AI's role in improving operational efficiency (Allam & Dhunny, 2019). The significant improvements in e-commerce, particularly in dynamic pricing and real-time stock management, echo earlier findings that AI models provide more accurate demand forecasts by continuously learning from new data (Carter et al., 2017).

One of the more interesting findings was the capability of AI to process real-time data from multiple sources, resulting in more responsive and agile supply chains. This capability aligns with previous research that highlighted the limitations of traditional models, which often rely solely on historical data and are unable to incorporate real-time information effectively (Pournader et al., 2020). AI's ability to integrate real-time data from diverse sources, such as IoT sensors and social media trends, allows for more accurate demand forecasts and quicker responses to market changes. This is particularly relevant in industries with highly variable demand, such as fashion and consumer goods, where earlier studies have shown that AI can significantly reduce lead times and improve inventory management (McCarthy et al., 2006). These findings further support the notion that AI technologies are crucial for developing more agile and responsive supply chains. However, the review also identified significant challenges in implementing AI-driven demand forecasting models, particularly regarding costs, data quality, and model complexity. These challenges are consistent with earlier studies, which have noted that the high costs of AI implementation, including the need for specialized infrastructure and expertise, are significant barriers for small and medium-sized enterprises (You et al., 2009). Similarly, issues related to data quality, such as inconsistent or incomplete data, have been noted as a major obstacle in previous research (Márquez & Blanchar, 2004). AI models require large volumes of high-quality data to function effectively, and poor data quality can significantly undermine their accuracy. Moreover, the complexity of AI models, especially deep learning techniques, continues to be a challenge in terms of transparency and interpretability, as noted in earlier studies that highlight the "black box" nature of AI models (Yu & Li, 2000).

In addition, the review's findings regarding the challenges of model interpretability and transparency contribute to the growing body of literature that stresses the need for explainable AI (XAI). Prior studies have pointed out that AI models, particularly those using deep learning, are often difficult to interpret, making it challenging for decision-makers to trust their outputs (Abbasi et al., 2020). The lack of transparency in AI models poses a significant barrier to adoption, particularly in highly regulated industries such as finance and healthcare, where understanding the rationale behind decisions is critical (Allam & Dhunny, 2019). This review reaffirms the importance of developing more interpretable AI models, which can provide insights into how predictions are made without compromising accuracy. Future research should focus on advancing XAI techniques to bridge the gap between model accuracy and interpretability. In summary, while the findings of this review reinforce the effectiveness of AI in supply chain demand forecasting, they also highlight ongoing challenges that must be addressed to fully realize the potential of AI technologies. These challenges, including high implementation costs, data quality issues, and model complexity, echo concerns raised in earlier studies. Nevertheless, the growing body of evidence supporting AI's superiority over traditional models in various industries suggests that AI will continue to play an increasingly important role in demand forecasting and supply chain management.

6 Conclusion

This systematic review highlights the transformative impact of artificial intelligence (AI) in supply chain demand forecasting, demonstrating its superiority over traditional models in terms of accuracy, scalability, and real-time adaptability. AI-driven models, including machine learning and deep learning algorithms, have proven to be highly effective in handling complex, non-linear data and integrating real-time information from diverse sources, enabling businesses to improve inventory management, production scheduling, and responsiveness to market shifts. However, the review also emphasizes significant challenges, such as high implementation costs, data quality issues, and the complexity of AI models, which pose barriers to wider adoption, especially for small and medium-sized enterprises. Despite these limitations, the potential of AI to enhance supply chain efficiency and agility across various industries, including retail, manufacturing, e-commerce, and logistics, is undeniable. Moving forward, addressing these challenges—particularly by improving data management practices and developing more interpretable AI models—will be crucial for maximizing the benefits of AI in demand forecasting and ensuring its sustainable integration into supply chain operations.

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