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Artificial Intelligence-Based Demand Forecasting for Industrial Supply Chains

Renita Amara Roesnadi [1✉], Binar Ayustika Nugroho [2], Jennifer Jones [3]
(1) Department of Industrial Engineering, Institut Teknologi Bandung, Bandung, Indonesia
(2) Department of Management, Universitas Indonesia, Depok, Indonesia
(3) Department of Supply Chain and Operations Management, University of Manchester, Manchester, United Kingdom

Abstract: Accurate demand forecasting is a critical determinant of efficiency and resilience in industrial supply chains. Increasing market volatility, shortened product life cycles, and complex global networks have exposed the limitations of traditional statistical forecasting approaches. Artificial Intelligence (AI), particularly machine learning and deep learning, has emerged as a transformative solution capable of processing large-scale, heterogeneous data and capturing nonlinear demand patterns. This study aims to systematically analyze and synthesize empirical and conceptual evidence on AI-based demand forecasting in industrial supply chains. Using a structured literature-based analytical method, this research reviews and integrates findings from peer-reviewed journal articles, conference proceedings, and authoritative preprints published between 2020 and 2025. The results demonstrate that AI-based forecasting models—such as neural networks, ensemble learning, hybrid ARIMA–LSTM architectures, and predictive analytics—consistently outperform traditional methods in terms of accuracy, adaptability, and responsiveness. Moreover, AI-driven forecasting contributes significantly to improved inventory optimization, cost reduction, and supply chain resilience. However, challenges related to data quality, implementation cost, system integration, and skill gaps remain substantial barriers. The study concludes that AI-based demand forecasting is not merely a technological enhancement but a strategic capability for industrial supply chains. Practical implications and directions for future research are discussed to support broader and more effective adoption of AI-driven forecasting systems.

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INTRODUCTION

Demand forecasting constitutes a core analytical activity in supply chain management, as it directly influences production planning, procurement, inventory control, and distribution decisions. In industrial supply chains, forecasting accuracy is particularly critical because demand uncertainty is amplified by large-scale operations, capital-intensive assets, and complex coordination among multiple stakeholders. Inaccurate forecasts frequently result in excess inventory, stock shortages, increased operational costs, and reduced service levels, which ultimately weaken organizational competitiveness and supply chain performance (Tulli, 2020). Consequently, demand forecasting is not merely an operational task but a strategic function that determines the efficiency and resilience of industrial supply chains.

Historically, demand forecasting in industrial contexts has relied on traditional statistical methods such as moving averages, exponential smoothing, autoregressive integrated moving average models, and linear regression. These approaches are grounded in assumptions of linearity, stationarity, and relatively stable demand patterns. While such methods remain useful in environments with limited

✉ *Corresponding author: renita.aroesnadi@itb.ac.id*

variability, their performance deteriorates significantly under conditions of market volatility, demand seasonality, and structural change. Empirical evidence demonstrates that conventional forecasting models often fail to adapt to sudden demand shifts and nonlinear relationships inherent in modern industrial markets (Terrada et al., 2022). As a result, organizations increasingly recognize the limitations of traditional forecasting techniques in supporting data-driven decision-making.

The rapid digital transformation of industrial systems has fundamentally altered the demand forecasting landscape. The widespread adoption of enterprise resource planning systems, Internet of Things devices, and digital platforms has generated vast volumes of structured and unstructured data. These data sources include historical sales records, production logs, inventory transactions, market signals, and external environmental factors. Artificial Intelligence, particularly machine learning and deep learning, has emerged as a powerful analytical paradigm capable of processing such complex and high-dimensional data. Unlike traditional statistical models, AI-based approaches can automatically learn patterns from data, capture nonlinear dependencies, and continuously improve forecasting performance as new information becomes available (Hu & Han, 2024).

Recent studies consistently report that AI-based demand forecasting models outperform conventional methods in terms of accuracy, robustness, and scalability. Machine learning algorithms such as random forests, gradient boosting, and support vector machines have demonstrated superior predictive performance across diverse industrial sectors (Dalimunthe et al., 2023; Ashok, 2025). Furthermore, deep learning architectures, including long short-term memory networks and convolutional neural networks, are particularly effective in modeling temporal dynamics and complex demand patterns. Empirical findings indicate that hybrid models combining statistical and deep learning approaches, such as ARIMA–LSTM frameworks, achieve higher accuracy and stability under volatile demand conditions (Suddala, 2024).

Beyond predictive accuracy, Artificial Intelligence-based demand forecasting has significant implications for inventory optimization and cost efficiency. Accurate forecasts enable organizations to align production and procurement decisions with actual market demand, thereby reducing inventory holding costs and minimizing the risk of stockouts. AI-driven predictive analytics support proactive planning by identifying demand trends and anomalies at an early stage, allowing timely managerial interventions (Patil, 2025). Empirical evidence shows that organizations implementing AI-based forecasting systems achieve measurable improvements in service levels and inventory turnover, contributing to enhanced operational efficiency (Eldred et al., 2023).

At a strategic level, AI-based demand forecasting strengthens supply chain resilience and adaptability. Industrial supply chains are increasingly exposed to disruptions caused by demand shocks, geopolitical uncertainty, and technological change. AI-enabled forecasting systems facilitate dynamic adjustment by integrating real-time data and continuously updating demand predictions. Integrated AI platforms support scenario analysis and risk mitigation by providing decision-makers with timely and reliable demand insights (Singh, 2025). As demonstrated in recent empirical studies, AI-driven forecasting plays a crucial role in enhancing supply chain responsiveness and reducing the negative impacts of uncertainty (Liu et al., 2025).

Despite these advantages, the adoption of Artificial Intelligence in industrial demand forecasting remains uneven. Several studies highlight persistent barriers, including data quality issues, high implementation costs, system integration challenges, and shortages of skilled human resources (Akanbi et al., 2024; Nweje & Taiwo, 2025). In many industrial organizations, fragmented data infrastructures and limited analytical capabilities hinder the effective deployment of AI-based forecasting solutions. Moreover, concerns regarding model transparency and interpretability reduce managerial trust and slow organizational acceptance, particularly in high-stakes industrial decision environments (Nathany, 2022).

The existing literature also reveals a gap between methodological advancements and practical implementation. While numerous studies focus on improving forecasting algorithms, fewer contributions address the integration of AI-based forecasting within broader supply chain decision-support systems. Scholars emphasize the need for holistic frameworks that align technological capabilities with organizational processes and strategic objectives (Boualam et al., 2025). Additionally, the growing complexity of AI models underscores the importance of explainable and user-oriented forecasting systems to facilitate informed managerial decision-making (Jahin et al., 2024).

Based on this background, this article aims to provide a comprehensive synthesis of research on Artificial Intelligence-based demand forecasting in industrial supply chains. The study focuses on identifying dominant AI techniques, evaluating their performance impacts, and examining implementation challenges reported in empirical and conceptual studies. By integrating evidence from recent literature, this article contributes to a clearer understanding of how AI-based forecasting enhances operational efficiency, inventory management, and supply chain resilience. The findings are expected to support both academic inquiry and practical implementation by offering a structured and up-to-date perspective on AI-driven demand forecasting in industrial supply chains.

RESEARCH METHOD

Research Design

This study adopts a qualitative literature-based research design with a structured and systematic analytical approach. The research focuses on synthesizing existing empirical and conceptual studies related to Artificial Intelligence-based demand forecasting in industrial supply chains. This design is appropriate because the objective of the study is not to test new hypotheses or generate primary empirical data, but to critically analyze, integrate, and interpret findings that have been reported in prior peer-reviewed research. The approach allows for an in-depth understanding of methodological trends, performance outcomes, and implementation challenges associated with AI-driven demand forecasting.

Data Sources and Selection Criteria

The data sources consist exclusively of secondary data obtained from published journal articles, conference proceedings, and reputable preprint repositories. Only studies included in the article's reference list were considered, ensuring consistency between in-text citations and the Daftar Pustaka. The selection criteria focused on publications that explicitly examine the application of Artificial Intelligence, machine learning, or deep learning techniques for demand forecasting within industrial supply chain contexts. Studies published between 2020 and 2025 were prioritized to ensure the relevance and currency of the analysis. Articles that addressed demand forecasting in non-industrial contexts or without a clear AI component were excluded.

Data Collection Procedure

The data collection process followed a structured documentation technique. Each selected study was systematically reviewed to extract relevant information, including forecasting methods employed, data characteristics described, performance metrics reported, and operational or strategic implications discussed. To maintain analytical consistency, the same extraction framework was applied across all reviewed studies. This procedure ensured that comparable dimensions of analysis were captured, enabling cross-study synthesis without altering the original findings or interpretations reported by the respective authors.

Data Analysis Technique

Data analysis was conducted using qualitative thematic analysis. The extracted information was organized into thematic categories reflecting core aspects of AI-based demand forecasting. These categories included types of AI models used, forecasting performance outcomes, impacts on inventory and operational efficiency, and implementation challenges. Thematic patterns were identified through iterative comparison across studies, allowing common findings and divergences to be systematically documented. This analytical process emphasizes interpretation and synthesis rather than statistical aggregation, in line with the qualitative nature of the research design.

Analytical Framework

To ensure a coherent structure, the analysis was guided by an analytical framework that links AI-based forecasting methods to operational and strategic outcomes in industrial supply chains. The framework examines how specific AI techniques contribute to improvements in forecasting accuracy, inventory optimization, cost efficiency, and supply chain resilience. At the same time, it captures organizational and technological barriers that influence implementation effectiveness. This framework supports logical consistency across the Results and Discussion section and enhances the replicability of the analytical process.

Research Validity and Reliability

The validity of this study is supported by the exclusive use of peer-reviewed and academically credible sources, which enhances the reliability of the synthesized findings. Consistency in data extraction and thematic categorization further strengthens internal validity. To reduce interpretative bias, the analysis focuses on explicitly reported results and conclusions from the reviewed studies, without inference beyond the original authors' claims. Reliability is reinforced by the transparent description of selection criteria, data extraction procedures, and analytical steps, enabling replication by other researchers using the same set of references.

Ethical Considerations

As this research relies solely on secondary data from publicly available academic sources, no ethical approval was required. All original authors are appropriately cited, and the intellectual integrity of the reviewed studies is fully respected. The analysis does not manipulate, reinterpret, or misrepresent the original data, findings, or conclusions presented in the source publications.

RESULTS AND DISCUSSION

Distribution of AI Techniques in Demand Forecasting Studies

The reviewed literature demonstrates a clear dominance of machine learning and deep learning approaches in industrial demand forecasting research. Table 1 summarizes the distribution of AI techniques reported across the analyzed studies. Neural networks, including LSTM and BiLSTM architectures, are the most frequently applied models, followed by ensemble learning methods and hybrid statistical–AI models. This pattern indicates a strong research focus on capturing temporal dependencies and nonlinear demand behavior, which are common characteristics of industrial demand data (Terrada et al., 2022; Douaioui et al., 2024).

Table 1. AI Techniques Used in Industrial Demand Forecasting Studies

AI Technique Category	Representative Models	Key References
Machine Learning	Random Forest, Gradient Boosting, SVM	Dalimunthe et al. (2023); Ashok (2025)
Deep Learning	LSTM, BiLSTM, CNN	Terrada et al. (2022); Aldahmani et al. (2024)
Hybrid Models	ARIMA–LSTM, CNN–LSTM	Suddala (2024); Jahin et al. (2024)
Predictive Analytics Platforms	Integrated AI systems	Patil (2025); Singh (2025)

The predominance of deep learning and hybrid models reflects the need for forecasting approaches that can adapt to volatile and complex industrial demand environments.

Forecasting Performance and Accuracy Improvements

Across the reviewed studies, AI-based demand forecasting models consistently outperform traditional statistical methods in terms of predictive accuracy. Comparative analyses show that machine learning and deep learning models achieve lower forecasting error metrics and higher stability under demand variability (Tulli, 2020; Saha et al., 2024). Hybrid architectures further enhance robustness by combining the strengths of linear statistical models and nonlinear learning algorithms. Empirical evidence from industrial case studies indicates that these models provide more reliable forecasts during periods of demand fluctuation and structural change (Suddala, 2024).

Impact on Inventory Management and Operational Efficiency

Improved forecasting accuracy directly translates into better inventory management and operational performance. The reviewed studies report reductions in inventory holding costs, improved service levels, and enhanced production planning accuracy following the implementation of AI-based forecasting systems. AI-driven demand insights enable organizations to synchronize supply decisions with actual market needs, reducing inefficiencies associated with overstocking and stockouts (Eldred et al., 2023; Danach et al., 2024). Table 2 summarizes the operational impacts of AI-based demand forecasting as reported in empirical studies. The findings indicate that AI adoption supports both cost efficiency and responsiveness, which are critical performance dimensions in industrial supply chains.

Table 2. Reported Operational Impacts of AI-Based Demand Forecasting

Operational Dimension	Reported Impact	Key References
Inventory Management	Reduced overstock and stockouts	Eldred et al. (2023); Pal (2023)
Cost Efficiency	Lower holding and operational costs	Patil (2025); Danach et al. (2024)
Service Level	Improved order fulfillment reliability	Luo (2024); Singh (2025)

These results confirm that AI-based forecasting serves as a critical enabler of operational excellence in industrial supply chains.

Strategic Implications for Supply Chain Resilience

Beyond operational benefits, AI-based demand forecasting contributes to strategic supply chain resilience. By integrating real-time data and continuously updating forecasts, AI systems support dynamic planning and proactive risk management. Studies highlight the role of AI-driven forecasting in mitigating the impact of demand shocks and supply disruptions, thereby enhancing overall supply chain adaptability (Maru, 2025; Liu et al., 2025).

Implementation Challenges and Research Implications

Despite the documented benefits, the reviewed studies also identify significant implementation challenges. Data quality limitations, high system integration costs, and shortages of skilled personnel are repeatedly cited as major barriers to effective AI adoption (Akanbi et al., 2024; Nweje & Taiwo, 2025). Additionally, limited model transparency and explainability reduce managerial trust, particularly in high-risk industrial decision contexts (Nathany, 2022).

From a research perspective, these findings indicate a need to balance methodological sophistication with practical applicability. Future research should focus on scalable and interpretable AI-based forecasting solutions that align with organizational capabilities and strategic objectives. Addressing these challenges is essential to ensure that the performance gains demonstrated in the literature can be realized consistently in industrial practice.

CONCLUSION

This study concludes that artificial intelligence-based demand forecasting provides substantial improvements in forecasting accuracy and decision support within industrial supply chains. The synthesis of prior empirical studies demonstrates that machine learning, deep learning, and hybrid forecasting models are more effective than traditional statistical approaches in capturing nonlinear patterns and temporal dynamics of industrial demand. These capabilities enable organizations to generate more reliable demand projections, particularly under conditions of high volatility and structural change.

From an operational perspective, improved forecasting accuracy contributes directly to enhanced inventory management, cost efficiency, and service level performance. The reviewed evidence indicates that AI-based forecasting supports better alignment between supply and demand, reduces inefficiencies associated with overstocking and stockouts, and strengthens coordination across supply chain functions. As a result, industrial firms can achieve higher operational responsiveness while maintaining cost control.

At the strategic level, AI-driven demand forecasting plays a critical role in strengthening supply chain resilience. By enabling continuous forecast updates and data-driven planning, AI systems support proactive decision-making and risk mitigation in the face of demand uncertainty and external disruptions. However, the findings also highlight persistent challenges related to data quality, system integration, and model interpretability, which may limit the realization of these benefits if not adequately addressed.

Overall, this study contributes to the growing body of knowledge on AI applications in supply chain management by providing a structured synthesis of empirical evidence on demand forecasting performance and its operational implications. Future research is recommended to focus on the development of scalable, transparent, and practically deployable AI forecasting solutions that align with organizational capabilities and industrial contexts.

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