



IJRTSM

INTERNATIONAL JOURNAL OF RECENT TECHNOLOGY SCIENCE & MANAGEMENT

“A STUDY ON AI AND MACHINE LEARNING-BASED OPTIMIZATION OF SUPPLY CHAIN MANAGEMENT IN MANUFACTURING”

Ujjawal Panika ¹, Harimohan Soni ², Dr. Piyush Kumar Jain ³

¹ MTech Scholar, Bansal Institute of Science and Technology, Bhopal (M.P.), India, 462021

² Assistant Professor, Bansal Institute of Science and Technology, Bhopal (M.P.) India, 462021

³ Associate Professor, Bansal Institute of Science and Technology, Bhopal (M.P.) India, 462021

ABSTRACT

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into supply chain management has emerged as an important approach for improving operational efficiency, reducing costs, and enhancing decision-making in manufacturing industries. Traditional supply chain systems often face challenges such as demand uncertainty, inventory imbalance, production delays, transportation inefficiencies, and limited coordination among suppliers, manufacturers, and distributors. AI and ML techniques can address these challenges by analyzing historical and real-time data, predicting future demand, optimizing inventory levels, identifying potential disruptions, and improving production and logistics planning. This study investigates the role of AI and ML in optimizing manufacturing supply chains through intelligent forecasting, inventory management, supplier selection, predictive analytics, and transportation optimization. A conceptual research framework is proposed that integrates data collection, preprocessing, machine learning model development, performance evaluation, and optimization-based decision-making. Relevant performance indicators include demand forecasting error, inventory holding cost, order fulfilment time, transportation cost, and overall supply chain efficiency. The study also examines implementation challenges related to data quality, system integration, cybersecurity, and computational requirements. The proposed framework provides a structured foundation for developing data-driven and resilient manufacturing supply chains. The findings discussed in this study are based on a conceptual synthesis of existing research rather than a newly conducted industrial experiment.

Key Words: Artificial Intelligence, Machine Learning, Supply Chain Management, Manufacturing Industry, Demand Forecasting, Inventory Optimization, Predictive Analytics, Logistics Optimization..

I. INTRODUCTION

Supply chain management (SCM) plays a vital role in manufacturing industries by coordinating the flow of raw materials, components, information, and finished products from suppliers to end customers. An efficient supply chain helps organizations reduce operational costs, improve product quality, maintain optimal inventory levels, and deliver products within the required time. However, modern manufacturing systems operate in increasingly complex and uncertain environments. Fluctuations in customer demand, supplier reliability issues, transportation delays, raw material shortages, and changing market conditions can significantly affect production schedules and business performance.

Conventional supply chain management approaches generally depend on historical averages, fixed inventory policies, statistical forecasting, and manual decision-making. Although these approaches can be effective in relatively stable environments, they may struggle to respond rapidly to unexpected disruptions and changing demand patterns.

<https://www.ijrtsm.com> © International Journal of Recent Technology Science & Management

Consequently, manufacturing organizations are increasingly exploring intelligent technologies to improve the accuracy, flexibility, and responsiveness of their supply chain operations.

Artificial Intelligence provides a broad set of computational techniques that enable machines to perform tasks involving prediction, reasoning, pattern recognition, and decision support. Machine Learning, a major branch of AI, develops predictive models by learning patterns from historical and real-time data. Techniques such as linear regression, random forests, support vector regression, artificial neural networks, gradient boosting, and deep learning can support demand forecasting, inventory planning, quality monitoring, and logistics management.

In manufacturing supply chains, AI and ML can be applied across several interconnected activities. Demand forecasting models estimate future product requirements, while inventory optimization systems determine appropriate stock levels and reorder points. Predictive analytics can identify possible supplier delays and equipment failures, whereas intelligent routing algorithms can improve transportation planning. When integrated with enterprise resource planning (ERP), manufacturing execution systems, Internet of Things (IoT) devices, and warehouse management systems, these technologies can support more informed and timely operational decisions.

Despite these benefits, successful implementation requires reliable data, suitable algorithms, appropriate computing infrastructure, and effective collaboration among supply chain partners. In addition, model interpretability, cybersecurity, employee skills, and the financial cost of implementation must be considered.

The present study therefore examines the application of AI and ML for manufacturing supply chain optimization and proposes a conceptual framework for evaluating their contribution to operational performance.



Fig.1 AI in supply chain and logistics

1.1 Research objectives

1. To examine the role of AI and ML in manufacturing supply chain management.
2. To identify suitable machine learning techniques for demand forecasting and inventory optimization.
3. To develop a conceptual framework for integrating predictive analytics with supply chain decision-making.
4. To identify appropriate performance indicators for evaluating supply chain optimization.
5. To discuss implementation challenges and future research opportunities.

1.2 Research questions

- How can AI and ML improve demand forecasting and inventory management?
- Which machine learning approaches are suitable for different manufacturing supply chain activities?
- How can the performance of AI-enabled supply chains be evaluated?
- What technical and organizational barriers affect their implementation?

II. LITERATURE SURVEY

Artificial Intelligence and Machine Learning have received increasing attention in supply chain management because of their ability to process complex data and support decision-making across procurement, production, inventory, and distribution. Existing research indicates that these technologies are most useful when predictive models are combined with operational optimization techniques.

2.1 Review of existing studies

Min (2010) [1] examined the application of artificial intelligence in supply chain management, including intelligent systems for logistics, supplier selection, and operational decision-making. The research highlighted the potential of AI to improve complex supply chain decisions. However, the practical effectiveness of intelligent systems depends on data availability, system integration, and the ability to incorporate them into existing business processes.

Baryannis et al. (2019) [2] investigated the application of artificial intelligence in supply chain risk management. Their work discussed the role of AI techniques in identifying and assessing supply chain risks. The study established a foundation for using intelligent analytical methods to improve risk identification, although the effectiveness of such methods depends on the quality and completeness of available information.

Toorajipour et al. [3] conducted a systematic review of AI and ML applications in supply chains. Their research examined the use of intelligent algorithms across multiple supply chain activities and identified opportunities for improving forecasting, logistics, and operational decisions. The study also emphasized the need for additional research into practical implementation and the integration of AI technologies with existing supply chain systems.

A study published in *Procedia CIRP* (2022) [4] reviewed AI techniques for demand forecasting in supply chain management. The researchers examined methods reported between 2017 and 2021 and discussed the selection of forecasting algorithms according to data characteristics, volume, and forecasting horizon. This research is particularly relevant to manufacturing industries, where demand predictions influence raw material procurement, production scheduling, and inventory requirements.

Polo-Triana et al. (2024) [5] reviewed machine learning applications in supply chain decision-making. Their review selected 70 articles from an initial set of 410 publications and identified applications involving inventory management, logistics, transportation, and related decisions. The study highlighted the value of combining machine learning with conventional analytical and optimization techniques rather than treating prediction as an isolated activity.

A systematic review published in *Computers in Industry* (2024) [6] investigated empirical research on AI applications in supply chain management. It examined evidence concerning the practical adoption of AI and identified directions for future research. The work is relevant because it emphasizes the importance of evaluating AI applications in real operational settings instead of assuming that algorithmic capabilities automatically translate into measurable business improvements.

Vlachos and Reddy (2025) [7] conducted a systematic literature review of 107 machine learning studies published between 2019 and 2023. They identified four major research themes: demand forecasting, procurement, supply chain risk and resilience, and supply chain network optimization. The authors also highlighted technical, social, and contextual barriers, including scalability, security, resistance to change, and regulatory considerations.

A review published in *IEEE Access* (2025) [8] analyzed 109 journal articles published between 2007 and 2025. It classified research into five thematic clusters and identified applications involving demand prediction, inventory management, and risk analysis. The review also discussed emerging opportunities in generative AI, explainable AI, and advanced analytical methods, while recognizing that further research is needed to establish their practical value.

2.2 Comparative analysis of AI and ML techniques

Technique	Supply chain application	Expected benefit
Linear regression	Demand and cost estimation	Interpretable baseline predictions
Random forest	Demand forecasting and supplier risk classification	Captures nonlinear relationships
Support vector	Demand and lead-time prediction	Effective for suitable structured datasets

regression		
Artificial neural networks	Demand forecasting and production planning	Learns complex data patterns
Gradient boosting	Demand prediction and delivery-delay estimation	Strong predictive performance when properly tuned
Reinforcement learning	Dynamic inventory and scheduling decisions	Supports sequential decision-making
Optimization algorithms	Inventory, routing, and production scheduling	Converts predictions into feasible operational decisions

Note: The benefits listed are potential benefits; actual performance depends on the dataset, baseline methods, model configuration, and manufacturing environment.

2.3 Research gap

The literature demonstrates considerable progress in applying AI and ML to individual supply chain functions. However, several research gaps remain.

1. Fragmented optimization: Forecasting, procurement, production, inventory, and distribution are often studied separately, limiting end-to-end coordination.
2. Limited operational validation: Results obtained from historical datasets or simulations may not translate directly into industrial performance.
3. Data quality and integration: Incomplete, inconsistent, or delayed data can reduce the reliability of predictions.
4. Limited interpretability: Manufacturing managers need understandable explanations for recommendations that affect purchasing, scheduling, and inventory.
5. Resilience and sustainability: Supply chain optimization should consider disruption risk, energy use, emissions, and cost simultaneously.
6. Scalability: Small and medium-sized manufacturers may face limitations in computing resources, technical skills, and implementation budgets.

The main research gap addressed by the present study is the need for an integrated, data-driven framework that links machine learning predictions with operational optimization and evaluates the resulting decisions using common supply chain performance indicators.

III. RESEARCH METHODOLOGY

3.1 Research design

The study adopts a conceptual, literature-based research methodology to investigate how AI and ML can optimize manufacturing supply chain management. It synthesizes findings from existing research and develops a framework connecting data collection, machine learning, optimization, and performance evaluation.

The methodology is structured into five major stages: literature identification, data preparation, model selection, operational optimization, and performance assessment.

3.2 Data collection

For an empirical implementation, data can be collected from manufacturing organizations, ERP systems, warehouse management systems, supplier databases, and transportation records. Relevant variables include:

- Historical customer demand and sales orders.
- Raw material inventory and finished goods stock.
- Supplier delivery time and order fulfilment history.
- Production capacity, machine availability, and manufacturing schedules.
- Purchasing, warehousing, and transportation costs.
- Product lead times, order quantities, and delivery performance.

For the literature-based component, relevant publications can be identified through databases such as Scopus, Web of Science, IEEE Xplore, and ScienceDirect using combinations of the terms artificial intelligence, machine learning, manufacturing supply chain, demand forecasting, inventory optimization, and logistics management.

A formal systematic review should additionally document the search dates, publication period, inclusion and exclusion criteria, screening process, and number of papers retained. Since that screening has not been conducted as part of the present study, no original review-paper count is claimed.

3.3 Data preprocessing

The collected data should be cleaned and prepared before model development. This stage involves handling missing values, removing duplicate records, identifying outliers, standardizing formats, and encoding categorical variables where required.

For time-dependent demand data, chronological ordering is essential to prevent future information from leaking into model training. Training, validation, and test datasets should be separated by time where appropriate.

Feature engineering may include seasonal indicators, historical demand lags, supplier lead-time averages, promotional periods, inventory turnover, and production utilization.

3.4 Machine learning model development

Three principal model groups are proposed for the framework.

A. Demand forecasting

Linear regression can establish a baseline, while random forest, gradient boosting, and artificial neural networks can model more complex relationships. Model selection should depend on data volume, seasonality, forecast horizon, interpretability, and computational requirements.

B. Inventory and procurement optimization

Forecast demand and supplier lead times can be used to estimate safety stock, reorder points, and order quantities. An optimization model can then minimize inventory and ordering costs while satisfying service-level and storage-capacity constraints.

C. Logistics and production planning

Predicted order volumes, delivery times, transportation costs, and machine capacities can be incorporated into scheduling and routing models. Mathematical programming or suitable heuristic algorithms can determine feasible production and distribution plans.

3.5 Proposed research framework

Stage 1: Supply Chain Data Collection

Demand, inventory, suppliers, production, transportation

Stage 2: Data Preprocessing

Cleaning, integration, feature engineering, chronological splitting

Stage 3: AI and ML Models

Demand forecasting, supplier risk prediction, lead-time estimation

Stage 4: Operational Optimization

Inventory control, procurement, production scheduling, routing

Stage 5: Performance Evaluation

Forecast accuracy, cost, delivery time, inventory and service level

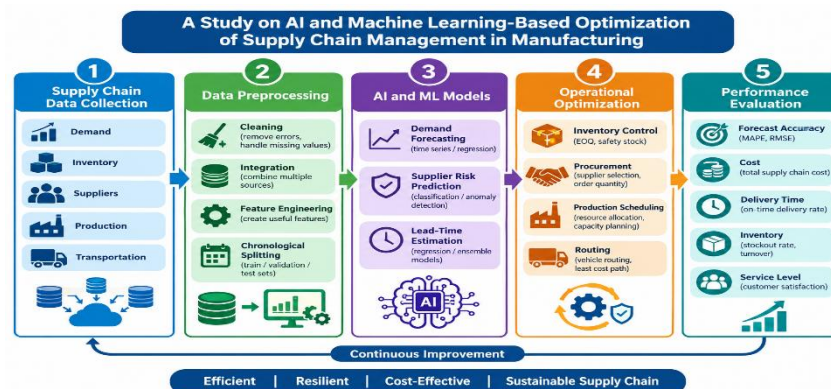


Figure 1. Proposed framework for AI and ML-based manufacturing supply chain optimization.

IV. RESULT AND DISCUSSION

4.1 Literature-based findings

The synthesis of the reviewed studies indicates that AI and ML offer several opportunities to improve manufacturing supply chain performance. The most relevant findings are summarized below.

1. Improvement in demand forecasting: Machine learning can identify nonlinear relationships, seasonal trends, and demand patterns that may be difficult to capture using simple forecasting methods. More reliable forecasts can help manufacturers align purchasing and production decisions with expected customer demand.

2. Inventory cost optimization: Forecasting models can support decisions concerning reorder points, safety stock, and replenishment quantities. When combined with inventory optimization, these predictions can help reduce excessive stock while maintaining adequate product availability.

3. Supplier selection and risk management: AI-based classification and predictive models can evaluate supplier performance, historical delivery reliability, quality records, and lead-time variability. Such models can assist managers in identifying high-risk suppliers and developing contingency plans.

4. Production and logistics coordination: Integrating demand forecasts with production schedules, machine capacity, warehouse availability, and transportation plans can improve coordination across supply chain functions. Optimization algorithms can then identify feasible schedules and distribution plans.

5. Supply chain resilience: Predictive analytics can help detect warning signals associated with shortages, delayed deliveries, and changing demand. However, the effectiveness of these systems depends on timely data, suitable models, and the availability of practical response strategies.

These observations are consistent with published reviews that identify demand forecasting, procurement, supply chain risk management, and network optimization as major areas of AI and ML application.

4.2 Expected impact on manufacturing performance

The following table presents the anticipated direction of improvement from implementing the proposed framework. These are qualitative expectations, not experimentally measured results.

Performance indicator	Traditional approach	AI/ML-supported approach	Expected direction
Demand forecasting	Historical averages and conventional statistical methods	Data-driven predictive models	Lower forecasting error, if the model performs better
Inventory management	Fixed reorder rules	Forecast-informed inventory optimization	Lower excess inventory and stockout risk
Procurement	Periodic supplier evaluation	Continuous supplier performance prediction	Better risk visibility
Production planning	Manual or rule-based scheduling	Predictive and optimization-based scheduling	Improved resource utilization
Transportation	Fixed routes and schedules	Data-driven routing and load planning	Potential reduction in delivery cost and delay
Risk management	Reactive disruption handling	Predictive alerts and contingency planning	Earlier identification of potential disruptions

4.3 Model evaluation and validation

To demonstrate measurable improvements, future empirical implementation should compare machine learning models against a defined baseline using the same test period and data conditions.

For example, a manufacturing company could compare linear regression, random forest, gradient boosting, and an artificial neural network for demand forecasting. The model with the lowest appropriate forecasting error would then provide demand estimates to an inventory optimization model.

The resulting supply chain plans should be compared with the company's existing planning method using total cost, inventory turnover, stockout rate, order fulfilment time, and on-time delivery rate.

No numerical accuracy values, percentage cost reductions, or experimental improvements are reported here because no original manufacturing dataset or model execution results were supplied. Actual quantitative results should be calculated after model training and validation.

4.4 Managerial implications

Manufacturing organizations should introduce AI and ML through a phased implementation strategy. Initially, they can select one high-impact application, such as demand forecasting or supplier delay prediction. Once the model has been validated, its outputs can be integrated with inventory, procurement, and production planning systems.

Managers should also monitor prediction errors, data drift, system reliability, and the cost of implementation. Human oversight remains important for decisions involving exceptional customer requirements, supplier negotiations, production disruptions, and major procurement commitments.

V. CONCLUSION

This study examined the potential of Artificial Intelligence and Machine Learning to optimize supply chain management in manufacturing industries. The literature-based analysis indicates that these technologies can support demand forecasting, inventory control, supplier evaluation, production scheduling, transportation planning, and supply chain risk management.

The proposed framework integrates data collection and preprocessing with predictive modelling, operational optimization, and performance evaluation. This integrated approach is important because accurate predictions alone do not guarantee better supply chain performance; they must be converted into feasible decisions that account for production capacity, supplier constraints, inventory costs, and delivery requirements.

The study also identifies important implementation challenges, including data quality, system integration, cybersecurity, model interpretability, computational requirements, and employee readiness. Addressing these issues is essential for the reliable adoption of AI-enabled supply chain systems.

Future research should implement the proposed framework using real manufacturing data and compare machine learning models with established forecasting and planning methods. Additional investigation should evaluate the combined effects of cost, service level, resilience, energy consumption, and environmental sustainability. Overall, AI and ML provide a promising foundation for more responsive, data-driven, and efficient manufacturing supply chains, provided that their benefits are verified through systematic empirical evaluation.

REFERENCES

- [1] H. Min, "Artificial intelligence in supply chain management: Theory and applications," *International Journal of Logistics Research and Applications*, vol. 13, no. 1, pp. 13–39, 2010. <https://doi.org/10.1080/13675560902736537>
- [2] G. Baryannis, S. Validi, S. Dani, and G. Antoniou, "Supply chain risk management and artificial intelligence: State of the art and future research directions," *International Journal of Production Research*, vol. 57, no. 7, pp. 2179–2202, 2019. <https://doi.org/10.1080/00207543.2018.1530476>
- [3] R. Toorajipour, V. Sohrabpour, A. Nazarpour, P. Oghazi, and M. Fischl, "Artificial intelligence in supply chain management: A systematic literature review," *Journal of Business Research*, vol. 122, pp. 502–517, 2021. <https://doi.org/10.1016/j.jbusres.2020.09.009>
- [4] Mario Angos Mediavilla "Review and analysis of artificial intelligence methods for demand forecasting in supply chain management," *Procedia CIRP*, vol. 107, pp. 1126–1131, 2022. <https://doi.org/10.1016/j.procir.2022.05.119>

- [5] S. Polo-Triana, J. C. Gutierrez, and J. Leon-Becerra, "Integration of machine learning in the supply chain for decision making: A systematic literature review," *Journal of Industrial Engineering and Management*, vol. 17, no. 2, 2024. <https://doi.org/10.3926/jiem.6403>
- [6] Giovanna Culot "Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions," *Computers in Industry*, vol. 162, Art. no. 104132, 2024. <https://doi.org/10.1016/j.compind.2024.104132>
- [7] S. A. Ganjare, S. M. Satao, and V. Narwane, "Systematic literature review of machine learning for manufacturing supply chain," *The TQM Journal*, vol. 36, no. 8, pp. 2236–2259, 2024. <https://doi.org/10.1108/TQM-12-2022-0365>
- [8] I. Vlachos and P. G. Reddy, "Machine learning in supply chain management: Systematic literature review and future research agenda," *International Journal of Production Research*, vol. 63, no. 16, pp. 5987–6016, 2025. <https://doi.org/10.1080/00207543.2025.2466062>
- [9] Ana Claudia Andrade Ferreira "The use of artificial intelligence in supply chain management: Systematic literature review and future research directions," *IEEE Access*, vol. 13, pp. 157828–157841, 2025. <https://doi.org/10.1109/ACCESS.2025.3603866>
- [10] Adane Kassa "Artificial intelligence techniques for enhancing supply chain resilience: A systematic literature review, holistic framework, and future research," *Computers & Industrial Engineering*, vol. 186, Art. no. 109714, 2023. <https://doi.org/10.1016/j.cie.2023.109714>