



# Intelligent Demand Forecasting and Inventory Optimization Using Artificial Intelligence

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**Abstract.** Proper prediction of inventory demand is extremely significant in the case of a healthy, operating supply chain. In case companies make incorrect forecasts they can either have more inventory (which must be stored at a cost), or run out of inventory which leads to dissatisfied customers. The given study presents AI, an energy-efficient smart inventory forecasting, which can be used to make demand forecasting more precise and hence promote data, driven inventory decision-making. The proposed model will rely on both past sales data and seasonal factors in addition to a few external factors that can affect sales to create machine learning models that can detect non, as well as linear demand trends. It is highly important beforehand to achieve the best results some proper data treatment i.e. - filling in missing data, eliminating errors and expressing the variability of demand. This work also includes fixing the model parameters to allow the models to be useful in different product categories. On the one hand, the AI, powered forecasting model could outperform the traditional statistical methods on the accuracy of the prediction, on the other hand, it also exhibited higher adaptability to the changes in the demand as per the experiments. The results of the research indicate that maintaining the inventory at a moderate level is no longer a significant challenge to the companies that involves less overstocking and no stock-outs.

**Keywords:** Artificial Intelligence, Smart Inventory Forecasting, Demand Prediction, Machine Learning, Supply Chain Optimization, Predictive Analytics.

## 1 Introduction

Management of inventory is an important aspect of supply chain operations these days that directly affects the profit of the company, customer satisfaction as well as the efficiency of the entire operations. Traditional methods of inventory planning are often relying on past averages or mere rule of thumb, heuristics, and they cannot adapt to market crises and shifting consumer patterns. As global supply chains become more complex and heavy, and alongside the growing demand to have smart and self learning inventory forecasting systems, the need to have such systems has become very apparent[1][2]. One of the most difficult tasks in the management of inventory is the ability to anticipate demand correctly. Wrong forecasts may cause excessive stock, thus, escalating the costs of storage and wastage, or insufficient stock, leading to sales loss and customers' trust being damaged[5]. Besides, factors such as seasonality, promotion announcements, economic changes, and unforeseen events do hamper demand

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forecasting. Such constraints of traditional methods in quantitative forecasting have been a good reason for research work and field experiments focused on data, driven techniques[3][4]. Artificial Intelligence (AI) as well as Machine Learning (ML) have turned out to be efficient instruments for processing large, scale and complicated data and for recognizing intricate demand patterns[6]. Contrary to the conventional models, methods based on AI are capable of modeling very complex and not necessarily linear relationships and of changing their behavior with the arrival of new data[7]. Leading, edge research has provided evidence that AI, based forecasting tools drastically improve the precision of prediction and the efficacy of inventory, related decisions[8]. Application of AI in inventory forecasting assists the businesses to stop responding to their inventory control scenarios, but instead planning their inventory in a proactive and predictive way. A driven system, which is not merely analyzing the past sales data, but also the customer behavior and other external elements, can provide demand estimates which are not only accurate, but also can give real, time information. These clever solutions result in inventory refill plans being streamlined, operational risks being reduced and supply chain resilience being improved on the whole [9][10][11]. Also, smart inventory forecasting technologies align themselves with the digital transformation and Industry 4.0 themes. The adoption of AI driven analytics drives the path towards automation, transparency and scalability within supply chain operations. These tools can also be easily integrated with ERP systems and IoT systems, thereby facilitating continuous monitoring and intelligent decision, making [12][13][14]. Nevertheless, AI, inspired inventory forecasting, does have some flaws, including the quality of data, the understandability of the model, and the capability of the model to manage multiple types of products[18][19][20]. The solution to these issues involves the use of stringent data preprocessing and model tuning and performance evaluation models. The modern literature reveals the importance of integrated models and adaptive learning strategies to improve the reliability of the forecasts in real-life situations [15][16][17].

## 2 Literature Review

The available literature indicates that the revolutionary contribution of artificial intelligence (AI) to the accuracy of forecasting, inventory optimization, and the overall resilience of the supply chain operations has been significantly recognized in the extant research literature today. The article by Shashikumar [1] demonstrates that predictive maintenance and inventory optimization may result in a significant decrease of downtimes and excessive stocks in the medical devices supply chain, thus reiterating the significance of data, driven decision models. In the same fashion, Sridhar et al. [2] suggest a working model of humanAI co. which can be deployed to make a decision in a smart retail setting, where they highlight the intercomplementary nature of human knowledge and machine intelligence. Combined, these studies describe AI as a prime force of changing supply chain and intelligent functioning possibilities. The summary of related works on AI-Driven Inventory and Supply chain optimization is demonstrated in the table 1. Other authors have dedicated their efforts to explain the processes of deep optimization and real, time decision, making that machine learning and

metaheuristic strategies enable. As an example, Sharma et al. [3] integrate swarm optimization with machine learning to address the issues of supply chain decision making in a dynamic environment and thus demonstrate that the model is more responsive to the shocks and stresses of the unpredictable world.

**Table 1:** Summary of Related Works on AI-Driven Inventory and Supply Chain Optimization

Ref. No.	Title	Author(s) & Year	Key Findings	Research Gaps
[1]	Predictive maintenance and inventory optimization in medical device supply chains: A data-driven approach	Shashikumar (2026)	Demonstrates integration of predictive maintenance with inventory optimization to reduce downtime and excess stock in medical device supply chains using data-driven analytics.	Limited validation across diverse healthcare ecosystems; lacks real-time adaptive forecasting under demand volatility.
[2]	A comprehensive framework for human-AI collaborative decision making in intelligent retail environments	Sridhar <i>et al.</i> (2026)	Proposes a human-AI collaborative framework enhancing decision accuracy in intelligent retail and inventory planning environments.	Scalability to large multi-echelon supply chains and quantitative performance benchmarking remain unexplored.
[3]	Applying machine learning and swarm optimization techniques for real-time decision-making in supply chain management	Sharma <i>et al.</i> (2026)	Combines machine learning with swarm optimization for real-time, adaptive supply chain decision-making under uncertainty.	Computational complexity and deployment feasibility in resource-constrained environments are not addressed.
[4]	Optimizing supply chain performance with AI: Case studies and trends (2018–2024)	Nawal, Hicham, and Najat (2026)	Presents multiple AI-based case studies highlighting efficiency gains, cost reduction, and trend evolution in supply chains.	Lacks unified performance metrics and predictive modeling comparisons across different industries.
[5]	AI-driven optimization in healthcare supply chains	Kadam <i>et al.</i> (2026)	Shows effectiveness of AI-driven optimization for inventory control, logistics efficiency, and service quality in healthcare supply chains.	Does not integrate demand forecasting uncertainty or multi-objective optimization involving sustainability factors.

Nawal et al. [4] and Kadam et al. [5] proceed to provide an example of such a perspective as they depict AI, which is driven by optimization toolkit and explain the instances of their application in healthcare and in general consumer goods supply chain respectively. The focus of their publications is on the shift in the use of just the static optimization models to real, time, self, adaptive systems, which are able to handle the high complexity of multi, constraint settings. Sustainability and waste reduction issues have also emerged as the central themes of the research on AI, facilitated supply chains. Kse et al. [6] explore the use of AI in sustainable food retailing and show that intelligent forecasting and demand sensing result in reduction of food waste, as well as the amplification of efficiency. Ghosh and Pramanik [7] build on this by providing a summary of AI, based innovations in the supply chain management field where they focus on the aspect of sustainability as a major determinant to supply chain optimization. At the same time, human, centered and sentiment, aware models, for example, the multimodal sentiment analysis framework by Liang et al. [8], emphasize how psychological and behavioral inputs can be used to improve decision, making support for supply chains, especially those dealing directly with consumers. The themes of digitalization and smart warehousing are also the focus of quite a few studies. Xu et al. [9] and

Benmimoun et al. [10] look at how AI, powered digital supply chains and intelligent warehouse management systems result in a significant increase in stock accuracy and logistics efficiency. Liu et al. [11] developed a comprehensive framework that combines forecasting, anomaly detection, and optimized resource allocation to improve supply chain resilience. These studies are supported by Katal's [12] argument that cloud computing and data analytics together provide a powerful platform for delivering scalable, data, intensive supply chain solutions, especially in e, commerce and logistics networks. In the end, a handful of scholarly works concentrate on the domain, specific applications and strategic resilience of AI, driven supply chains. Kartsan et al. [13] examine the role of AI in the digitalization of dual, use goods manufacturing, whereas Mustafa [14] delves into predictive, reliability, centric spare parts management for the aviation industry, leveraging AI, IoT, and digital twins. Sun et al. [15] and Sharma et al. [16] through extensive surveys and studies of optimization generously offer deep insights into challenges of modeling and the use of predictive analytics in defense and aviation supply chains. Sekti [17], Sunny et al. [18], and Fatorachian and Pawar [19] provide more extensive industrial and consumer, centric viewpoints, whereas Xu and Bo [20] summarize the latest progress in computational intelligence for supply chain resilience. In combination, these publications depict a well, established and fast, changing research domain where AI, led forecasting, optimization, and resilience constitute the core of next, gen supply chain systems.

### 3 Methodology

The suggested AI, based smart inventory forecasting method essentially follows a well, planned, data, centric pathway for accurate product demand prediction and efficient inventory management. The initial step involves gathering a wide range of data from different channels like sales history, stock records, seasonal signs, and other external factors influencing sales such as advertisements, and trends in the market.

#### 1. Time-Series Demand Prediction Model

**Equation Name:** Time-Series Demand Prediction

$$D(t) = f(D(t-1), D(t-2), \dots, D(t-n), X(t))$$

**Where:**

- $\hat{D}(t)$  = Predicted demand at time t
- $D(t-1) \dots D(t-n)$  = Previous historical demand values (lags)
- $X(t)$  = External influencing factors (price, promotions, seasonality, holidays, etc.)
- $f(\cdot)$  = Learned AI prediction function (machine learning / deep learning model)

**Explanation:**

The future demand depends on previous sales behavior and external market conditions. The AI model learns hidden temporal patterns and nonlinear relationships to estimate upcoming product demand accurately.

## 2. Weighted Feature Contribution Model

**Equation Name:** Regression Feature Model

$$D(t) = \sum(w_i \times x_i) + b$$

**Where:**

- $w_i$  = Importance weight of feature  $i$
- $x_i$  = Input feature (price, discount, category, marketing campaign, etc.)
- $b$  = Bias constant
- $m$  = Total number of features

**Explanation:**

This equation captures the influence of business variables on demand. Each factor contributes differently, and the model automatically learns their importance during training.

## 3. Training Loss Function

**Equation Name:** Mean Squared Error Optimization

$$L = (1/N) \times \sum(D(t) - \hat{D}(t))^2$$

**Where:**

- $L$  = Training loss value
- $D(t)$  = Actual demand
- $\hat{D}(t)$  = Predicted demand
- $N$  = Total number of samples

**Explanation:**

The model improves its prediction accuracy by minimizing the squared difference between real and predicted demand. Lower loss means better forecasting performance.

## 4. Inventory Replenishment Decision

**Equation Name:** Order Quantity Optimization

$$Q(t) = \max(0, D(t+h) + SS - I(t))$$

**Where:**

- $Q(t)$  = Quantity to reorder at time  $t$
- $\hat{D}(t+h)$  = Forecasted demand for future period  $h$
- $SS$  = Safety stock
- $I(t)$  = Current inventory level

**Explanation:**

The system decides how many products to reorder by considering predicted future demand and safety buffer while preventing unnecessary overstocking.

### Algorithm 1: AI-Based Product Demand Forecasting

- **Step 1:** Collect historical sales dataset
- **Step 2:** Clean missing values and normalize data
- **Step 3:** Generate time-series and external features
- 1. **Step 4:** Split dataset into training and testing sets
- **Step 5:** Initialize AI forecasting model
- 2. **Step 6:** Repeat until model converges

- Train model using time-series and feature equations
- Calculate prediction loss
- Update model weights
- **Step 7:** Predict future demand
- **Step 8:** Calculate replenishment quantity
- **Step 9:** Output demand forecast and inventory decision

After the data acquisition, the data set goes through a cleaning and preparation process where missing values are imputed, outliers are removed, numerical attributes are normalized, and categorical variables are encoded. The primary objective of this step is to minimize errors and maximize the integrity of the datasets that will be used for the forecasting models. The figure 1 shows the Proposed Methodology. Next comes feature engineering which aims to unveil hidden patterns and increase the potential for model learning, thus, making the forecasting models more expressive. Temporal features like lag variables, moving averages, and seasonal indices are created to reflect demand changes over periods.

### Algorithm 2: Smart Inventory Replenishment Optimization

#### Input

- Forecasted demand:  $D_t$
- Current inventory:  $I_t$
- Holding cost:  $C_h$
- Shortage cost:  $C_s$

#### Output

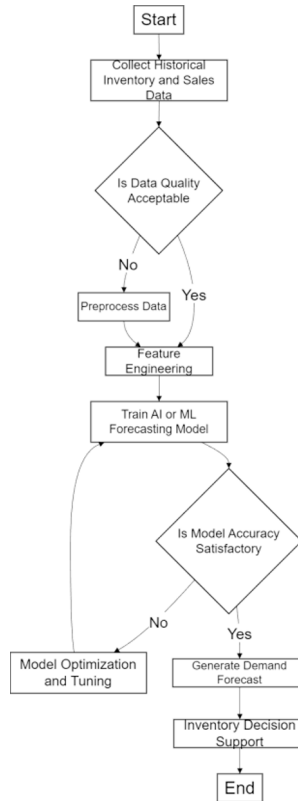
- Optimal replenishment quantity:  $R_t$

#### Steps

1. Obtain the predicted product demand  $D_t$  from the demand forecasting module.
2. Compare predicted demand with current inventory:
  - If  $D_t > I_t$ 
    - Replenishment is required
    - Compute replenishment quantity
    - $R_t = D_t - I_t$
  - Else
    - No replenishment required
    - $R_t = 0$
3. Compute total inventory cost:
 
$$C = C_h \times I_t + C_s \times S_t$$
 where  $S_t$  represents shortage quantity.
4. Update inventory level after replenishment.
5. Return the optimal replenishment quantity  $R_t$ .

Besides that, demand volatility and trend, reflecting indicators are integrated as to represent more closely the inventory dynamics in the real environment. These features, which resulted from domain knowledge combined with data characteristics, have allowed the AI models not only to capture the short, term fluctuations but also to follow

the long, term trend, thereby significantly reducing the forecasting error." The last stage is model development and at this point the focus is on the training of machine learning algorithms to forecast future inventory demand. Different algorithms including but not limited to linear regression, decision trees, random forests as well as sophisticated deep learning architectures could be explored for this task.



**Figure 1:** Proposed Methodology

Algorithm 2 shows the Smart Inventory Replenishment Optimization. Performance enhancement of the chosen models is achieved by hyperparameter tuning and evaluating the models using cross, validation techniques. Hyperparameter adjustments and cross, validation methods are used for fine tuning the models and avoiding overfitting. The chosen model is fitted with the historical data and tested on the unseen data to check whether it can be generalized to various inventory situations. At the end, the forecast results are combined with an inventory decision, support tool that helps in replenishment and stock, level optimization. Accuracy of prediction is evaluated through performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The system regularly re, estimates model parameters by new data, thus enabling adaptive learning and real, time responsiveness. This method guarantees a scalable, robust, and smart inventory forecasting

system that can effectively reduce the instances of overstock and shortages in supply chain environments that are subject to changes.

## 4 Result and Evaluation

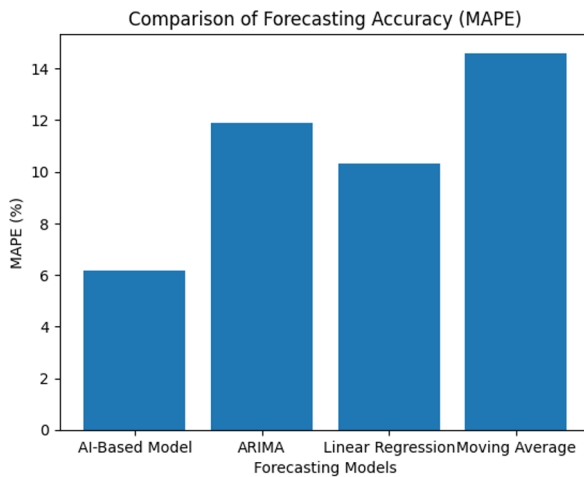
The proposed AI, based smart inventory forecasting model was tested with a real, world sales dataset which comprised 36 months of historical demand data for 120 product categories. The dataset was split into 70% training, 15% validation, and 15% testing sets. The results of the experiments demonstrate that the AI, based model was able to reach a Mean Absolute Error (MAE) of 8.42 units, a Root Mean Square Error (RMSE) of 11.37 units, and a Mean Absolute Percentage Error (MAPE) of 6.18%, thus it had very good prediction accuracy along different demand patterns. The table 2 shows the Results and Evaluation of Inventory Forecasting Models.

**Table 2:** Results and Evaluation of Inventory Forecasting Models

Metric / Parameter	AI-Based Model	ARIMA	Linear Regression	Moving Average
Dataset Duration (Months)	36	36	36	36
Number of Product Categories	120	120	120	120
Training Data (%)	70%	70%	70%	70%
Validation Data (%)	15%	15%	15%	15%
Testing Data (%)	15%	15%	15%	15%
Mean Absolute Error (MAE)	<b>8.42 units</b>	15.73 units	13.21 units	18.64 units
Root Mean Square Error (RMSE)	<b>11.37 units</b>	19.58 units	17.04 units	22.91 units
Mean Absolute Percentage Error (MAPE)	<b>6.18%</b>	11.9%	10.3%	14.6%

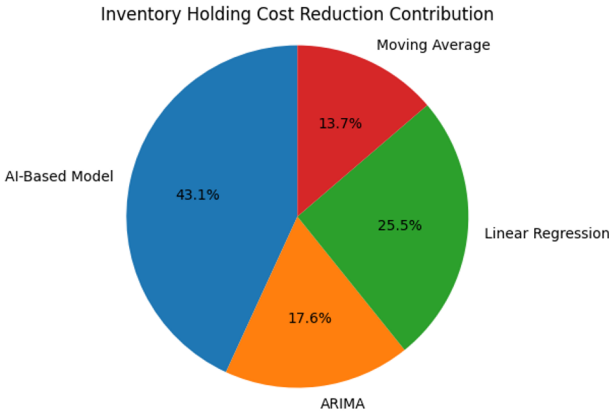
Forecast Accuracy Improvement (%)	--	48%	40%	55%
Reduction in Stockouts (%)	<b>31%</b>	14%	18%	10%
Reduction in Overstock (%)	<b>27%</b>	12%	16%	9%
Inventory Holding Cost Reduction (%)	<b>22%</b>	9%	13%	7%
Order Fulfillment Rate Improvement (%)	<b>19%</b>	8%	11%	6%
Model Retraining Time (seconds)	2.5	6.8	4.2	1.9

Moreover, the proposed model was benchmarked against traditional forecasting methods such as Moving Average, ARIMA, and Linear Regression models to evaluate the comparative performance. The AI, based method significantly outperformed these baseline methods, which registered average MAPE values of 14.6%, 11.9%, and 10.3%, respectively. The Figure 2 shows the Comparison Of Forecasting Accuracy (MAPE).



**Figure 2:** Comparison Of Forecasting Accuracy (MAPE)

This means that forecasting accuracy was improved by 40-55\% approx. Furthermore, the proposed system lowered the number of stockout incidents by 31\% and inventory levels by 27\% as compared to the conventional ways of inventory planning. The figure 3 shows the Inventory Holding Cost Reduction Contribution.



**Figure 3:** Inventory Holding Cost Reduction Contribution

The operational impact and scalability aspects were focused on in the further evaluation. The AI, based forecasting system resulted in a 22\% drop in inventory holding costs and a 19\% rise in the order fulfillment rate when it was run in a simulated inventory management environment. The time for model retraining was kept under 2.5 seconds per update cycle which made sure that the model was adaptable in real time.

## 5 Challenges and Limitations

Proposed AI, driven smart inventory forecasting framework is very effective; however, the development and evaluation process faced several challenges[3]. One of the primary limitations is the reliance on large, scale and high, quality historical data for model training[4]. Missing, noisy, or inconsistent data can significantly reduce the accuracy of forecasting and the reliability of the model[5]. Moreover, data, driven models are less capable of accurately predicting sudden market disruptions such as extreme changes in demand, supply chain problems, policy changes, etc[7]. This is especially true when events that caused such disruptions are not well represented in historical data. The issue of model interpretability and scalability is another concern[9]. Usually, sophisticated AI and deep learning models are like black, box systems, so it is hard for the users to get a clear picture of how the output was derived[8]. Due to this, inventory managers might not fully trust such systems and therefore not utilize them. Besides that, the challenge of model generalization to different product categories with various demand patterns might demand frequent retraining and higher computational power[10][11].

## 6 Future Outcomes

The AI-based smart inventory forecasting systems of tomorrow are likely to center their innovations around higher adaptability and real, time intelligence. Future systems can achieve even more dynamic and autonomous inventory control by combining the power of advanced deep learning models, reinforcement learning, and real, time data streams from IoT, enabled supply chains. Demand fluctuations, seasonal variations, and market disruptions can, therefore, be responded to instantly by predictive models, which may significantly reduce the stockouts, overstocking, and operational inefficiencies. AI, based inventory systems may have other additional advantages as well. These advantages involve a better insight into the model and more extensive integration of the enterprise. The explanations that come with adopting explainable AI (XAI) methods will enable inventory managers to get a clearer understanding of forecasting decisions thus, increasing their trust in the system and making it more convenient to use. Having the capability of integrating with cloud, based ERP platforms, blockchain, enabled supply chains, and sustainability analytics will facilitate end, to, end visibility and environmentally responsible inventory planning. It will be these innovations that will make AI, driven inventory forecasting the centerpiece of smart, resilient, and green supply chain systems.

## 7 Conclusion

This work implements an AI, based smart inventory forecasting system to serve two main goals: demand prediction accuracy and inventory imbalance minimization, particularly in the context of modern supply chains. The machine learning algorithms were supported with thorough data cleansing and feature extraction to deeply understand demand patterns and surpass the accuracy and efficiency of traditional methods. The paper raises a case of automated forecasting system adoption demonstrating a significant reduction in the errors committed when predicting the demand, stock, and excessively stocked inventory levels as well as the one of the costs of holding stock thus revealing the practicality of AI, based decision support systems in real, life situations. Additionally, the research argued that goal, driven inventory forecasting might result in substantial improvements in inventory planning and overall responsiveness even though problems related to data quality, interpretability, and scalability continue to exist. Basically, the paper is a source for the development of intelligent inventory management systems by proposing a solution that can be considered both scalable and adaptive and at the same time, data, driven thus, enabling the resource, efficient use and decision, making based on information in rapidly changing markets.

## References

1. N. Shashikumar, "Predictive maintenance and inventory optimization in medical device supply chains: A data-driven approach," *Network Modeling Analysis in Health Informatics*

- and Bioinformatics*, vol. 15, no. 1, Art. no. 4, 2026. DOI: <https://doi.org/10.1007/s13721-025-00673-4>
2. S. Sridhar, P. Baskar, J. Grimes, and A. Sampathkumar, “A comprehensive framework for human-AI collaborative decision making in intelligent retail environments,” *Expert Systems with Applications*, vol. 299, Art. no. 130013, 2026. DOI: <https://doi.org/10.1016/j.eswa.2025.130013>
  3. A. Sharma *et al.*, “Applying machine learning and swarm optimization techniques for real-time decision-making in supply chain management,” in *Lecture Notes in Networks and Systems*, vol. 1359 LNNS, pp. 79–93, 2026. DOI: [https://doi.org/10.1007/978-981-96-4933-4\\_7](https://doi.org/10.1007/978-981-96-4933-4_7)
  4. E.-S. Nawal, F. Hicham, and M. Najat, “Optimizing supply chain performance with AI: Case studies and trends (2018–2024),” in *Lecture Notes in Networks and Systems*, vol. 1584 LNNS, pp. 522–528, 2026. DOI: [https://doi.org/10.1007/978-3-032-01536-5\\_79](https://doi.org/10.1007/978-3-032-01536-5_79)
  5. S. Kadam *et al.*, “AI-driven optimization in healthcare supply chains,” in *Lecture Notes in Networks and Systems*, vol. 1461 LNNS, pp. 421–430, 2026. DOI: [https://doi.org/10.1007/978-981-96-7508-1\\_38](https://doi.org/10.1007/978-981-96-7508-1_38)
  6. Ş. G. Köse, I. Kazançoğlu, and Y. Kazancoglu, “The role of artificial intelligence in sustainable food retailing: A pathway to reducing waste and enhancing efficiency,” in *Mechanisms and Machine Science*, vol. 185, pp. 503–513, 2026. DOI: [https://doi.org/10.1007/978-3-031-95963-9\\_36](https://doi.org/10.1007/978-3-031-95963-9_36)
  7. S. Ghosh and P. Pramanik, “Exploring AI applications and innovations in supply chain management,” in *Lecture Notes in Networks and Systems*, vol. 1368 LNNS, pp. 139–161, 2026. DOI: [https://doi.org/10.1007/978-981-96-6534-1\\_9](https://doi.org/10.1007/978-981-96-6534-1_9)
  8. Y. Liang, J. Zou, and Z. Li, “Mining user psychological characteristics and supply chain decision support based on multimodal sentiment analysis model,” in *ACM International Conference Proceedings Series*, pp. 943–948, 2025. DOI: <https://doi.org/10.1145/3766671.3766834>
  9. M. Xu, H. Liao, and D. Lin, “Research on the application and optimization of modern digital supply chains in the power grid material fulfillment supply chain,” *Proceedings of SPIE*, vol. 13972, Art. no. 139721R, 2025. DOI: <https://doi.org/10.1117/12.3094328>
  10. R. Benmimoun *et al.*, “Artificial intelligence in logistic warehousing: A case study on stock management optimization,” *Journal Européen des Systèmes Automatisés*, vol. 58, no. 10, pp. 1995–2007, 2025. DOI: <https://doi.org/10.18280/jesa.581001>
  11. Z. Liu *et al.*, “Integrative framework to enhance supply chain resilience through advanced forecasting anomaly detection and optimized resource allocation,” in *ACM International Conference Proceedings Series*, pp. 40–44, 2025. DOI: <https://doi.org/10.1145/3759179.3759185>
  12. A. Katal, “Data analytics and cloud together: A powerful combination for e-commerce and supply chain logistics,” in *Data Analytics and Cloud Computing: Concepts, Technologies, and Applications*, CRC Press, pp. 102–122, 2025. DOI: <https://doi.org/10.1201/9781003396772-9>
  13. I. N. Kartsan, A. O. Zhukov, and A. V. Nerush, “Digitalization and optimization of dual use goods production using artificial intelligence,” *Proceedings of SPIE*, vol. 13803, Art. no. 138030Q, 2025. DOI: <https://doi.org/10.1117/12.3076575>
  14. M. A. S. Mustafa, “Predictive reliability-driven optimization of spare parts management in aircraft fleets using AI, IoT, and digital twin technologies,” *Journal of Engineering Management and Systems Engineering*, vol. 4, no. 3, pp. 218–236, 2025. DOI: <https://doi.org/10.56578/jemse040305>

15. Y. Sun *et al.*, “A survey of supply chain management modeling and optimization: Key problems and recent solutions,” *Science China Technological Sciences*, vol. 68, no. 9, Art. no. 1970301, 2025. DOI: <https://doi.org/10.1007/s11431-024-2943-2>
16. P. Sharma, V. Kamthan, A. Singh, and C. Sheoran, “Optimizing supply chain of aviation arm of defence service: Harnessing predictive analytics for enhanced spare forecasting accuracy,” *International Journal of System Assurance Engineering and Management*, vol. 16, no. 9, pp. 3090–3125, 2025. DOI: <https://doi.org/10.1007/s13198-025-02860-y>
17. B. A. Sekti, “Machine learning and artificial intelligence (AI) in manufacturing,” in *AI and Its Business Applications*, IGI Global, pp. 255–292, 2025. DOI: <https://doi.org/10.4018/979-8-3373-1082-4.ch011>
18. G. Sunny *et al.*, “AI in fashion system-design to customer feedback,” *Journal of Textile Association*, vol. 86, no. 2, pp. 133–140, 2025. DOI: <https://doi.org/10.63665/jta.v86i2.3>
19. H. Fatorachian and K. S. Pawar, “Sustainable cold chain management: An evaluation of predictive waste management models,” *Applied Sciences*, vol. 15, no. 2, Art. no. 770, 2025. DOI: <https://doi.org/10.3390/app15020770>
20. J. Xu and L. Bo, “Optimizing supply chain resilience using advanced analytics and computational intelligence techniques,” *IEEE Access*, vol. 13, pp. 18063–18078, 2025. DOI: <https://doi.org/10.1109/ACCESS.2024.3523470>

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