

Machine Learning-Driven Predictive Analytics for Real-Time Supply Chain Risk Management

Nagham Ja'far Hussein and Abdulhussein Mansoor Ali

Shatt Al-Arab University College, 61014 Basrah, Iraq
naghamhussein@sa-uc.edu.iq, mansoormohsin117@gmail.com

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Abstract: A resilient and efficient supply chain requires real-time risk management in an increasingly volatile global marketplace. This study examines a supply chain risk management system based on machine learning-driven prediction analytics. This research utilizes supervised and unsupervised learning methods, regression models, clustering techniques, and neural networks to improve decision-making, resource allocation, and operational efficiency. Data from logistics, inventory records, and external sources were collected, processed, and analyzed to develop predictive models capable of anomaly detection, forecasting, and planning dynamic responses. Key performance metrics were used in evaluating the proposed system, including MSE, RMSE, MAE, and R^2 . Machine learning models significantly improve supply chain operations, particularly those that use continuous learning and dynamic thresholds. Predictive analytics can transform traditional supply chain management into an intelligent, proactive, and resilient system that enhances performance, mitigates risks, reduces costs, supports rapid decision-making, strengthens responsiveness to disruptions, and effectively addresses uncertainty in highly dynamic and competitive market environments.

1 INTRODUCTION

Across today's globally interconnected economy, supply chains are becoming more complex, dynamic, and prone to disruption due to shifts in demand, transportation disruptions, geopolitical conflicts, and environmental concerns. Risk management in real-time has become a crucial priority for organizations seeking to maintain resilience, continuity, and competitiveness. Today's supply chains are marked by rapidly evolving uncertainty, which makes risk management approaches based on historical data and reactive measures insufficient. Using predictive analytics powered by machine learning, organizations can anticipate risks before they arise with a transformative solution [1]. By gaining these insights, supply chain managers are able to make proactive, data-driven decisions, optimize resources, and design networks that are more agile and resilient. The capabilities of predictive analytics systems have been further enhanced by advances in machine learning algorithms, including deep learning, ensemble methods, and reinforcement learning. Through real-time data processing combined with scalable cloud computing platforms and Internet of Things (IoT)

technologies, supply chains can be continuously monitored, and threats can be rapidly addressed [2]. As supply chain risk running processes are integrated with ML and predictive analytics, a new era is emerging for operational efficiency, customer satisfaction, and strategic planning.

SCM (supply chain management) is an important aspect of business operations that ensures efficient delivery of goods and services. Modern supply chains are complex and require robust strategies to manage uncertainty and optimize processes due to globalization, technological advancements, and market fluctuations. The use of machine learning (ML) and predictive analytics in this domain is enabling better decisions and operational efficiency. It is essential for forecasting demand, optimizing inventory, enhancing supplier relationships, and mitigating risks to have this capability. As ML is incorporated into predictive analytics, SCM is reshaping, providing unprecedented opportunities for enhancing agility, resilience, and competitive advantage. Increasing globalization, e-commerce, and rapidly changing consumer preferences have driven modern supply chains to become increasingly complex. As suppliers, manufacturers, distributors,

and retailers become more interconnected, advanced tools and techniques become more necessary.

It enables companies to align their production and inventory strategies with the anticipated market demand through the identification of hidden patterns and correlations [3]. Additionally, machine learning can benefit supply chain management in addition to inventory optimization. Consequently, substantial cost savings can be achieved, customer satisfaction can be improved, and overstocks can be avoided [4]. A predictive model can predict supplier behaviour based on historical performance and external factors and assess the likelihood of disruptions. Manage supplier relationships proactively to mitigate risks, negotiate better terms, and improve supply chain resilience [5].

A circular economy is also enabled by predictive models that can identify the most effective ways to recycle and reuse materials. As companies seek to align with global sustainability initiatives and meet the expectations of socially conscious consumers, balancing economic performance with environmental responsibility becomes increasingly important [6]. As data availability, computing power, and algorithmic capabilities improve, machine learning is increasingly adopted in supply chain management. Moreover, explainable AI techniques facilitate transparency and understanding of ML decision-making processes, creating confidence among stakeholders [7]. Supply chain management isn't without challenges despite its numerous benefits when it comes to implementing machine learning. The quality and availability of the data determine a predictive model's Accuracy and reliability. Similarly, collaborations with technology partners and academic institutions can facilitate access to cutting-edge supply chain analytics and machine learning research [8]. It is also challenging to integrate machine learning models with existing supply chains and processes [9]. It can be difficult for predictive analytics to be effective with legacy systems and siloed data sources.

Machine learning initiatives can be successfully adapted and used by aligning them with business objectives and stakeholder expectations [10]. Supply chain management also involves ethical considerations when using machine learning. There are concerns about the privacy, security, and algorithmic bias associated with predictive analytics. Companies must follow regulations and ethical standards when collecting and analyzing data. A transparent and accountable process is crucial to preventing unintended consequences and building stakeholder trust as ML models are developed and

deployed. A key component of fair decision-making is addressing algorithmic bias, especially when it comes to supplier selection and workforce management [11], [12].

2 LITERATURE REVIEW

The supply chain ecosystem should have quality control in order to promote customer-centricity and minimize risk. Increasing consumer satisfaction through quality control has been shown to increase satisfaction, according to one study [13]. Further, by integrating ERP systems and automation technologies, you can mitigate global supply chain complexity, resulting in significant cost savings [14]. It is recommended that further research be carried out on how AI can further improve supply chain management through a robust data infrastructure and stakeholder engagement.

ML-driven quality control can enhance supply chain performance, improving ROI while mitigating quality-related risks and optimizing operational efficiency. It is possible to prevent defects and ensure consistent quality with machine learning-based defect prediction systems. In addition to reducing defects and rework costs, this proactive approach also improves customer satisfaction and loyalty. By leveraging predictive modelling, ML-driven quality control drives business success by enabling continuous improvement. Machine learning has a profound impact on supply chain management (SCM). A real-world dataset is crucial to understanding how AI interacts with advanced technologies in production, according to the paper [1], [15]. The authors of [16], emphasize the importance of real-world data for meaningful innovation in healthcare start-ups, while the authors of [17] emphasize the importance of real-world data for building trustworthy AI applications.

When based on historical datasets, SCM quality control goes beyond just product quality. Furthermore, the Author [18] discusses IoT and AI technologies' role in predictive analytics and data security for ERP-based supply chain collaborations. As a result, [19] indicates that choosing suppliers involves multiple factors, including costs, delivery times, and quality, as well as environmental considerations.

In SCM, quality control plays a crucial role in improving processes, reducing inefficiencies, reducing costs, and maximizing return on investment. To reduce costs and maximize ROI across the SC, historical data can be leveraged to enhance quality

control initiatives. Analyzing historical data is the first step in improving quality control by identifying and eliminating root causes of errors and defects. Preventative measures reduce defects and reduce excessive costs. The result is that enterprises reduce costs associated with corrective actions, resulting in improved profitability. As a result of supply chain quality management, customers' needs are addressed, performance is increased, and sustainability is assured [20]. A historical data analysis improves workflow, reduces cycle time, and optimizes resource allocation by identifying supply chain inefficiencies and bottlenecks [21]. Applying quality management (QM) principles to supply chain management (SCM) can improve its operation.

By leveraging historical data, quality control procedures enhance both client satisfaction and supply chain quality, contributing to return on investment. The likelihood of repeat business increases when customers are satisfied, thereby improving profitability. A quality control method must take into account how operators comply with data collection activities about the amount of work, fatigue, and experience [22].

3 METHODOLOGY

As part of this research, supervised and unsupervised machine learning algorithms will be used. A number of researchers and industry practitioners have demonstrated the effectiveness of these algorithms in solving complex SC problems. In forecasting demand or inventory levels, supervised algorithms, such as regression models, are used because they are capable of predicting continuous outcomes.

3.1 Supply Chain Agility

Agile supply chains are multidimensional and cross-disciplinary [23]. There are two avenues for examining SCA, according to [24]: (1) speed and responsiveness to uncertain markets [25], [26] (2) information-driven relationships [27]. Agile firms are capable of adapting rapidly to changing markets, according to the Authors [26]. Unexpected circumstances can be handled more effectively by firms with agile SCs. Agile processes can be described as the integration of different companies into a streamlined material, as well as the flexible flow of information and performance [28]. There are two broad dimensions of SCA, according to the Author [29]: alertness and capability.

Firms need to ensure service continuity and manage disruption risks as they take advantage of changes and synchronize supply with demand, even though there is no consensus on what agility means [30], [31]. There is a need to differentiate agility from resilience. The key to firm success when facing low probability, difficult risks is agility [32]. In this study, four dimensions of SCA are identified: decisiveness, visibility, response to demand, and customer responsiveness.

3.2 AI-Risk Management and SCA

Firms operating in dynamic environments can leverage their dynamic capabilities to generate cutting-edge knowledge [33]. Integrating advanced analytics into core processes enables faster, more accurate information processing and better-informed decisions. Artificial intelligence augments big-data analytics [34]; for example, AIRM synthesizes multi-source data to provide end-to-end visibility and predictive insights, reducing inefficiencies in cold-chain logistics and optimizing resource utilization [35]. AI also improves demand forecasting, streamlines resource allocation, and lowers capacity uncertainty [33]. Analytics-enabled supply-chain (SC) practices support the reconfiguration of resources, and this study shows that firms can adapt resources to changing conditions using AIRM [36]. In combination, AIRM and analytics capabilities enhance supply-chain agility (SCA).

In this paper, we used the following supervised algorithms:

- Linear Regression. Using one or more independent variables, this form of regression predicts a continuous dependent variable. There is an assumption that the inputs (predictors) and the outputs (response) are linear [37].
- Ridge Regression. The loss function is regularized in this method, which extends linear regression. A multicollinear prediction model or a model with more predictors than observations will result in a penalty reducing the coefficient of correlated predictors.
- Lasso Regression. This operator reduces overfitting by introducing a regularization term that can also select features.
- Elastic Net Regression. A lasso-ridge regression combined with an elastic net is particularly useful when data have high correlations. Likened to ordinary least squares, it reduces the variability of coefficient estimates and is robust to overfitting.

- **Gradient Boosted Trees.** By allowing the optimization of any differentiable loss function, ensemble methods are similar to other boosting methods, except that they construct models stage-by-stage instead of boosting them.

3.2.1 Clustering Algorithms

By allowing the optimization of any differentiable loss function, ensemble methods are similar to other boosting methods, except that they construct models stage-by-stage instead of boosting them. The study used the following methods:

- **K-means Clustering:** This method is popular for its simplicity and efficiency and is employed in operational optimization for inventory categorization [27].
- **DBSCAN (Density-Based Spatial Clustering of Applications with Noise):** Clusters of irregular shapes and outliers can be identified using this algorithm [28]. As DBSCAN detects and analyzes atypical patterns in logistics data, it improves the capability to monitor supply chain risks.

3.2.2 Neural Networks

This research relies heavily on neural networks as they can interpret structured and unstructured inputs to model complex relationships within data. Atypical patterns can be identified using DBSCAN in SCM, which allows for improved risk management:

- **Convolutional Neural Networks (CNNs).** They are larger at processing grid-like data, enabling them to process images and spatial structures quickly [29]. The purpose of logistics optimization is to find the most efficient route and schedule for transportation by analyzing traffic patterns and route maps [38].
- **RNNs with LSTM units.** Forecasting demand and managing inventory levels can be done using historical sales data, market trends, and seasonal fluctuations.
- **FFNN with Attention Mechanisms.** To assess and make decisions about supply chain risks, we will assess the effectiveness of these networks in enhancing model interpretability and managing complex multivariate time series data.

3.3 Data Sources and Collection

The purpose of this study was to develop and test machine learning models tailored for supply chain optimization by utilizing a variety of data sources. Data can be divided into two categories:

- **Transportation Data.** Data provided by a global logistics provider includes detailed records of about 500,000 shipment transactions, including the locations of pickup and delivery, weights, modes of transportation, and carriers. On the basis of this structured dataset, logistics optimization tasks, such as route planning and freight management, can be modelled.
- **Inventory Data.** A retailer's omnichannel sales, demand fulfilment, and replenishment transactions spanning two years are included in the dataset. By providing granular inventory information, it is possible to forecast demand and optimize stock levels.
- **External Data.** There are approximately 10 million documents in these databases, including traffic and road closure reports. It is possible to improve supply chain performance by incorporating external contextual factors through unstructured data.

Collaborations with retail chains and logistics companies were utilized to collect data for this study. It is important to have access to real-time and historical data that reflects the current market conditions and operational reality. Data feeds must be consistent and reliable, data-sharing agreements must respect privacy, and disparate source data must be integrated into coherent datasets.

To give you an idea of the size and complexity of the data, here is a summary: Furthermore, to illustrates the volume of data processed as well as the comprehensiveness of the analysis, taking into account both structured and unstructured data, so that a solid foundation would support the machine learning tasks described in this study, as shown in Figure 1.

3.4 Data Processing Steps

In machine learning, raw data must be processed before it can be analyzed. Process pipelines include:

- **Data Cleaning:** Data inaccuracies and inconsistencies, including missing values and duplicate records, should be identified and corrected. By performing this step, we ensure the inputs of the models are accurate and reliable.
- **Data Transformation.** Creating a format for analyzing raw data. In this process, scales may be normalized, categorical variables may be encoded, or datetime features may be generated from timestamps.
- **Feature Engineering.** To enhance model performance, combine or transform existing

features to create new variables. Data such as inventory and transportation records can benefit from PCA by reducing dimensionality or creating interaction terms between features.

- Integration. A dataset created by combining data from different sources. As a result, data must be aligned on common identifiers, discrepancies between related datasets need to be reconciled, and timeframes need to be synchronized.

Pipelines feed high-quality, relevant data to machine learning models so that they can build robust foundations for analyzing supply chain data.

3.5 Machine Learning Models for Risk Prediction

Detecting anomalies in data is crucial to identifying issues or disruptions in the supply chain [39]. Analysis of historical data identifies patterns that differ from those established in the past and can detect deviations from normal behavior. There are several methods for detecting anomalies, including Z-scores, Grubbs' tests, Isolation Forests, One-Class SVMs, and Autoencoders [40].

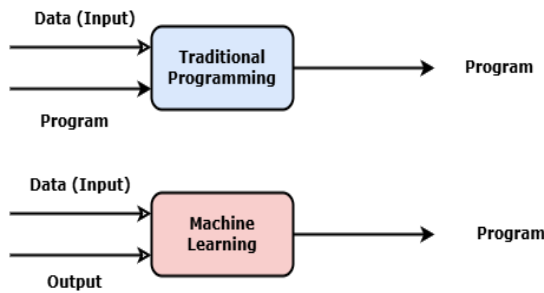


Figure 1: Models that use machine learning to predict risk.

By detecting anomalies in data streams in real time, organizations have the ability to prevent major problems, such as equipment failure, fraud, or supply chain irregularities, from occurring. A time series forecast uses historical trends and patterns to predict values. A time series forecast uses historical trends and patterns to predict values. Time series data can be analyzed by using time series models such as ARIMA and LSTM. Modelling stationary time series with ARIMA involves combining autoregression, differencing, and moving averages, which makes it suitable for forecasting time series with time-dependent variables. Time series forecasting can be performed using LSTMs, which are recurrent neural networks (RNNs) that handle sequential data and long-term dependencies. Forecasting future trends, optimizing inventory levels, and adjusting

procurement strategies can be done with both models based on changing demand and supply conditions.

3.6 Performance Evaluation

Our paper evaluates these models based on certain metrics. There are many types of error, including MSE, RMSE, and MEA, as well as Adjusted Mean Square Error.

Mean Squared Error (MSE) – the MSE is calculated by taking the square root of the difference between the actual and predicted values. Therefore, MSE measures how closely a line of best fit fits the data set. It is always positive when the MSE is calculated. When negative signs are taken out of the square, they are eliminated. Predictions are more accurate when the MSE is close to 0.

MSE is calculated using the following (1):

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 . \quad (1)$$

Root Mean Squared Error (RMSE) – this is also known as the RMSD or the RMSE. This is referred to as RMSE or root mean square error. Once again, RMSE indicates how close the line of best fit is to the points.

RMSE can be calculated using the following (2):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} . \quad (2)$$

Mean Absolute Error (MAE) – a MAE can be used to calculate the absolute difference between observational and predicted values, also referred to as MAD. Using MAE, we consider the absolute difference between predicted and observed values, while using MSE, we consider the squared difference. MAE is calculated as follows (3):

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| . \quad (3)$$

R-squared (R^2) – determination coefficients are known as R^2 . Based on R-squared, it is more likely that the independent variable accounts for more variance in the dependent variable. A regression model's goodness of fit (how closely the observed values match the predicted values) can be determined by R-squared:

$$R^2 = 1 - \frac{SSR}{TSS} . \quad (4)$$

4 RESULTS AND DISCUSSION

Based on Accuracy, Precision, Recall, and F1-Scores, Figure 2 shows the performance of a predictive analytics model. The model achieves the highest performance in Accuracy (around 88%), followed by Precision (about 82%). Approximately 75% of recalls are accurate, whereas the F1-Score is 78% accurate. Despite its Accuracy and Precision, the model could be improved to capture all the positives.

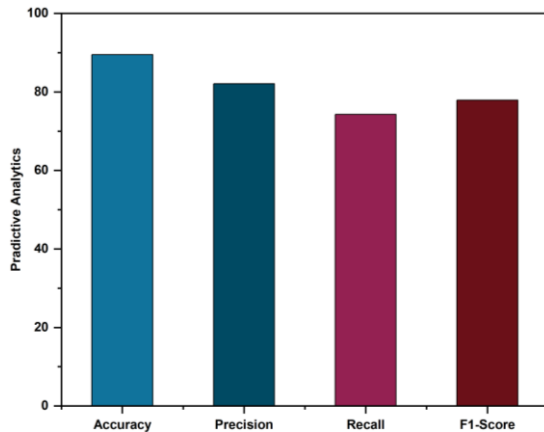


Figure 2: Performance metrics of predictive analytics model.

Figure 3 shows four metrics used to measure early warning system performance: Accuracy, Precision, Recall, and F1-Score. Accuracy (around 96%) is the highest, indicating strong overall predictions. There is a slight decrease in Precision and Recall, around 80%, with the F1-Score almost matching the Recall. Although the system is highly accurate and balanced, its precision and recall rates can be further improved for better early warnings.

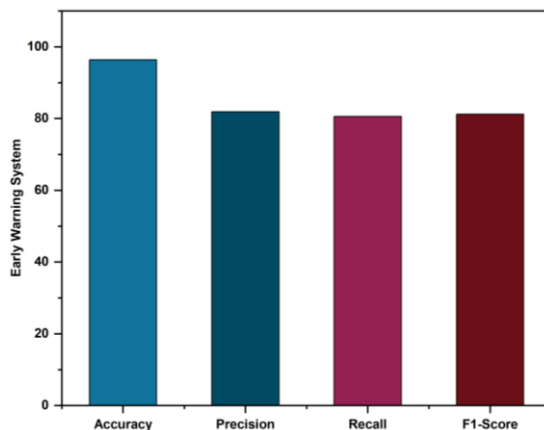


Figure 3: Performance metrics of the early warning system.

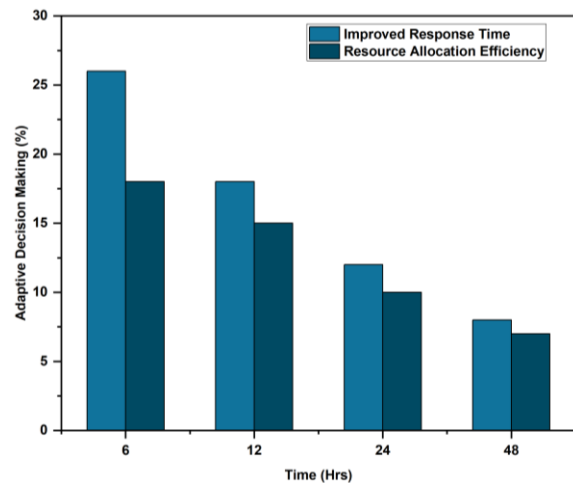


Figure 4: Impact of time on adaptive decision-making performance.

A bar chart shows improvements in resource allocation and response time over six, twelve, twenty-four, and forty-eight-hour periods in adaptive decision-making (Fig. 4). At 6 hours, the metrics improve the most, while at 48 hours, they improve the least. A faster intervention yields better adaptive decision outcomes at all-time points, illustrating the importance of improving response time over resource allocation efficiency.

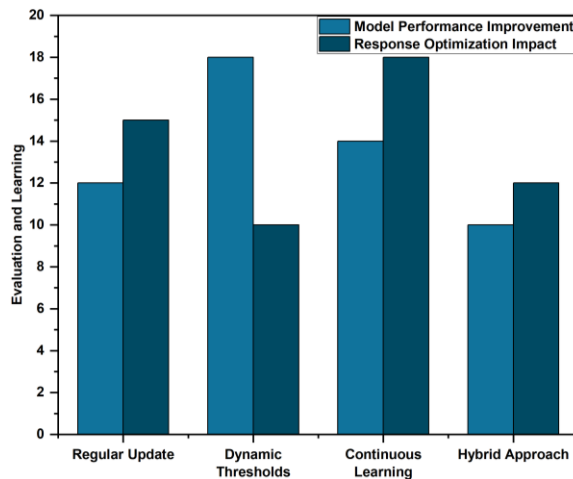


Figure 5: Comparison of model performance and response optimization across learning strategies.

Model Performance Improvement and Response Optimization are illustrated in Figure 5 using a bar chart comparing four strategies: Regular Updates, Dynamic Thresholds, Continuous Learning, and Hybrid Approaches. Model Performance Improvements are achieved through Continuous

Learning, while Response Optimization Impacts are achieved through Dynamic Thresholds. The results show that Continuous Learning and Dynamic Thresholds are more effective in improving evaluation and learning than Regular Update and Hybrid Approaches.

5 CONCLUSIONS

Our study presents a real-time risk management framework based on machine learning. This study shows how predictive models can effectively identify anomalies, forecast disruptions in supply chains, and optimize decisions by leveraging advanced supervised algorithms, clustering techniques, and neural network architectures. A robust model capable of dynamic adaptation was developed using comprehensive real-world data from logistics and inventory operations, enabling precise, data-driven decision-making. Comparative studies have demonstrated that models employing continuous learning methods and dynamic thresholds consistently outperform traditional approaches in terms of accuracy, responsiveness, and operational efficiency. Additionally, the strategic integration of anomaly detection techniques with sophisticated time-series forecasting significantly enhanced early-warning capabilities, providing timely alerts and empowering adaptive, informed responses to disruptions. According to the findings, the implementation of advanced machine learning technologies can fundamentally transform conventional supply chains into agile, resilient, and sustainable systems, better prepared to manage uncertainty and complexity. Future research could further examine the potential for integrating explainable AI within ethical decision-making frameworks, aiming to create predictive models for supply chain ecosystems that are not only transparent and fair but also accountable and aligned with societal values and regulatory expectations.

REFERENCES

- [1] P. Rani, S. P. Yadav, P. N. Singh, and M. Almusawi, "Real-World Case Studies: Transforming Mental Healthcare With Natural Language Processing," in *Demystifying the Role of Natural Language Processing (NLP) in Mental Health*, A. Mishra, S. P. Yadav, M. Kumar, S. M. Biju, and G. C. Deka, Eds., IGI Global, 2025, pp. 303-324, doi: 10.4018/979-8-3693-4203-9.ch016.
- [2] B. Bhola et al., "Quality-enabled decentralized dynamic IoT platform with scalable resources integration," *IET Commun.*, 2022.
- [3] T. Choi, S. W. Wallace, and Y. Wang, "Big Data Analytics in Operations Management," *Prod. Oper. Manag.*, vol. 27, no. 10, pp. 1868-1883, Oct. 2018, doi: 10.1111/poms.12838.
- [4] G. Wilson, O. Johnson, and W. Brown, "The Role of Machine Learning in Predictive Analytics for Supply Chain Management," 2024, Accessed: Apr. 27, 2025. [Online]. Available: https://www.preprints.org/manuscript/202408.0343/download/final_file.
- [5] V. Singh, S. Verma, and S. S. Chaurasia, "Mapping the themes and intellectual structure of corporate university: co-citation and cluster analyses," *Scientometrics*, vol. 122, no. 3, pp. 1275-1302, Mar. 2020, doi: 10.1007/s11192-019-03328-0.
- [6] J. Sarkis, "Supply chain sustainability: learning from the COVID-19 pandemic," *Int. J. Oper. Prod. Manag.*, vol. 41, no. 1, pp. 63-73, Dec. 2020, doi: 10.1108/IJOPM-08-2020-0568.
- [7] R. Y. Zhong, X. Xu, and L. Wang, "IoT-enabled Smart Factory Visibility and Traceability Using Laser-scanners," *Procedia Manuf.*, vol. 10, pp. 1-14, 2017, doi: 10.1016/j.promfg.2017.07.103.
- [8] Z. Chen, X. Ming, E. Vareilles, and O. Battaia, "Modularization of smart product service: A framework integrating smart product service blueprint and weighted complex network," *Comput. Ind.*, vol. 123, p. 103302, Dec. 2020, doi: 10.1016/j.compind.2020.103302.
- [9] P. Rani and R. Sharma, "An experimental study of IEEE 802.11 n devices for vehicular networks with various propagation loss models," in *International Conference on Signal Processing and Integrated Networks*, Springer, 2022, pp. 125-135.
- [10] G. Bressanelli, M. Perona, and N. Saccani, "Challenges in supply chain redesign for the Circular Economy: a literature review and a multiple case study," *Int. J. Prod. Res.*, vol. 57, no. 23, pp. 7395-7422, Dec. 2019, doi: 10.1080/00207543.2018.1542176.
- [11] A. Rai, "Explainable AI: from black box to glass box," *J. Acad. Mark. Sci.*, vol. 48, no. 1, pp. 137-141, Jan. 2020, doi: 10.1007/s11747-019-00710-5.
- [12] P. Rani, S. Verma, S. P. Yadav, B. K. Rai, M. S. Naruka, and D. Kumar, "Simulation of the lightweight blockchain technique based on privacy and security for healthcare data for the cloud system," *Int. J. E-Health Med. Commun. IJEHMC*, vol. 13, no. 4, pp. 1-15, 2022.
- [13] Y. Zhao, S. Jing, and R. Wang, "Quality Control Decision Research of Two-Level Supply Chain Based on the 'ERC' Fairness Preference," in *Advances in Transdisciplinary Engineering*, M. Shafik, Ed., IOS Press, 2023, doi: 10.3233/ATDE230019.
- [14] J. Agbelusi, T. A. Ashi, and S. O. Chukwunweike, "Breaking Down Silos: Enhancing Supply Chain Efficiency Through Erp Integration and Automation," Accessed: Apr. 27, 2025. [Online]. Available: <https://www.researchgate.net/profile/Thomas->

- [15] V. Varriale, A. Cammarano, F. Michelino, and M. Caputo, "Critical analysis of the impact of artificial intelligence integration with cutting-edge technologies for production systems," *J. Intell. Manuf.*, vol. 36, no. 1, pp. 61-93, Jan. 2025, doi: 10.1007/s10845-023-02244-8.
- [16] A. Zahlan, R. P. Ranjan, and D. Hayes, "Artificial intelligence innovation in healthcare: Literature review, exploratory analysis, and future research," *Technol. Soc.*, vol. 74, p. 102321, Aug. 2023, doi: 10.1016/j.techsoc.2023.102321.
- [17] L. Alzubaidi et al., "Towards Risk-Free Trustworthy Artificial Intelligence: Significance and Requirements," *Int. J. Intell. Syst.*, vol. 2023, no. 1, p. 4459198, Jan. 2023, doi: 10.1155/2023/4459198.
- [18] E. Akinbamini, A. Vargas, A. Traill, A. Boza, and L. Cuenca, "Critical Analysis of Technologies Enhancing Supply Chain Collaboration in the Food Industry: A Nigerian Survey," *Logistics*, vol. 9, no. 1, p. 8, Jan. 2025, doi: 10.3390/logistics9010008.
- [19] R. Eslamipoor, "A fuzzy multi-objective model for supplier selection to mitigate the impact of vehicle transportation gases and delivery time," *J. Data Inf. Manag.*, vol. 4, no. 3-4, pp. 231-241, Dec. 2022, doi: 10.1007/s42488-022-00076-4.
- [20] R. Oliveira, P. Sampaio, C. Cubo, M. Sameiro Carvalho, and A. Cristina Fernandes, "Defining the Supply Chain Quality Management concept," in *Handbook of Research Methods for Supply Chain Management*, S. Childe and A. Soares, Eds., Edward Elgar Publishing, 2022, pp. 307-322, doi: 10.4337/9781788975865.00025.
- [21] T. O. Olaleye, O. T. Arogundade, S. Misra, A. Abayomi-Ali, and U. Kose, "Predictive Analytics and Software Defect Severity: A Systematic Review and Future Directions," *Sci. Program.*, vol. 2023, pp. 1-18, Feb. 2023, doi: 10.1155/2023/6221388.
- [22] P. Rani, K. Ur Rehman, S. P. Yadav, and L. Hussein, "Deep Learning and AI in Behavioral Analysis for Revolutionizing Mental Healthcare," in *Demystifying the Role of Natural Language Processing (NLP) in Mental Health*, A. Mishra, S. P. Yadav, M. Kumar, S. M. Biju, and G. C. Deka, Eds., IGI Global, 2025, pp. 263-282, doi: 10.4018/979-8-3693-4203-9.ch014.
- [23] D. M. Gligor and M. Holcomb, "The road to supply chain agility: an RBV perspective on the role of logistics capabilities," *Int. J. Logist. Manag.*, vol. 25, no. 1, pp. 160-179, May 2014, doi: 10.1108/IJLM-07-2012-0062.
- [24] J. Yang, "Supply chain agility: Securing performance for Chinese manufacturers," *Int. J. Prod. Econ.*, vol. 150, pp. 104-113, Apr. 2014, doi: 10.1016/j.ijpe.2013.12.018.
- [25] R. I. Van Hoek, A. Harrison, and M. Christopher, "Measuring agile capabilities in the supply chain," *Int. J. Oper. Prod. Manag.*, vol. 21, no. 1/2, pp. 126-148, Jan. 2001, doi: 10.1108/01443570110358495.
- [26] P. M. Swafford, S. Ghosh, and N. Murthy, "Achieving supply chain agility through IT integration and flexibility," *Int. J. Prod. Econ.*, vol. 116, no. 2, pp. 288-297, Dec. 2008, doi: 10.1016/j.ijpe.2008.09.002.
- [27] B. Huo, Z. Han, and D. Prajogo, "Antecedents and consequences of supply chain information integration: a resource-based view," *Supply Chain Manag. Int. J.*, vol. 21, no. 6, pp. 661-677, Sep. 2016, doi: 10.1108/SCM-08-2015-0336.
- [28] N. Costantino, M. Dotoli, M. Falagario, M. P. Fanti, and A. M. Mangini, "A model for supply management of agile manufacturing supply chains," *Int. J. Prod. Econ.*, vol. 135, no. 1, pp. 451-457, Jan. 2012, doi: 10.1016/j.ijpe.2011.08.021.
- [29] X. Li, T. J. Goldsby, and C. W. Holsapple, "Supply chain agility: scale development," *J. Oper. Manag.*, vol. 20, no. 3, pp. 408-424, Nov. 2009, doi: 10.1108/09574090911002841.
- [30] M. J. Braunscheidel and N. C. Suresh, "The organizational antecedents of a firm's supply chain agility for risk mitigation and response," *J. Oper. Manag.*, vol. 27, no. 2, pp. 119-140, Apr. 2009, doi: 10.1016/j.jom.2008.09.006.
- [31] C.-J. Chen, "Developing a model for supply chain agility and innovativeness to enhance firms' competitive advantage," *Manag. Decis.*, vol. 57, no. 7, pp. 1511-1534, Jul. 2019, doi: 10.1108/MD-12-2017-1236.
- [32] N. Abeysekara, H. Wang, and D. Kuruppuarachchi, "Effect of supply-chain resilience on firm performance and competitive advantage: A study of the Sri Lankan apparel industry," *Bus. Process Manag. J.*, vol. 25, no. 7, pp. 1673-1695, Oct. 2019, doi: 10.1108/BPMJ-09-2018-0241.
- [33] D. Q. Chen, D. S. Preston, and M. Swink, "How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management," *J. Manag. Inf. Syst.*, vol. 32, no. 4, pp. 4-39, Oct. 2015, doi: 10.1080/07421222.2015.1138364.
- [34] R. Dubey, D. J. Bryde, C. Foropon, M. Tiwari, Y. Dwivedi, and S. Schiffling, "An investigation of information alignment and collaboration as complements to supply chain agility in humanitarian supply chain," *Int. J. Prod. Res.*, vol. 59, no. 5, pp. 1586-1605, Mar. 2021, doi: 10.1080/00207543.2020.1865583.
- [35] K. Myers, "How artificial intelligence is improving the efficiency of bim," *Plan. BIM*, 2020.
- [36] D. Q. Chen, D. S. Preston, and M. Swink, "How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management," *J. Manag. Inf. Syst.*, vol. 32, no. 4, pp. 4-39, Oct. 2015, doi: 10.1080/07421222.2015.1138364.
- [37] Y. Duan, J. S. Edwards, and Y. K. Dwivedi, "Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda," *Int. J. Inf. Manag.*, vol. 48, pp. 63-71, Oct. 2019, doi: 10.1016/j.ijinfomgt.2019.01.021.
- [38] G. Ansari, P. Rani, and V. Kumar, "A novel technique of mixed gas identification based on the group method of data handling (GMDH) on time-dependent MOX gas sensor data," in *Proceedings of International Conference on Recent Trends in Computing: ICRTC 2022*, Springer, 2023, pp. 641-654.
- [39] P. Rani, U. C. Garjola, and H. Abbas, "A Predictive IoT and Cloud Framework for Smart Healthcare Monitoring Using Integrated Deep Learning Model," *NJF Intell. Eng. J.*, vol. 1, no. 1, pp. 53-65, 2024.
- [40] G. Baryannis, S. Validi, S. Dani, and G. Antoniou, "Supply chain risk management and artificial intelligence: state of the art and future research directions," *Int. J. Prod. Res.*, vol. 57, no. 7, pp. 2179-2202, Apr. 2019, doi: 10.1080/00207543.2018.1530476.