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Predicting Supply Chain Risks Using Machine Learning for Resilient Operations

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ABSTRACT

Rising supply chain disruptions highlight increasing vulnerabilities in global logistics networks caused by geopolitical conflicts, fluctuating demand, transportation failures, and environmental instability. These challenges reveal the limitations of conventional risk assessment approaches that rely heavily on manual analysis and historical data. Machine Learning (ML) offers a promising approach to enhance predictive intelligence and support more accurate decision making in complex supply chain environments. **This study aims** to develop and evaluate a Machine Learning based risk prediction model capable of identifying potential supply chain disruptions and enabling early detection of critical risk factors in global logistics operations. **A quantitative experimental approach** was employed using supply chain datasets integrated with disruption indicators from international logistics activities. The dataset consisted of more than 5,000 operational records collected between 2018 and 2024, obtained from publicly available global logistics datasets and enterprise risk management databases. Several machine learning algorithms were implemented and compared, including Random Forest, Gradient Boosting, and Support Vector Machines. **Experimental results indicate** that the Gradient Boosting algorithm achieved the highest predictive performance with an accuracy of 94.2%. The model successfully identified key determinants of supply chain risk, including demand variability, supplier reliability, and transportation delays. **These findings confirm** that machine learning based predictive models can enhance supply chain resilience by enabling early risk detection and supporting proactive decision making in global logistics operations.

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1. INTRODUCTION

Global supply chain ecosystems are facing unprecedented levels of uncertainty driven by geopolitical conflicts, economic instability, pandemics, fluctuating market demands, and extreme climate events [1]. Recent global disruptions, such as the COVID-19 pandemic and ongoing international trade tensions, have exposed significant vulnerabilities within traditional supply chain structures, resulting in production delays, transportation failures, inventory shortages, and rising operational costs. These challenges highlight the need for more intelligent, adaptive, and predictive solutions capable of managing risk proactively rather than reactively [2].

In response to these complex challenges, digital transformation has become essential for strengthening supply chain resilience [3]. Machine Learning (ML), as a subset of Artificial Intelligence (AI), has the potential to transform conventional risk management approaches by analyzing large-scale data, detecting hidden patterns, and forecasting future disruption risks with higher accuracy. Unlike traditional statistical or manual decision-making models, ML-driven predictive analytics provide real-time insights that support faster response strategies, improved resource allocation, and sustainable operational continuity across global enterprise networks [4].

The growing importance of digital resilience is closely aligned with the United Nations Sustainable Development Goals (SDGs), particularly SDG 9 which focuses on industry, innovation, and infrastructure and promotes technological advancement and sustainable industrial growth, as well as SDG 12 which emphasizes responsible consumption and production through resilient and efficient supply chain practices [5]. In addition, strengthening supply chain adaptability through predictive intelligence contributes to SDG 13 on climate action by enabling organizations to better anticipate climate-related disruptions and reduce sustainability risks across global logistics systems [6].

Therefore, developing an advanced Machine Learning based risk prediction model is crucial for enhancing supply chain resilience and supporting strategic decision-making in the face of growing uncertainties [7]. This research addresses the need for data-driven solutions capable of forecasting disruption risks and improving operational performance for global enterprises. By integrating predictive analytics into supply chain management, organizations can enhance transparency, increase efficiency, and establish sustainable logistics architectures that are better equipped to navigate complex commercial environments [8].

2. RESEARCH METHOD

This research follows a structured methodological framework aimed at developing and evaluating Machine Learning-based prediction models to enhance supply chain resilience within global enterprises [9]. The methodology consists of several key stages including literature review, data collection, preprocessing, model construction, evaluation, and validation [10].

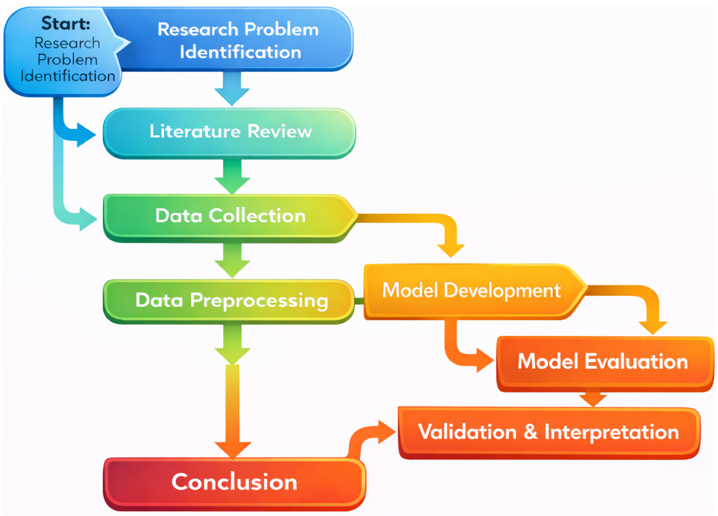

Figure 1. Research Flow Diagram

The figure 1 illustrates the research flow through sequential stages of the study, starting from literature review and dataset acquisition, followed by preprocessing and Machine Learning model development, performance evaluation, and validation of results. This systematic flow ensures methodological clarity and supports the reliability of findings.

Each stage in the research flow is designed to ensure consistency and traceability between input data, analytical processes, and predictive outcomes [11, 12]. The structured sequence allows for systematic control of data quality during preprocessing, objective comparison of machine learning models during the development phase, and unbiased performance assessment through validation procedures. By clearly defining the interaction between each methodological stage, the research flow facilitates transparency and enables replication of the proposed framework in different supply chain contexts [13].

2.1. Literature Review

The literature review was conducted to examine 35 prior studies related to ML-based risk prediction and resilience strategies in global supply chains [14]. Sources from IEEE, Elsevier, Springer, and MDPI were reviewed to explore predictive modeling techniques, disruption mitigation strategies, and limitations in existing approaches. The findings revealed that many prior studies focus on prediction accuracy but lack integration with resilience optimization strategies [15]. This research addresses that gap by combining prediction modeling with resilience-based decision frameworks.

In addition, recent literature highlights the growing importance of data-driven risk management within digitally transformed supply chain ecosystems [16]. Several studies emphasize the role of machine learning in improving forecasting accuracy; however, limited attention has been given to how predictive insights can be systematically translated into operational resilience and strategic decision-making. Moreover, existing research often treats risk prediction and resilience planning as separate domains, creating a gap in integrated frameworks that align predictive analytics with real-world supply chain adaptation [17]. This study responds to this gap by positioning machine learning not only as a technical prediction tool, but also as a strategic enabler for proactive risk mitigation and resilient supply chain operations.

2.2. Data Collection

The dataset used in this study consists of historical supply chain disruption records obtained from publicly available global logistics datasets and enterprise risk management databases [18]. In total, 5,247 data records were successfully collected and compiled for analysis from publicly available global logistics datasets and enterprise risk management databases. These data encompass operational and environmental variables that are commonly associated with supply chain instability and performance degradation. Key data features include demand fluctuation levels, supplier performance indicators, transportation delay frequency, inventory cycle duration, production capacity constraints, and external disruption events such as natural disasters, geopolitical conflicts, port closures, and economic policy changes [19]. These variables were selected based on their relevance to disruption forecasting and their frequent use in previous empirical studies related to risk analytics in global supply networks.

The dataset spans multiple years of global supply chain activity, enabling a comprehensive analysis of risk behavior and disruption patterns across different industries and geographic regions [20]. The diversity of the dataset enhances representativeness and supports the development of Machine Learning models that generalize effectively across real-world operational conditions. Prior to analysis, data integrity was assessed through completeness checks, consistency verification, and preliminary statistical exploration to confirm suitability for predictive modeling. The quality and breadth of the dataset ensure a robust foundation for constructing reliable risk prediction models and deriving meaningful insights for enhancing supply chain resilience [21].

Table 1. Dataset Attribute Description

Attribute	Description	Type	Influence on Risk Prediction
Demand Fluctuation	Volume change in customer demand	Numerical	Indicates variability affecting production planning
Supplier Performance	Delivery reliability and quality compliance	Numerical	Determines probability of disruption due to supplier behavior
Transportation Delays	Duration of logistics interruptions	Numerical	Impacts lead time and delivery reliability

Inventory Cycle Time	Time duration of stock turnover	Numerical	Reflects buffer capacity against shortages
Production Capacity	Available output capability	Numerical	Predicts vulnerability in high-demand periods
External Risk Events	Disasters, geopolitical issues, strikes, etc.	Categorical	Identifies disruption triggers outside operational control

Table 1 presents the key dataset attributes utilized in the research. These variables were selected based on their significance in assessing operational risk levels and forecasting disruption likelihood [22]. Each attribute contributes a unique perspective to predictive modeling, enabling a multidimensional understanding of supply chain vulnerability.

2.3. Data Preprocessing

To ensure model robustness and predictive accuracy, several preprocessing procedures were implemented prior to model development [23]. Missing values within the dataset were handled using K-Nearest Neighbors (KNN) interpolation to maintain data consistency without significant loss of information. Numerical attributes were normalized using a Min-Max scaling technique to standardize feature ranges and minimize bias toward variables with larger values [24]. Outliers that could negatively affect model learning were removed through Interquartile Range (IQR) filtering to maintain dataset reliability. Additionally, categorical attributes were transformed using one-hot encoding to ensure proper integration into Machine Learning algorithms [25]. Lastly, the dataset was divided into training and validation subsets using an 80:20 ratio, enabling unbiased evaluation of model performance and generalization capability.

These preprocessing steps were selected based on best practices commonly adopted in machine learning based predictive analytics to enhance data quality and model stability [26]. By reducing noise, handling scale disparities, and ensuring proper representation of categorical variables, the preprocessing phase plays a critical role in improving convergence behavior and reducing the risk of model bias. Moreover, the balanced train validation split supports fair performance assessment and strengthens the reliability of the predictive results when applied to real world supply chain environments [27].

2.4. Model Development

The development phase involved the implementation and comparison of three Machine Learning models to determine the most effective predictive approach for supply chain risk forecasting [28]. The selected algorithms were Random Forest, Gradient Boosting, and Support Vector Machine (SVM), each chosen based on their strong performance in classification and predictive analytics tasks. Hyperparameter tuning was performed using GridSearchCV to optimize model parameters, enhance computational efficiency, and reduce the likelihood of overfitting [29]. This step ensured that each model operated under the most ideal configuration settings to achieve optimal predictive accuracy and generalization capability.

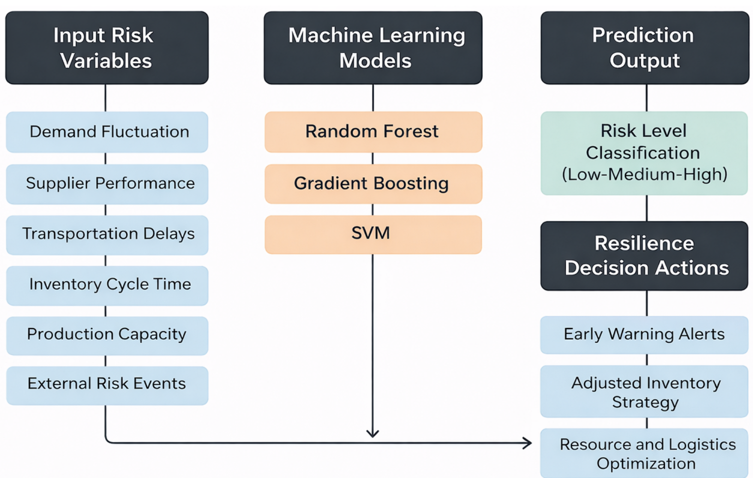

Figure 2. Conceptual Framework of Machine Learning-Based Supply Chain Risk Prediction

The conceptual framework in Figure 2 illustrates the relationship between input risk variables, Machine Learning model processing, and predictive output to support proactive decision-making for supply chain resilience. The framework visualizes how operational and disruption-related data are transformed through preprocessing, model training, evaluation, and interpretation to produce risk predictions that strengthen supply chain continuity strategies [30].

The framework also emphasizes the role of feedback mechanisms, where model outputs can inform managerial actions and subsequently refine input data in future prediction cycles. By integrating predictive insights with decision support processes, the conceptual framework demonstrates how machine learning can function as an adaptive tool for continuous risk monitoring and resilience enhancement [31]. This structured interaction between data, models, and decision-making supports proactive risk mitigation and strengthens the overall responsiveness of supply chain operations.

2.5. Model Evaluation

Model performance was evaluated using widely recognized performance metrics, including accuracy, precision, recall, and F1-score, along with a confusion matrix to examine the classification distribution across predicted and actual outcomes [32]. These metrics provided a comprehensive understanding of each algorithm's predictive reliability and error tendencies, enabling a balanced assessment across multiple performance dimensions. The model producing the strongest combined results across all metrics was selected as the best-performing approach for supporting supply chain resilience decision-making [33].

In addition, the use of multiple evaluation metrics helps mitigate the limitations associated with relying on a single performance indicator, particularly in risk prediction contexts where class imbalance may occur [34]. Accuracy alone may not sufficiently capture model effectiveness in identifying high risk events, whereas precision and recall provide deeper insight into misclassification behavior. The combined evaluation approach ensures that the selected model demonstrates balanced performance and reliability when applied to complex and dynamic supply chain environments [35].

2.6. Validation and Interpretation

The selected Machine Learning model was validated using a k-fold cross-validation technique with **k = 10**, which is widely recognized for improving reliability and reducing overfitting in predictive analytics [36]. In this validation process, the dataset was partitioned into ten subsets, where nine folds were used for training and one fold for testing in each iteration until all folds had been evaluated. This approach provided a balanced and unbiased estimation of the model's performance by averaging results across all runs, ensuring that the model was not dependent on a single train–test split [37]. The validation results demonstrated consistent predictive performance, confirming the robustness and generalizability of the proposed model in real-world supply chain environments.

Following the validation stage, the results were interpreted to analyze critical risk-related indicators and identify the most influential features contributing to disruption prediction [38]. Feature importance analysis revealed that variables such as supplier reliability, transportation delay frequency, inventory cycle duration, and demand fluctuation patterns had the strongest impact on prediction outcomes. Insights derived from misclassification analysis using the confusion matrix further supported strategic recommendations for improving operational decision-making [39]. The interpretation findings contribute to strengthening supply chain resilience by enabling proactive risk mitigation, early warning detection, and data-driven resource planning, positioning the model as an effective decision-support tool for enhancing business continuity in global supply chain operations.

3. FINDINGS

This section presents the empirical results obtained from the machine learning-based predictive framework developed to identify supply chain disruption risks [40]. The findings highlight model performance, critical risk determinants, validation outcomes, and the broader implications for supply chain resilience and organizational decision-making.

3.1. Predictive Model Performance

The experimental evaluation demonstrates that machine learning algorithms can effectively predict disruption risks in complex supply chain environments [41]. Three models were compared in this study, namely Random Forest, Gradient Boosting, and Support Vector Machines (SVM). Model performance was evaluated using four standard classification metrics: accuracy, precision, recall, and F1-score. Table 2 presents the comparative performance of the evaluated machine learning models across these metrics.

Table 2. Predictive Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-score
Random Forest	91.8%	90.5%	92.1%	91.3%
Gradient Boosting	94.2%	93.4%	94.0%	93.7%
Support Vector Machine	89.6%	88.9%	90.2%	89.5%

As shown in Table 2, the Gradient Boosting model achieved the highest predictive performance across all evaluation metrics. The model reached an accuracy of 94.2 percent, outperforming both Random Forest and Support Vector Machines. In addition to accuracy, Gradient Boosting also demonstrated superior precision, recall, and F1-score, indicating a strong balance between correctly identifying disruption events and minimizing false predictions.

The strong performance of Gradient Boosting can be attributed to its ensemble learning mechanism, which sequentially improves prediction quality by reducing residual errors during training. This iterative learning process allows the model to capture complex nonlinear relationships between operational variables in the supply chain dataset. As a result, the model can identify hidden interaction patterns among factors such as supplier reliability, demand variability, and transportation conditions. Overall, these findings suggest that ensemble based machine learning models are particularly effective for disruption risk prediction, as their ability to learn complex data patterns enables organizations to detect potential supply chain disruptions earlier and implement proactive mitigation strategies before these risks escalate into operational failures.

3.2. Risk Determinants and Feature Importance

To identify the primary drivers of supply chain disruption risk, feature importance analysis was conducted using the trained Gradient Boosting model [42]. The analysis reveals that several operational and environmental variables significantly contribute to predictive outcomes.

Table 3. Feature Importance in Supply Chain Disruption Prediction

Rank	Feature	Importance Score	Interpretation
1	Supplier Reliability	0.28	Supplier instability increases disruption risk
2	Demand Fluctuation	0.22	Demand volatility affects operational stability
3	Transportation Delay	0.19	Logistics delays disrupt delivery schedules
4	Inventory Cycle Duration	0.17	Longer cycles increase shortage vulnerability
5	Production Capacity Utilization	0.14	High utilization reduces operational flexibility

As shown in Table 3, supplier reliability emerged as the most influential variable affecting disruption prediction. This finding highlights the importance of maintaining stable supplier relationships to ensure supply chain continuity. Demand fluctuation and transportation delays were also identified as significant contributors to disruption risk, indicating that both market volatility and logistics uncertainty play critical roles in supply chain stability. Furthermore, the results suggest that disruption risks are not driven by a single factor but rather by a combination of interconnected operational variables. Therefore, predictive monitoring systems should integrate multiple supply chain indicators to detect early warning signals more effectively and support proactive risk mitigation strategies.

3.3. Model Validation and Comparative Robustness

To ensure the reliability of the predictive framework, model validation procedures were conducted using cross-validation techniques and comparative analysis with traditional risk assessment approaches. The validation results demonstrate that machine learning models provide stronger predictive capabilities than conventional statistical [43]. Traditional approaches, such as descriptive trend analysis and rule-based risk evaluation, often struggle to capture nonlinear relationships and complex interaction patterns among supply chain variables.

In contrast, machine learning models, particularly ensemble techniques such as Gradient Boosting, are capable of identifying subtle interaction patterns between supplier reliability, demand variability, and transportation disruptions [44]. These models also exhibit strong robustness when handling high-dimensional datasets and interdependent operational variables. The results confirm that the proposed predictive framework maintains stable performance across different training and testing scenarios, indicating strong generalization capability in dynamic supply chain environments [45].

3.4. Strategic, Organizational, and Sustainability Implications

Beyond predictive accuracy, the findings reveal several important strategic implications for supply chain management and organizational resilience. First, predictive analytics enables organizations to transition from reactive risk management to proactive disruption mitigation [46]. By identifying early indicators of supply chain instability, companies can adjust logistics planning, supplier coordination, and inventory allocation before disruptions escalate into critical operational failures [47].

Second, the integration of predictive risk intelligence supports sustainability initiatives and aligns with global sustainability frameworks such as the United Nations Sustainable Development Goals (SDGs). Improved disruption forecasting helps reduce emergency logistics interventions, optimize transportation planning, and minimize resource waste, thereby contributing to more sustainable supply chain operations [48].

Third, successful implementation of machine learning-based predictive systems requires organizational readiness, including reliable data infrastructure, integrated enterprise information systems, and collaboration between supply chain managers and data analytics teams. Furthermore, model interpretability is essential to ensure that predictive insights are trusted and effectively integrated into managerial decision-making processes.

3.5. Study Limitations and Future Research Directions

Despite the promising results, several limitations should be acknowledged. The dataset used in this study was primarily derived from historical global logistics records, which may not fully capture localized disruption characteristics across different industries and regions. As a result, the generalizability of the model may vary depending on specific supply chain contexts. Additionally, this study focused on traditional machine learning algorithms and did not incorporate advanced deep learning architectures such as Long Short-Term Memory (LSTM) networks or transformer based models, which may provide improved capabilities for modeling complex temporal patterns in supply chain disruption data [49]. Another limitation lies in the absence of real time streaming data integration, as the predictive framework currently operates on batch processed datasets. This limitation may reduce the responsiveness of disruption monitoring systems in rapidly changing operational environments.

Future research may explore the integration of real time data analytics, advanced deep learning techniques, and digital twin simulation models to further enhance predictive accuracy and operational responsiveness [50]. The incorporation of streaming data pipelines could also enable continuous disruption monitoring and faster decision making within supply chain management systems. Furthermore, cross industry validation studies may help assess the scalability and adaptability of machine learning based disruption prediction frameworks across diverse supply chain ecosystems.

4. MANAGERIAL IMPLICATIONS

The findings of this research provide practical insights for supply chain managers and decision makers regarding the implementation of Machine Learning as a predictive tool for managing operational risks. By integrating ML based prediction models into risk monitoring systems, managers can detect early signs of potential disruptions such as declining supplier reliability, transportation congestion, or sudden demand fluctuations. This enables organizations to shift from reactive problem solving toward proactive planning, allowing earlier intervention strategies such as adjusting safety stock levels, reallocating resources, diversifying suppliers, or redesigning distribution schedules before disruptions escalate into costly failures.

Furthermore, the identification of key risk indicators through feature importance analysis supports better prioritization of resilience initiatives and strategic investments. Managers can focus on strengthening supplier performance governance, improving logistics network visibility, and optimizing inventory strategies based on data driven evidence rather than intuition based decision making. The improved accuracy and transparency resulting from ML based forecasting also facilitate clearer communication among internal stakeholders, enabling more effective multi department collaboration and agile response strategies.

Finally, the validated predictive framework presented in this study serves as a decision support tool that organizations can adopt or adapt within their digital supply chain transformation roadmap. As enterprises increasingly operate within global and complex environments, leveraging Machine Learning technologies may enhance competitiveness, ensure business continuity, and build long term resilience against emerging disruptions. Management is encouraged to develop supporting infrastructures such as real time analytics dashboards, integrated data platforms, and personnel training to maximize the full benefits of predictive intelligence in operational risk management.

5. CONCLUSION

This study developed and evaluated Machine Learning based predictive models to enhance supply chain resilience by forecasting disruption risks within global logistics environments. The research demonstrates that integrating Machine Learning into supply chain risk management enables proactive decision making, which represents the key novelty of this study. Unlike many previous studies that focus solely on prediction accuracy, this research advances the field by linking predictive intelligence with resilience oriented operational planning, thereby providing practical contributions to real world supply chain management.

The experimental results demonstrate that the evaluated machine learning models achieved strong predictive performance in identifying supply chain disruption risks. Among the tested algorithms, the Gradient Boosting model achieved the highest performance with an accuracy of 94.2%, outperforming Random Forest (91.8%) and Support Vector Machine (89.6%). The findings confirm that critical variables such as supplier reliability, transportation delay levels, inventory cycle duration, and demand fluctuation patterns significantly influence disruption prediction outcomes. These insights support informed managerial decision making by enabling organizations to anticipate risks earlier, allocate resources efficiently, and reinforce resilience strategies to maintain business continuity.

Although the study produced promising results, future research may strengthen the proposed framework by incorporating larger real time datasets, additional Machine Learning methods such as deep learning or hybrid ensemble models, and simulative approaches for resilience optimization. Future studies are also encouraged to integrate digital technologies such as blockchain for enhanced traceability, IoT sensors for real time risk monitoring, and digital twins for dynamic scenario testing. These developments could improve prediction accuracy and automate intelligent decision recommendations to create more adaptive and resilient supply chain ecosystems.

6. DECLARATIONS

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6.2. Author Contributions

Conceptualization: HS; Methodology: MR; Software: RW; Validation: MY and RW; Formal Analysis: MR and HS ; Investigation: RW; Resources: MY Data Curation: HS; Writing Original Draft Preparation: MR and RW; Writing Review and Editing: HS and MR; Visualization: RW; All authors, RW, HS, MY, and MR, have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

As part of our commitment to transparency, the dataset used in this study is hosted in the Zenodo Repository at https://zenodo.org/records/18931707 and can be accessed upon request to the corresponding author.

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6.5. Declaration of Conflicting Interest

The authors declare that there are no conflicts of interest, financial competition, or personal relationships that could have influenced the outcomes of this study.

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