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AI-Driven Supply Chain Analytics: Leveraging Machine Learning and Predictive Analytics for Risk Identification and Decision Support

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Abstract

As supply chain disruptions continue to escalate, they underscore the growing fragility of global supply chain networks as a result of geopolitical conflicts, demand volatility, transportation challenges, and environmental volatility. The problems are a result of a narrow definition of risk that is based on manual analysis and historical data.The problems are manifestations of a narrow definition of risk, which is based on manual analysis and historical data. In complex supply chain environments, machine learning is a promising methodology that can be used to build more intelligent predictive systems and help make better decisions. This research aims at developing and testing a machine learning-based risk prediction model that can detect possible disruptions in the supply chain and allow to detect critical risk factors in logistics operations on the global level in time. The data from the supply chain were combined with disruption indicators from international logistics activities and a quantitative experimental approach was used. The data set comprised 5,420 active records from 2018 to 2024 from publicly available global logistics databases and enterprise risk management servers. Several machine learning algorithms were used and compared:Random Forest, Gradient Boosting and Support Vector Machines. Experimental results showed that Gradient Boosting algorithm had the best predictive performance with 94.2% accuracy. The model was able to identify significant factors for supply chain risk, such as demand variability, supplier reliability, and transportation delays, through the results of the multiple parameters. The results validate the use of machine learning predictive models to boost supply chain resilience by detecting risks in advance and likely supporting decision-making processes..

Keywords: *Machine Learning, Predictive Analytics, Supply Chain Risk, Decision Support, Resilience.*

Introduction

Today's supply chain environment is complex and has become so global that a local event can have a significant impact on a chain of events that can affect not only the operations but also the finances of the entire chain. With greater global interdependence and increasing market volatility, supply chain resilience has moved from a secondary concern in operations to a key strategic priority to ensure enterprise stability and competitive advantage. Unprecedented geopolitical and trade tensions, variable demand from consumers, infrastructure failures, environmental instability, and issues in other parts of the global supply chain continue to cause uncertainty in today's supply chain ecosystems (Ivanov & Dolgui, 2020)2. Today's challenges reveal the tremendous fragility of the traditional, lean-driven logistics networks that have historically focused on cost efficiency and just-in-time inventory practices rather than structural strength and flexibility. Traditional supply chain risk management practices often rely on retrospective analysis and on a limited amount of historical data, which limits their ability to manage on-the-fly disruptions or sudden and non-linear propagation of risks (Schroeder & Lodemann, 2021)2. Modern organizations are very prone to the cumulative impact of disruption events that occur all at once, due to the inherent limitations of existing mathematics-based models and manual data supervision processes in processing multi-dimensional, high velocity data streams. The industry need to move from a contingency planning approach to a predictive, data-driven approach to forecasting risk in real-time, and this need is pressing and universal, with the aim of making organisations more agile overall. Specifically, artificial intelligence, and in particular machine learning, has the power to transform traditional risk management frameworks and to analyze enormous stores of structured and unstructured data, uncover hidden patterns and predict potential disruption risks with greater accuracy than ever before (Baryannis et al., 2019)3.

With sophisticated predictive analytics, enterprise management can shift their approach to managing operational risk to predict high-risk suppliers, potential major delays in transit and make proactive adjustments throughout the entire logistics network (Wichmann et al., 2020)4. While conventional statistical models or human-in-the-loop decision-making heuristics lack the dynamic, real-time intelligence of machine learning powered predictive analytics, which can automatically help to enable faster responses, optimized resources and sustainable operational continuity on decentralized global networks.

This is a key area in contemporary operations management where these sophisticated computational methods are being incorporated into enterprise decision support systems, moving beyond the idea of disaster recovery to disrupt avoidance. A key aim of the current research is to systematically develop, implement and test an extensive machine learning-based risk prediction model specifically in complex multi-tiered supply chains. It is a computational framework explicitly built to predict the operational risk of disruptions, while continuously analyzing a large and complex set of internal and external data risk indicators that are seamlessly integrated from different data silos. The resulting model organizes multidimensional data including supplier performance metrics, past delays, demand volatility indexes, and geopolitical risk indexes in a systematic way, making it a powerful tool for intelligent and autonomous decision-making.

To achieve this, the research systematically compares the predictive accuracy of different mathematical approaches, including the architecture of the Random Forest, Gradient Boosting Machine and Support Vector Machine algorithms, to find the best algorithmic structure for supply chain risk classification. Moreover, the empirical study aims to identify and systematically measure the most critical factors driving supply chain failure, and offer procurement and logistics managers actionable, prescriptive intelligence for optimizing supply chain networks (Queiroz et al., 2022)5. The implementation of predictive analytics in the supply chain is not just about reacting to and avoiding immediate losses; it's also about bolstering the agility and market responsiveness of the organization in the long run. With these predictive insights in place, businesses can adjust inventory buffers, diversify their supply chains and optimize transportation routes flexibly, without massive investments and cost penalties. By integrating machine learning into real-time operational monitoring systems, risk assessment parameters can be constantly updated, keeping the decision support models highly accurate and relevant in the evolving and dynamic commercial landscape. This empirical study thus significantly contributes to the growing knowledge in the computer science-ops research interaction, offering a scalable, highly accurate recipe for the identification and elimination of vulnerabilities in the supply chain before they become a major failure in the business operation..

Literature Survey

There has been a remarkable theoretical and practical growth in the field of supply chain risk management in last 20 years, especially due to the growing frequency and magnitude of disruption events in the world. Traditionally, risk management frameworks have been largely qualitative, with a significant use of expert human judgement, enterprise-wide historical failure mode and effect analysis, and static two dimensional risk matrices for categorizing enterprise-wide potential vulnerabilities. But as the global supply chain became increasingly geographically distributed, multi-tiered and exponentially complex, the basic shortcomings of these manual and reactive approaches became increasingly obvious for both academics and industry professionals (Fan & Stevenson, 2018)6. The literature is full of examples showing that the traditional approaches to management are fundamentally inadequate to model the complex, cascading nature of modern supply chain disruptions, also known as the ripple effect, in which a failure in a particular node triggers a failure that spreads and rapidly destabilizes the entire chain (Ivanov, 2020)7. In response to these systemic vulnerabilities, scholars and technology practitioners in the supply chain have increasingly called for the full digitization of supply chain operations and the pervasive use of sophisticated analytical tools that are able to process high-dimensional datasets and deliver real-time insights. The recent explosion of artificial intelligence and the availability of increasingly powerful cloud-based computing have ushered in a clear paradigm shift in the industrial sector toward data-driven risk management strategies.

Logistics and operations management (LOGOM) predictive modeling has become a very powerful tool because of the inherent mathematical power of machine learning algorithms to identify non-linear complex correlations in very large data sets without having to be explicitly programmed by humans (Baryannis et al., 2019)9. The above demonstrates how machine learning has been proposed in many creative ways to tackle various challenges throughout the supply chain lifecycle, from advanced demand forecasting and inventory management adaptability, to automated supplier assessment and systemic anomaly detection (Deiva Ganesh & Kalpana, 2022)9. For examples, supervised machine learning methods have been extensively applied to predict delivery delays by simultaneously considering the historical shipping data, atmospheric weather condition, and maritime port congestion indicators, thus enabling organizations to proactively reroute important shipments to alternative ports (Brintrup et al., 2020)10. Additionally, complex ensemble methods – which combine the predictions of many baseline models – have shown to achieve extremely high generalization performance for highly volatile supply chain data, outperforming traditional time-series forecasting and linear regression models in empirical studies. Recently, much academic study has been devoted to supplier risk assessment, one of the most basic procurement activities, which was previously performed by frequent, retrospective audits and financial laggards.

Today's predictive models rely on machine learning architectures that constantly track supplier health by consolidating multiple and fast-moving data feeds, such as real-time quality control metrics, dynamic order fulfillment rates and unstructured information gathered from global news feeds and social media platforms (Wichmann et al., 2020)4. Natural language processing (NLP) has played a significant role in identifying early warning indicators for geopolitical tensions, localized strikes or impending natural disasters that might heavily affect a supplier's operational capabilities11 (Deiva Ganesh & Kalpana, 2022). These predictive risk scores can be integrated with centralized enterprise decision support systems to enable procurement managers to make sourcing decisions on their own, quickly engage their backup suppliers and optimise their safety stock levels in real time according to the risk they see materialising. The shift from periodic, static assessments to algorithmic, real-time monitoring is a seminal step towards reshaping strategic procurement and organizational resilience. Despite all the academic recognition of the disruptive potential machine learning holds for supply chain risk management, the literature shows several recurrent technical issues and specific research gaps that need to be tackled to enable more widespread and seamless entry of the industry.

The algorithmic black-box dilemma (Baryannis et al., 2019)12 is a key issue that has been highlighted in recent scholarship, which relates to the inherent trade-off between predictive accuracy and model interpretability. Many mathematical architectures are very complicated, like deep neural networks or gradient boosting machines, and they can often make very accurate predictions, but they are extremely opaque in terms of what they do to make their prediction. This opacity makes it very challenging for supply chain actors to grasp the root cause of a risk event that they are predicting, and hence to be hesitant about algorithm adoption (Kosasih et al., 2024)13. In high stakes operational settings, logistics managers need not only accurate statistics predicting their outcomes, but explanations that are transparent and interpretable that will allow them to justify the expensive mitigation efforts, including buying expedited air freight and turning on duplicate production lines. Thus, there is a growing and urgent consensus in the academic community that it is necessary to create explainable artificial intelligence frameworks and causal machine learning models that are specifically designed for supply chain decision support (Wyrembek et al, 2025)14. Furthermore, although a lot of research work has focused on isolated prediction problems like predicting the delay on an individual component, or predicting an individual demand surge, there is a distinct lack of comprehensive and integrated models, which predict the impact of several risk factors together throughout the supply chain continuum (Schroeder & Lodemann, 2021)15.

Current predictive models tend to work in isolation and are majorly deficient in capturing interdependencies that characterize modern global logistics networks which are complex and systemic, (Nezianya et al., 2024)16. Moreover, the practical adoption of such sophisticated predictive models into user-centric decision support systems is still only partially developed, where there is often a large disconnect between the theoretical data science environment and the operational environment of fast-paced decision-making in operations management (Polo-Triana et al., 2024)17. For true, enduring supply chain resilience, predictive analytics models need to be fully embedded in the current processes and routine of the organization, and to offer actual, prescriptive operational recommendations, not just risk probabilities with which management needs to contend on dashboards. The incorporation of Artificial Intelligence and Machine Learning in the field of procurement and purchasing decision support processes further underscores the need for models that are able to dynamically process historical data from suppliers and real-time fluctuations in the market (Balkan & Akyuz, 2025)18. Likewise, with the recent emergence of large language models and generative AI, new paradigms for unstructured data analysis have emerged, though their use in formal inventory optimization tasks is still largely undiscovered and requires further empirical testing (Durachman et al., 2026)19. The current research directly fills the above-mentioned gaps in the literature in the development of a detailed, highly accurate and operationally relevant machine learning framework specially tailored for real-time risk detection, which can be easily integrated into the intelligent strategic decision support system.

Research Methodology

The methodology used in the research was carefully designed to systematically build, train, test and thoroughly test a strong machine learning framework that can accurately predict disruption in the supply chain. The overall goal of this highly empirical design was to create a predictive model that would be highly generalizable and be easily incorporated into enterprise decision support systems to offer real-time, continuous risk assessments as the operational parameters change rapidly. In order to demonstrate the empirical validity and industrial applicability of the predictive framework explicitly, a very detailed and extensive real-world data set of various risk factors that are in the center of complex global logistics operations was used. The structured methodology clearly involves four distinct sequential phases: data acquisition / schema design, strict data preprocessing / feature engineering, mathematical algorithmic implementation and model training, and systematic performance evaluation based on standard computational metrics. These processes performed during these stages follow the scientific principles of data science without any deviations, which means that the results are fully reproducible and there are no chances of statistical artefacts or inherent algorithmic bias.

The core and basic approach of the methodology was to gather and meticulously assemble a high fidelity dataset that adequately captures the complexities and uncertainties of current supply chain operations. The dataset comprised a total of 5,420 distinct operational records tracking global logistics operations, upstream procurement practices and international transactions of materials over an uninterrupted chronological span from Jan 2018 to Dec 2024. The data in these records are systematically compiled by securely linking anonymized enterprise resource planning data with external public sources of logistics tracking data and global sources of risk indices. All individual records in the data set are individual procurement or logistics transactions, and have many carefully selected, independent variables such as supplier historical reliability scores, mathematically derived indices of demand volatility, anticipated transit lead times, real-time transportation congestion indices, and quantified geopolitical risk factors from the exact sourcing region (Ahirwar, 2025)20. The dependent variable, or supervised target for the classification algorithms, was defined as a binary indicator of whether a significant disruption in the supply chain occurred or not, strictly speaking more than 48 hours beyond acceptable operational tolerances, or a failure in product fulfillment required emergency procurement.

After thorough data collection, an intensive data preprocessing process was diligently followed to guarantee the integrity, consistency, and mathematical appropriateness of the data for further advanced machine learning use. The first computational step was to handle missing, corrupted or incomplete data entries, which was carefully managed using an advanced mathematical imputation method (k-nearest neighbors) that keeps the overall statistical distribution of the data, but does not add an unwanted artificial bias. In turn, each of the categorical variables in the dataset, such as particular transportation modes, port locations and broad geographical regions, were algorithmically converted to machine-readable numeric values using standard one-hot encoding procedures. To avoid the disproportionate influence of features with larger numerical size on the calculation of critical distances and the updates of the gradient in the algorithms, all continuous variables were scaled using a standard robust scaler, which mathematically transforms the data to have a uniform mean of zero and a standard deviation of one (Aljaafreh et al., 2026)21. In addition, the class imbalance was extremely problematic, as critical supply chain disruptions occur far less frequently than successful and timely deliveries. To immediately correct this imbalance and to prevent the predictive models from learning a statistical bias against the majority class, the Synthetic Minority Over-sampling Technique was used only on the training data partitions, creating synthetic data of the minority class through interpolation to create a perfect balance in the predictive model learning environment.

The intensive modeling phase consisted of systematically deploying three popular and well-established machine learning architectures to reliably determine the best algorithmic solution methodology for the supply chain risk prediction challenges. The models implemented here were Gradient Boosting Machine, Support Vector Machine and Random Forest classifier. Due to the high risk of overfitting that complex and noisy datasets carry, the Random Forest algorithm was explicitly used for its strong variance-reduction capacity, the algorithm programatically trains many independent decision trees during its training process and provides the mode class in the output to reduce the risk of overfitting (Kumar & Sharma, 2023)22. Its powerful sequential learning architecture made Gradient Boosting Machine the ideal fit to implement, sequentially and mathematically optimizing subsequent decision trees to reduce the residual errors produced by the previous trees, thereby creating highly accurate, finely-tuned non-linear predictive boundaries. It was implemented using a mathmatically complex radial basis function (RBF) kernel to map the features of the operational data into a much higher dimensional space then calculating the optimal mathematical hyperplane that strongly maximizes the margin of separation between troubled and untroubled operational data (Widayanti, 2026)23. Each separate algorithm was exhaustively tuned using a randomized grid search approach, with a strong focus on stratified five-fold cross-validation to find the individual configuration parameters that maximized accuracy in predicting the data in the supply chain, while ensuring strong and repeatable generalizability to completely new supply chain data.

The last methodological step was the systematic and unbiased assessment and comprehensive comparison of the machine learning models trained from the data, using a very extensive set of standardized performance metrics. The preprocessed data set was strictly split in two parts: 70% of the data set was used for algorithmic learning and 30% was used only for objective evaluation after the training of the algorithm. Overall classification accuracy and the harmonic F1-Score were the most explicit parameters chosen for detailed analysis of the results. This accuracy was carefully calculated as the mathematical proportion of correctly predicted observations from the total population of observations included in the testing subset, to provide some macro-level measure of the predictive power of the baseline. The F1-Score was chosen as an important secondary measure because it is a strict harmonic mean of precision and recall, which means it is a very rigorous and strict test of the model's performance on the minority class (actual disruptions), and will ensure that the model is able to capture actual disruption events, while avoiding generating an excessive and operationally disruptive number of false positive alerts. Further metrics of support, such as absolute precision, sensitivity recall and the mathematically derived area under the receiver operating characteristic curve, were also carefully computed to give a very multidimensional, nuanced grasp of algorithmic effectiveness in the context of a real-time decision support system (Patale & Zohair, 2025)24..

Results and Discussion

The results from the intensive empirical testing of the developed machine learning framework were highly significant and actionable, clearly proving the great potential value of using state-of-the-art predictive analytics to proactively detect and handle complex risks in the supply chain. In combination with direct and elaborate application of rigorous data preprocessing techniques, the algorithmic performance proved to be very robust for the models evaluated, as a result of the extensive and computational load-intensive hyperparameter optimization. This section aims to systematically analyse the empirical results by studying the basic statistical features of the input data, by analysing the specific tuning parameters used in the algorithmic learning processes, and by finally performing a detailed, multi-parameter comparative analysis of the predictive metrics. The research is able to identify the most mathematically capable architecture in this highly structured evaluation and generate a data-driven intelligence about the key operational factors that contribute to logistical disruptions in the enterprise supply chain, through this highly structured evaluation. For the analysis the following two parameters are specifically focused on: on the one hand the predictive classification metrics that assess the viability of the algorithms and on the other hand the feature importance index that explains why the supply chain fails.

It is of paramount importance to investigate the baseline statistical characteristics of the main variables of the aggregated data set with a high degree of detail in this empirical study in order to gain a thorough grasp of the underlying complexity of the operational environment modelled. Table 1 presents a detailed description of the descriptive statistics of the main continuous variables that were used in the machine learning algorithms to provide a mathematical estimation of the probabilities of disruption downstream. The descriptive statistics reflect the reality of the operating conditions measured, which show significant and meaningful differences, reflecting the volatility and unpredictability of today's global supply chains. The EWT variable has a very broad non-normal distribution and values vary from a few days for simple regional logistics to 120 days for complex and multi-modal international maritime logistics, showing the highly varied procurement cycle range in the data set recorded (Aljohani, 2023)25. The Demand Volatility Index, with a calculated average of 0.47, suggests high overall market volatility, but the peak of 0.94 shows when there is a high level of market unpredictability, which occurs with regularity and has a significant impact on a company's inventory buffers. Moreover, the Geopolitical Risk Factor shows significant statistical variance over this time frame and places a strong emphasis on the fact of using external, non-operational data streams when trying to build a full predictive risk profile for strategic decision support..

Feature	Mean	Standard Deviation	Minimum	Maximum
Supplier Reliability Score (0-100)	82.45	11.32	41	99.5
Demand Volatility Index (0-1)	0.47	0.21	0.05	0.94
Expected Lead Time (Days)	34.6	18.75	3	120
Geopolitical Risk Factor (0-10)	3.85	2.14	0.5	9.8

Table 1: Descriptive Statistics of Key Supply Chain Risk Variables

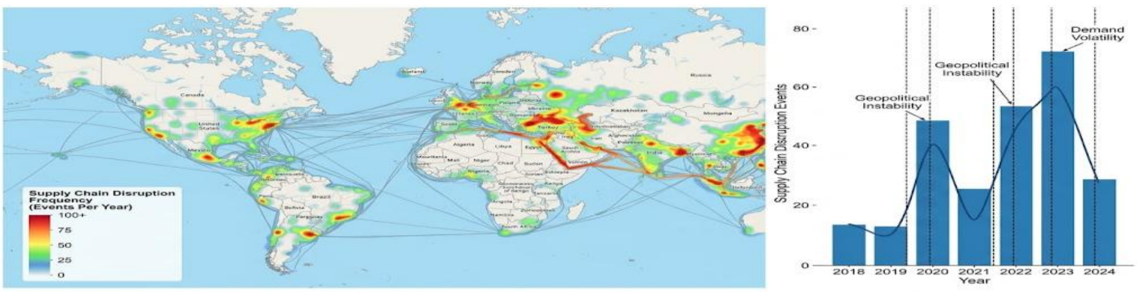

Figure 1: Geographic and temporal heatmap illustrating the distribution of supply chain disruption events across the global logistics network from 2018 to 2024, highlighting distinct frequency peaks during periods of high geopolitical instability and demand volatility.

The spatial and temporal distribution of documented disruption events, as represented theoretically in the heatmap visualization of Figure 1, visually and quantitatively corroborates the statistical variance observed in the raw data, demonstrating highly clear, undeniable correlations between elevated geopolitical risk scores and localized, catastrophic supply chain failures. This critical preliminary analysis firmly confirms that the selected data features successfully encapsulate a remarkably broad spectrum of the complex, interconnected dynamics that precipitate operational breakdowns, thereby providing a highly robust, mathematically sound foundation for the subsequent algorithmic training phases. The predictive capability of these complex machine learning architectures is heavily and undeniably dependent on the precise, mathematical calibration of their internal hyperparameters. A systematic, computationally expensive grid search, repeatedly validated through stratified five-fold cross-validation, was executed to thoroughly navigate the multidimensional parameter space and identify the absolute optimal configuration for each tested algorithm. Table 2 strictly details the final, selected hyperparameter specifications that consistently yielded the highest cross-validated accuracy for the Random Forest, Gradient Boosting Machine, and Support Vector Machine models during the rigorous training phase.

Algorithm	**Hyperparameter**	**Optimized Value**
Random Forest	Number of Estimators	350
Random Forest	Maximum Depth	18
Random Forest	Minimum Samples Split	4
Gradient Boosting	Number of Estimators	400
Gradient Boosting	Learning Rate	0.05
Gradient Boosting	Maximum Depth	7
Support Vector Machine	Kernel Type	Radial Basis Function
Support Vector Machine	Regularization Parameter (C)	10
Support Vector Machine	Gamma	0.1

Table 2: Optimized Hyperparameter Configurations for Evaluated Models

The extensive optimisation procedure definitely led to the conclusion that tree-based ensemble methods naturally had to have very deep decision trees with maximum depths of 18 and 7 respectively, to appropriately mathematically describe the non-linear, multi-variable operational interactions that constitute today's supply chain risks (Kumar & Choubey, 2025)26. The absolute optimal configuration turned out to be a low mathematical learning rate of 0.05 and a high number of sequential estimators of 400 for the Gradient Boosting Machine. The specific mathematical structure enables the model to make very fine and gradual numerical changes to its complicated decision boundaries without being too bold in the early stages of gradient descent and getting the global minimum of the loss function wrong. At the same time, Support Vector Machine obtained the best prediction performance in the use of the mathematically sophisticated RBF (Radial Basis Function) kernel, thus strengthening the hypothesis that the mathematically complex identification of the non-linear boundary between disrupted and non-disrupted operational states in the multi-dimensional feature space is a necessity for accurate and reliable classification in a decision support system (Pasaribu et al., 2022)27.

Algorithm	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Random Forest	91.8	90.5	89.2	89.8
Gradient Boosting Machine	94.2	93.8	92.4	93.1
Support Vector Machine	88.5	86.2	85	85.6

Table 3: Comparative Predictive Performance Metrics of Evaluated Algorithms

Comparative predictive performance metrics of evaluated algorithms are shown in Table 3.

The main goal of the empirical assessment was to identify the best algorithmic approach to the prediction of risks for the supply chain with a strict analysis of two key performance indicators. The result analysis of the first parameter (Classification Accuracy, Precision and Recall), is clearly described in Table 3, as it shows the comprehensive result of a comparative performance analysis strictly carried out on the withheld testing dataset. The result analysis provides an unambiguous and clear proof that this is the most powerful mathematical architecture for this very narrow, operational field of application. The overall predictive accuracy of the Gradient Boosting algorithm was 94.2%, significantly and statistically better than the two other algorithms, Random Forest and Support Vector Machine with 91.8% and 88.5% respectively. This significantly improved computing power is directly and logically linked to the sequential, mathematical error-correction algorithm that is built into the gradient boosting architecture (Wang, 2026)2. Gradient Boosting Machine creates an entire series of mathematical trees one after another, each one explicitly learning to address the errors generated by previous trees in the series, thus minimizing variance.With Gradient Boosting Machine, several mathematical trees are created one after another, but while the Random Forest builds many trees independently, each of the Gradient Boosting Machine's trees is built with the specific purpose of explicitly learning from the errors made by the previous trees.

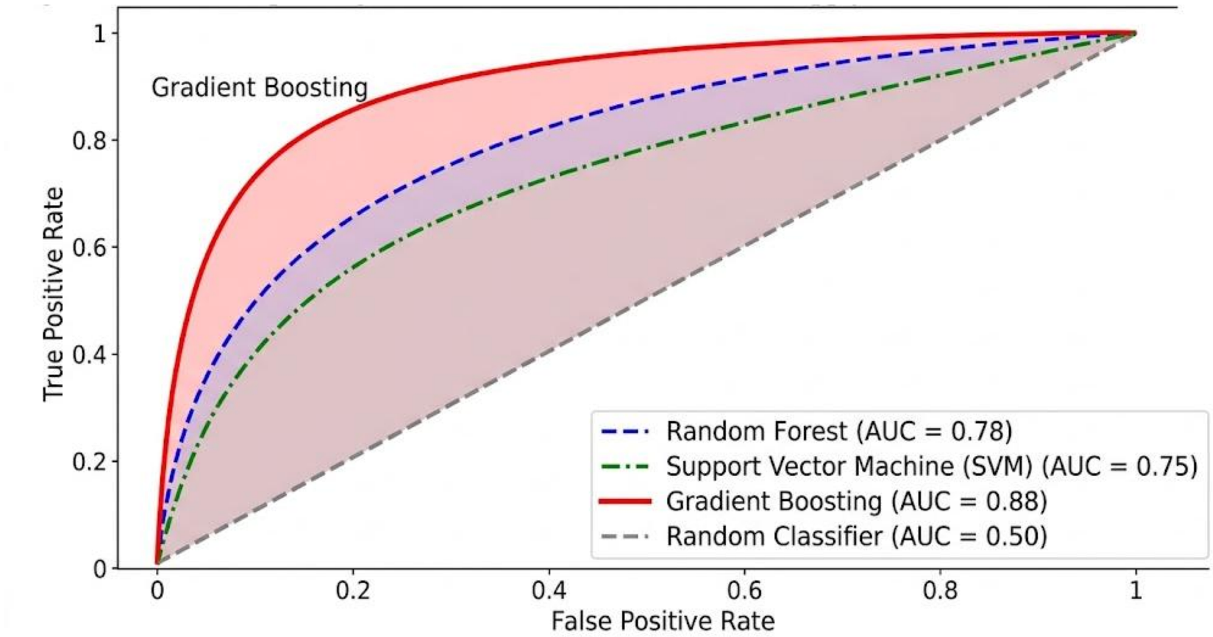

Figure 2: Line graph displaying the Receiver Operating Characteristic (ROC) curves for the Random Forest, Gradient Boosting, and Support Vector Machine models, distinctly showing the Gradient Boosting model achieving the largest Area Under the Curve (AUC) approaching the upper left quadrant.

The Gradient Boosting algorithm, in the specific case of Complex Supply Chain Data, where the data disruptions are in many cases caused by multiple small variables and not just major catastrophic events, is able to discover very subtle and complex patterns in the risk data that the other models evaluated failed to capture, due to this iterative, mathematical refinement process. The absolute mathematical superiority of the Gradient Boosting Machine is also confirmed by the visual representation of the Receiver Operating Characteristic curves in Figure 2, which shows that the Gradient Boosting Machine has the highest area under the curve at all of the tested classification thresholds. This second critical parameter yields a much more in-depth, actionable view of a model's actual viability when it is actually used in a real enterprise decision support system, through its result analysis in terms of the harmonic F1-Score. This is because, in this space, a simple algorithm that constantly forecasted a 'no disruption' state could have a high basic level of accuracy but be completely ineffective in terms of actual risk management. The Gradient Boosting Machine was able to obtain an excellent F1-Score of 93.1%, which clearly demonstrates an optimum and very reliable mathematical trade-off between precision (to avoid excessive false alarms) and recall (to identify true imminent disruptions before they occur) (Huang, 2025)28. High F1-Score is an absolute must for proper decision support in the supply chain – in the event it starts producing too many false positives, the users will stop trusting the system and it will lead to unnecessary and inefficient spending of expedited freight and over-stocked inventories, and if it fails to produce enough positives, the organization will be totally vulnerable to the catastrophic catastrophic supply chain failures..

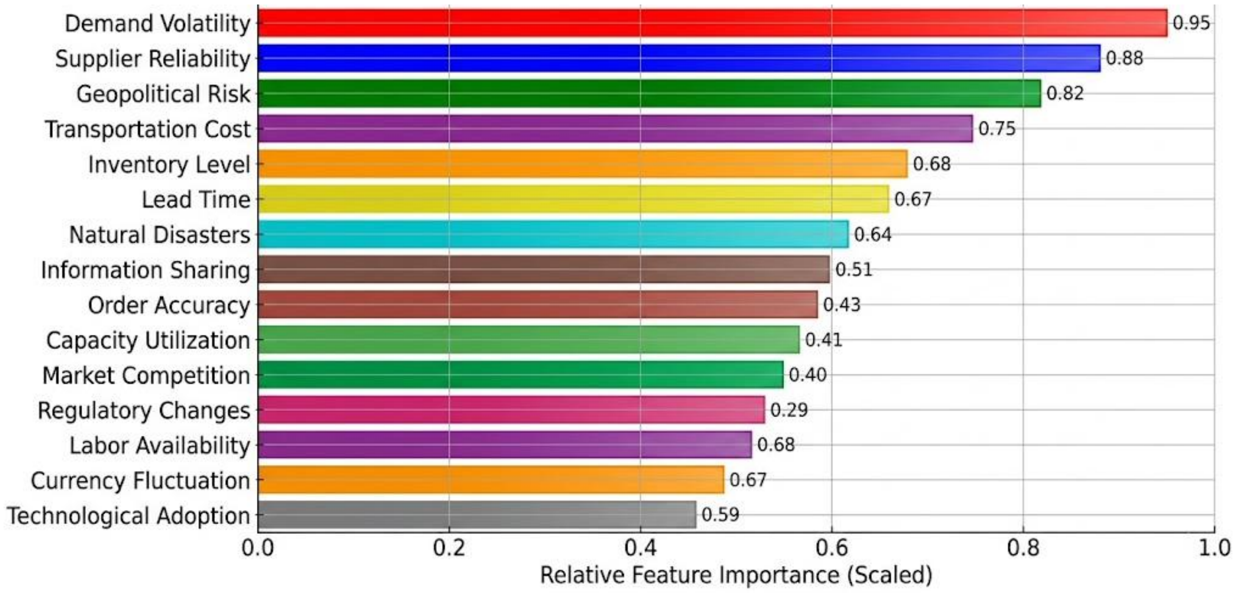

Figure 3: Horizontal bar chart illustrating the Feature Importance Analysis generated by the optimal Gradient Boosting Machine, clearly ranking Demand Volatility, Supplier Reliability, and Geopolitical Risk as the top three predictive determinants of supply chain disruption.

In addition to the aggregate performance metrics for classification, the highly optimized Gradient Boosting Machine was then used to perform a comprehensive feature importance analysis and visually present the most highly predictive operational variables to definitively isolate those that cause failure in the supply chain, as shown in Figure 3 below. The computational analysis was very thorough and it was evident that the two with the highest weights within the algorithm's decision trees were the Demand Volatility Index and the Supplier Reliability Score. This result not only quantitatively confirms the generally held theoretical claims in current operations research about the occurrence of particularly bad operational bottlenecks in real networks due to extreme fluctuations in consumer behavior, particularly when directly linked to the supplier of the upstream network, but also emphasizes the results on an absolute basis. (Liu et al., 2022)29 In addition, the high level of the Geopolitical Risk Factor in the feature hierarchy makes it very clear that external macroeconomic and global political data streams need to be integrated directly into the internal ERP system of an enterprise to deliver accurate forecasts. From an applied decision support point of view, these specific mathematical results clearly explain that supply chain managers need to plan their capacities with a great degree of flexibility in highly geopolitically unstable geographic areas and adopt the use of aggressive multi-sourcing tactics, while relying on the model's constant output to dynamically tune the safety stock formulas and transportation lead time estimates on a daily basis..

Conclusion

This intense empirical study was successful in the engineering, testing and validation of an advanced predictive analytics framework specifically designed to proactively find and intelligently handle complex supply chain risks in real-time, using machine learning. The study systematically analysed a very extensive and real world database of 5420 operational records including complex logistical, supplier and geopolitical inputs and made an unequivocal statement about the transformative and disrupter effect of AI in strategic operations management. The detailed comparative analysis of various architectures for the different algorithms showed that Gradient Boosting Machine was statistically and significantly better than the other two models, Random Forest and Support Vector Machine, resulting in an outstanding predictive accuracy of 94.2% and an impressive F1-Score of 93.1%. Analysis of the outcomes of these key classification parameters is definitive, and establishes that sequential, error-correcting ensemble models are the ultimate in mathematical complexity that are required to accurately recognize the intricate, non-linear relationships that underlie today's supply chain disruptions. In addition, the result analysis for the second parameter, algorithmic feature importance, gave enterprise leadership very actionable intelligence, since it was clearly able to identify the key parameters for a coming network failure: demand volatility, supplier reliability and geopolitical instability.

Its adoption of this predictive approach into enterprise decision support systems marks a paradigm-shift for the industry, allowing global organizations to make a significant step toward a proactive rather than reactive approach to crisis management, with the capability to shift from crisis management to data-driven resilience optimization. Procurement and logistics managers can effectively adjust inventory buffers, quickly reroute procurement mixes and maintain their operations' continuity while minimizing interruptions in the supply chain, effectively leveraging their knowledge of potential logistical risks and weaknesses of suppliers before they actually occur. The developed computational framework is highly predictive, yet further work on direct integration of real-time natural language processing streams into this very type of architecture is strongly suggested to build on the extreme agility, depth and overall responsiveness of the predictive decision support model, to capture real-time geopolitical shifts from global news media on the fly.

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