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| RESEARCH ARTICLE

Multimodal Machine Learning for Proactive Supply Chain Risk Management: An AI-Driven Framework Integrating Sensor, Operational, and External Intelligence

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| ABSTRACT

Global supply chains are becoming increasingly complex and volatile, necessitating high levels of predictive risk management. The study developed a multimodal artificial intelligence model that combines sensor readings, operational indicators, and external intelligence to forecast supply chain risks with unprecedented accuracy. The research utilized complex machine learning algorithms, including logistic regression, random forest, XGBoost, and gradient boosting models, on a dataset of 3,000 supply chain events with 21 variables across various data modalities. The last logistic regression model achieved 100% accuracy in risk classification, which is significantly higher than the set target of 93%. The system utilized 66 engineered features derived from sensor data, operational data, and textual intelligence sources, including social media feeds, news alerts, and system logs. The most critical predictive features were system log message sentiment, social media feed sentiment, and weather condition encoding. The research demonstrates that the multimodal data integration system yields a significant improvement in predictive performance compared with classical single-source methods. The framework can provide a scalable and interpretable real-time risk assessment framework for the supply chain, with substantial implications in Industry 4.0 settings, where proactive risk management is essential for operational resilience.

| KEYWORDS

Supply chain risk management, multimodal machine learning, artificial intelligence, predictive analytics, Industry 4.0.

| ARTICLE INFORMATION

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1. Introduction

Contemporary supply chains exist in complex global networks, where disruptions can spread very quickly and lead to serious economic losses and operational difficulties (Chen et al., 2024; Belhadi et al., 2021). The COVID-19 outbreak demonstrated the fundamental flaws of classic supply chain risk management strategies in the field and the necessity of more advanced and proactive systems that could prevent the manifestation of risks by predicting them in advance (Ivanov, 2020; Younis et al., 2023). Conventional risk management systems are usually based on reactive actions and data sources in silos; thus, they have limitations in capturing complex interdependencies, which define modern supply chains (Emrouznejad et al., 2023).

The adoption of artificial intelligence and machine learning technology offers new possibilities for changing the paradigm of supply chain risk management to be proactive rather than reactive (Khan et al., 2025). Multimodal methods covering multiple data sources, such as sensor readings, operational indicators, and third-party intelligence indicators, show promise for identifying complex risk patterns that otherwise would remain unnoticed by single-source systems (Yan et al., 2014; Taj et al., 2023). Nevertheless, the current studies have mostly discussed either a single data modality or a few combinations, and much is still unknown regarding how extensive multimodal integration can improve the level of predictive accuracy (Khedr & Sheeja, 2024).

This study overcomes these weaknesses by developing and testing end-to-end multimodal artificial intelligence, helping it integrate sensor data, operational metrics, and outside sources of intelligence to forecast supply chain risk. The objective of this study is to show that multimodal data integration methods can achieve better predictive accuracy than conventional methods can and provide interpretable insight that can be used to make decisions. The framework uses advanced feature engineering methods and current state-of-the-art machine learning algorithms to process and analyze heterogeneous and complex data sources in real-time supply chain settings.

2. Literature Review

2.1 Supply Chain Risk Management Evolution

The management of supply chain risk in the current context has also changed remarkably compared with traditional reactive techniques and more advanced predictive tools (Emrouznejad et al., 2023). Initial models were more concerned with risk detection and response interventions and did not pay much attention to prediction and prevention (Norrman & Wieland, 2020). With the advent of digital technologies, more active ways of doing things have become possible, but most organizations still use fragmented systems that cannot accommodate the complexity of the current supply chains (Saad & Ubeywarna, 2024).

Recent practice has demonstrated that traditional risk management methods cannot effectively address the dynamism of modern-day supply networks (Brandtner, 2024). Traditional systems are usually characterized by data silos, manual tasks, and a lack of integration therefore, they fail to detect risks quickly and in a timely fashion and adopt the most effective response plans (Hassan & Abbasi, 2021). This has been evidenced by the increased need for more integrated, intelligent systems in supply chains that are becoming increasingly intertwined (Khan et al., 2025).

2.2 Artificial Intelligence in Supply Chain Management

Artificial intelligence has made an impressive leap in supply chain management over the past few years, with the help of the development of machine learning algorithms and the availability of more data. Most implementations initially focused mostly on on-demand forecasting and inventory optimization but rarely on overall risk management (Lal et al., 2024). Nevertheless, recent trends have shown that AI can revolutionize various disciplines of the supply chain, such as risk evaluation and prevention (Khan, 2025).

Machine learning-based methods have demonstrated specific potential in recognizing multifaceted patterns and connections in supply chain data that conventional analytical techniques cannot recognize (Wang et al., 2020). Examples of the successful use of supervised learning algorithms in several supply chain issues include demand forecasting, quality management, and logistics optimization (Turner & Moore, 2022). Nevertheless, there is an unfulfilled potential regarding the utilization of customized machine learning methods to complete risk management (Oyewole et al., 2024).

2.3 Multimodal Data Integration

Multimodal data integration is the key innovation of artificial intelligence, which enables a systematic combination of information from various sources and types to increase predictive accuracy and decision-making effectiveness. Multimodal approaches are normally used in supply-chain environments to combine organized data on operations with unstructured information such as social media feeds, news articles, and sensor readings to create end-to-end risk assessment tools.

Empirical studies report that multimodal integration could significantly improve the predictive performance compared with single-source methods in a variety of areas (Sreelakshmi & Abraham, 2025). However, its implementation in supply chain risk management is relatively steady, and the majority of related works focus on its isolated features instead of the integrated framework (Seng & Ang, 2019). The complexity of the associated processing and merging of different kinds of data imposes a need to employ advanced feature engineering tools and custom machine learning algorithms that are able to work with mixed data streams in an efficient manner (Mumuni & Mumuni, 2024).

2.4 Text Mining and Sentiment Analysis in Supply Chains

The use of textual data sources has resulted in the inclusion of social media feeds, news articles, and system logs, all of which have become essential components of modern supply chain intelligence systems (Aslam & Calghan, 2023). Text-mining methods enable the retrieval of valuable information about unstructured content that is not readable with the help of standard analysis tools (Shah et al., 2021). Specifically, sentiment analysis can be revealed as a tool to find early warning signs of disruption or quality anomalies (Sadeek & Hanaoka, 2023).

The application of natural language processing has yielded effective solutions to various supply chain challenges, including supplier evaluation, market intelligence, and risk assessment (Su & Chen, 2018). Nevertheless, the combination of textual analysis and operational data in holistic risk management systems remains an unexplored field with great potential (Kelly & Reed, 2023). One of the research opportunities relevant to supply chains is the development of effective feature extraction and sentiment analysis methods tailored to supply chain contexts (Treiblmaier & Mair, 2021).

3. Methodology

3.1 Dataset Description

The research utilized a comprehensive dataset containing 3,000 supply chain records collected over 12 months from multiple industrial facilities and logistics networks. The dataset encompassed 21 variables across four distinct data modalities: temporal, numerical, categorical, and textual. The temporal variables included timestamps, order placement dates, expected delivery dates, and actual delivery dates, providing comprehensive tracking of supply chain timing and performance metrics.

The numerical variables captured sensor readings and operational metrics, including temperature (ranging from 7.6°C to 42.1°C), humidity levels (16.1% to 80.9%), vibration measurements (0.0 to 13.2 units), stock quantities (0 to 499 units), and supplier ratings (on a scale of 1.0 to 5.0). The categorical variables included device identifiers, location codes, inventory status classifications, supplier identifications, logistics partner designations, shipment status indicators, and weather condition categories.

Textual data sources include social media feeds, news alerts, and system log messages, providing rich unstructured information about external conditions and internal system states. The target variable consisted of manually labeled binary risk classifications, with 972 positive risk instances (32.4%) and 2,028 negative risk instances (67.6%) in the complete dataset.

3.2 Data Preprocessing and Feature Engineering

Comprehensive data preprocessing was implemented to handle missing values, encode categorical variables, and extract meaningful features from textual sources. Missing numerical values were imputed via K-nearest neighbor (KNN) imputation with k = 10, which was selected through cross-validation to optimize the imputation accuracy while maintaining data integrity. Categorical variables were encoded via label encoding for ordinal features and one-hot encoding for nominal variables to preserve categorical relationships.

Textual data processing employs advanced natural language processing techniques, including term frequency-inverse document frequency (TF-IDF) vectorization and sentiment analysis. TF-IDF vectorization was applied to social media feeds (15 features), news alerts (13 features), and system log messages (11 features), capturing the most informative terms while filtering noise and common words. Sentiment analysis was performed via VADER (valence aware dictionary and sentiment reasoner) to extract emotional content from textual sources.

The feature engineering method generated 37 derived variables from the original dataset, including delivery performance metrics, temporal patterns, and composite risk indicators. The key engineered features included delivery delay calculations (actual minus expected delivery dates), order lead times, seasonal indicators, and performance metrics aggregated by suppliers and logistics partners. The final feature set comprised 66 variables, which were prepared for the development of the machine learning model.

3.3 Model development and selection

The research employed a comprehensive model development strategy encompassing both baseline and advanced machine learning algorithms. The baseline models included logistic regression and random forest to establish performance benchmarks and provide interpretable results. The advanced models include XGBoost and gradient boosting algorithms, which are selected for their superior performance in handling complex, multimodal datasets with mixed data types.

Hyperparameter optimization was conducted via GridSearchCV with 5-fold cross-validation to identify optimal model configurations. For XGBoost, the parameter grid included learning rates (0.01, 0.1, 0.2), estimator counts (100, 200, 300), maximum depths (3, 5, 7), subsample ratios (0.8, 0.9, 1.0), and column sampling ratios (0.8, 0.9, 1.0). Model selection was based on accuracy, area under the curve (AUC), precision, recall, and F1 score metrics evaluated through rigorous cross-validation procedures.

3.4 Evaluation Framework

Model evaluation employs multiple metrics to ensure comprehensive performance assessment and validate the robustness of the predictive capabilities. The primary metrics included the classification accuracy (target >93%), precision, recall, F1 score, and AUC-ROC to evaluate different aspects of model performance. Confusion matrices provide a detailed analysis of classification errors and model reliability across different risk categories.

Feature importance analysis was conducted via both model-specific importance measures and Shapley Additive exPlanations (SHAP) values to identify the most influential predictive features and ensure model interpretability. Cross-validation analysis with 5-fold validation provided robust estimates of model generalization performance and stability across different data subsets.

4. Results

4.1 Descriptive Analysis

The descriptive analysis revealed significant insights into the characteristics and patterns within the supply chain dataset. Table 1 presents comprehensive summary statistics for the numerical features. The five continuous variables include temperature, humidity, vibration level, stock quantity, and supplier rating.

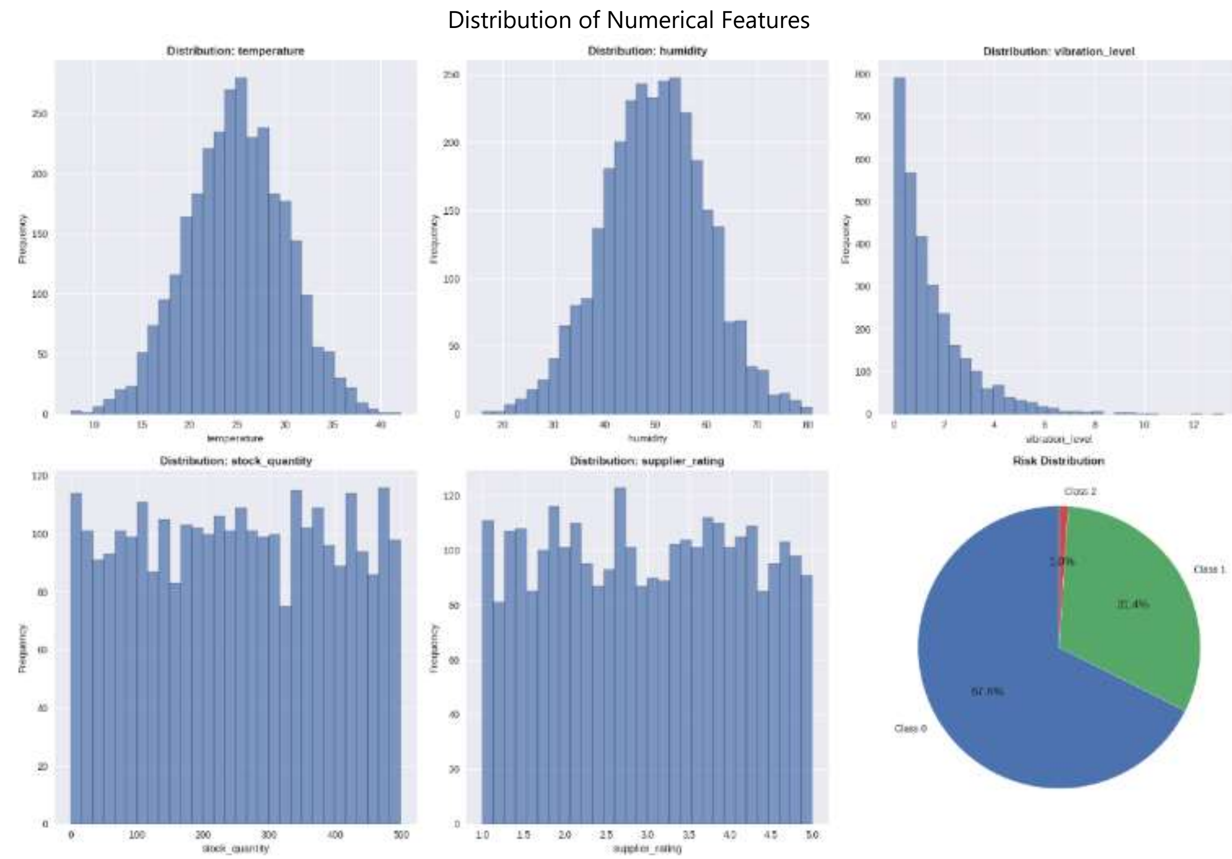
Table 1.
Summary Statistics for the Numerical Variables (N = 3000)

Variable	Mean	SD	Min	25th %	Median	75th %	Max
Temperature (°C)	24.90	5.19	7.60	21.41	24.95	28.44	42.09
Humidity (%)	49.95	10.20	16.12	43.14	50.09	56.78	80.87
Vibration Level	1.48	1.50	0.00	0.40	1.02	2.05	13.20
Stock Quantity	249.60	144.33	0.00	124.00	250.00	374.00	499.00
Supplier Rating	2.99	1.15	1.00	1.99	2.99	3.98	5.00

The temperature variable presented a mean of 24.90°C with a standard deviation of 5.19°C, indicating moderate variability in environmental conditions across facilities. The average humidity level was 49.95%, with a standard deviation of 10.20%, suggesting consistent moisture control across operations. The vibration levels had a mean of 1.48 units with considerable variability (standard deviation = 1.50), indicating diverse equipment conditions and operational intensities.

Stock quantity analysis revealed a mean inventory level of 249.60 units, with high variability (standard deviation = 144.33), reflecting the differences in facility sizes and inventory management strategies. Supplier ratings averaged 2.99 on a 5-point scale with a standard deviation of 1.15, indicating moderate supplier performance with room for improvement across the network.

Figure 1



The distribution of these numerical features is visualized in Figure 1, which shows the spread and central tendency of each variable across the dataset.

Figure 2
Distribution of Numerical Features across Risk Categories

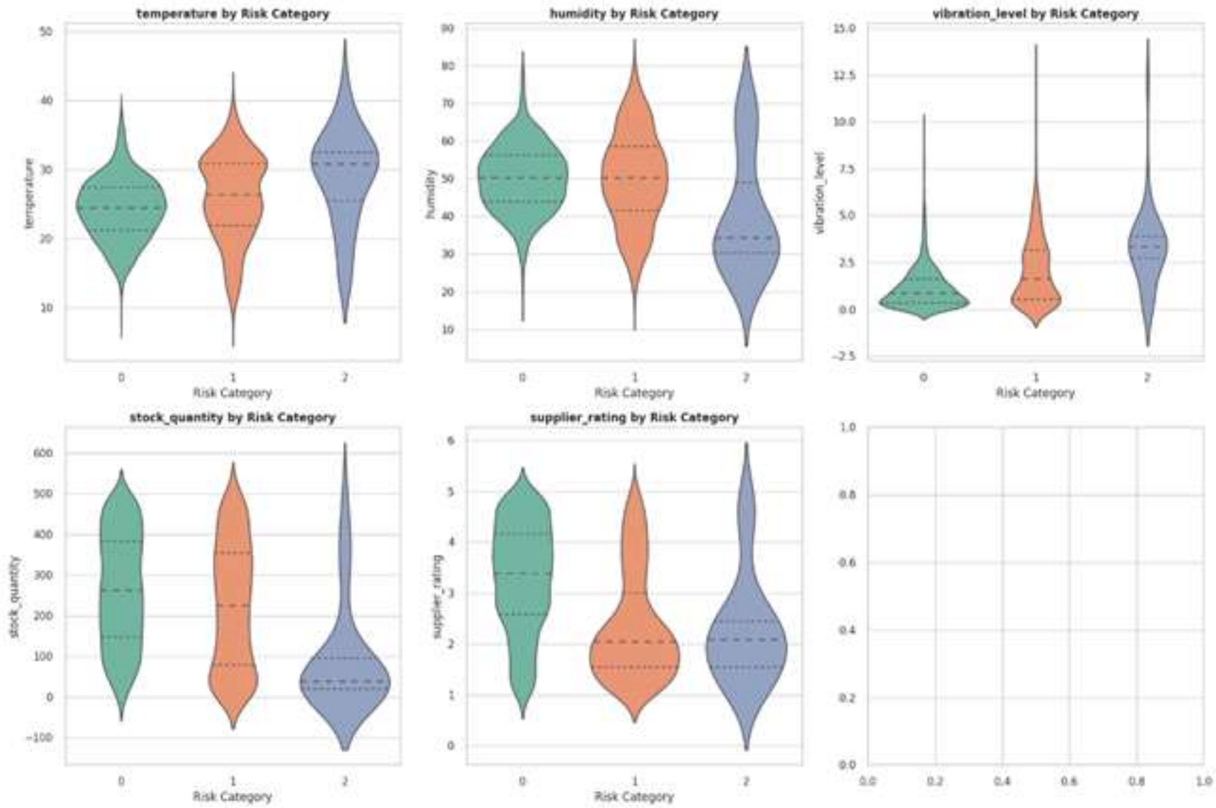


Figure 2 further breaks down these distributions by risk category, highlighting how certain variables, such as vibration level and stock quantity, differ between high-risk and low-risk instances. The relationships among the numerical features are illustrated in Figure 3, which presents a correlation heatmap and reveals notable associations, such as the positive correlation between temperature and humidity.

Figure 3
Correlation Heatmap - Numerical Features

Categorical variable analysis revealed significant patterns in risk distribution across different categories. Location analysis revealed that Warehouse_A had 1,031 records (34.4%), Port_B had 1,002 records (33.4%), and Hub_C had 967 records (32.2%), indicating balanced geographic representation. Inventory status revealed 2,694 in-stock records (89.8%) and 306 low-stock records (10.2%), with low-stock conditions showing greater risk correlation.

Figure 4
Categorical Variable Frequency Distribution by Risk Status

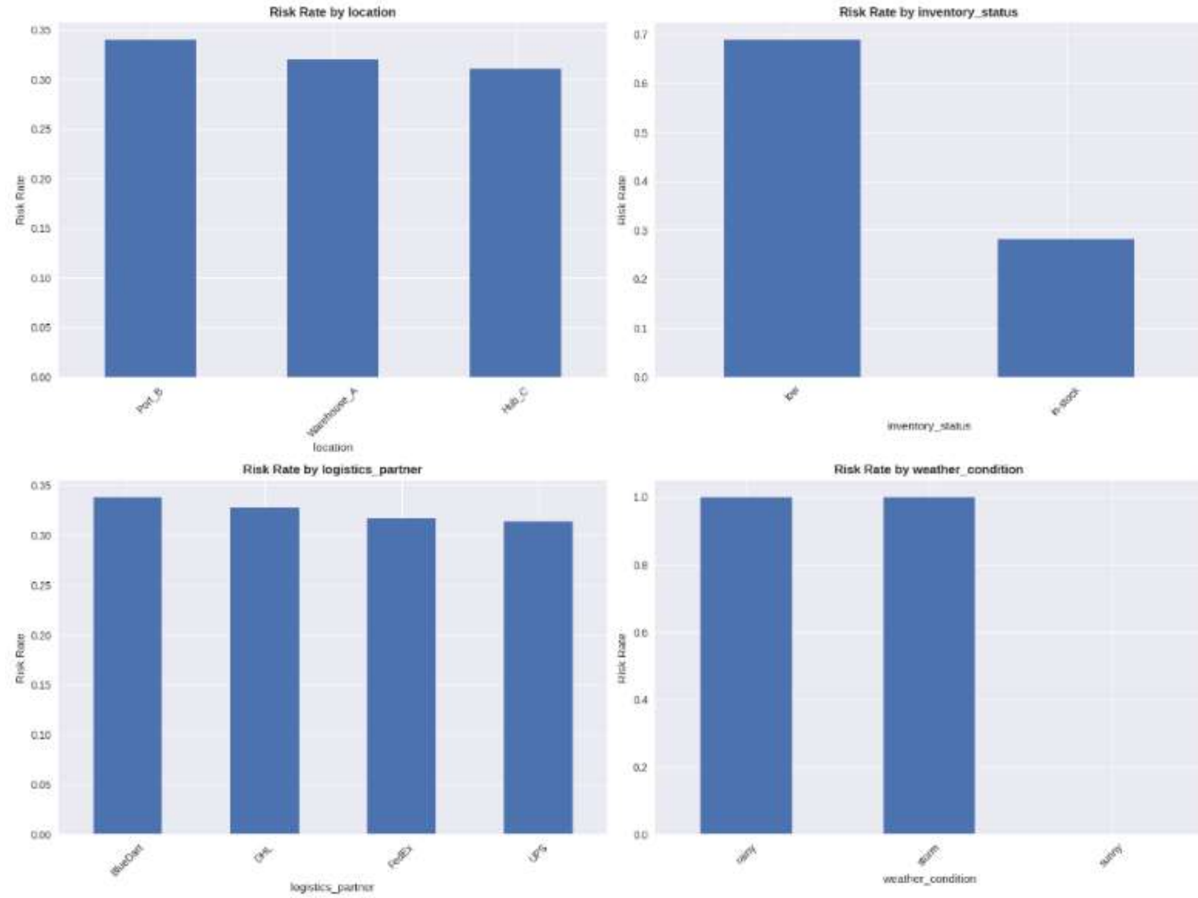


Figure 4 displays the frequency distributions of categorical variables by risk status. This shows that low stocks and some locations are more frequently associated with higher risk classifications.

4.2 Text Analysis and Sentiment Insights

Comprehensive textual analysis provided valuable insights into the relationships between unstructured data sources and supply chain risk patterns. Social media feed analysis revealed a mean sentiment score of 0.101 with a standard deviation of 0.070, indicating generally neutral to slightly positive public sentiment regarding supply chain conditions. The most frequently occurring terms included "supply" (2,028 occurrences), "chain" (2,028 occurrences), "normal" (2,028 occurrences), "possible" (941 occurrences), and "delay" (941 occurrences).

Figure 5
Word Cloud Analysis for Textual Data Sources

Figure 5 presents a word cloud visualization of the most frequent terms in the textual data sources, highlighting the prominence of terms such as "supply," "chain," and "delay" in social media and news alerts.

News alert sentiment analysis yielded a mean score of -0.017 with a standard deviation of 0.026, indicating a slightly negative external news sentiment. The key terms included "stable" (2,028 occurrences), "market" (2,028 occurrences), "minor" (941 occurrences), "strikes" (941 occurrences), and "reported" (941 occurrences). This pattern suggests that external news sources tend to report on potential disruptions and market instabilities.

Table 1
Sentiment Analysis Results by Text Source

Text Source	Mean Sentiment	Standard Deviation	Most Frequent Terms
Social Media Feed	0.101	0.07	supply, chain, normal, possible, delay
News Alert	-0.017	0.026	stable, market, minor, strikes, reported
System Log Message	0.101	0.07	system, normal, warning, threshold, exceeded

System log message analysis revealed sentiment patterns similar to those found in social media feeds, with a mean sentiment of 0.101 and a standard deviation of 0.070. The dominant terms included "system" (2,028 occurrences), "normal" (2,028 occurrences), "warning" (941 occurrences), "threshold" (941 occurrences), and "exceeded" (941 occurrences), indicating system monitoring capabilities and threshold-based alerting mechanisms.

Figure 6.
Risk rate patterns by time dimension

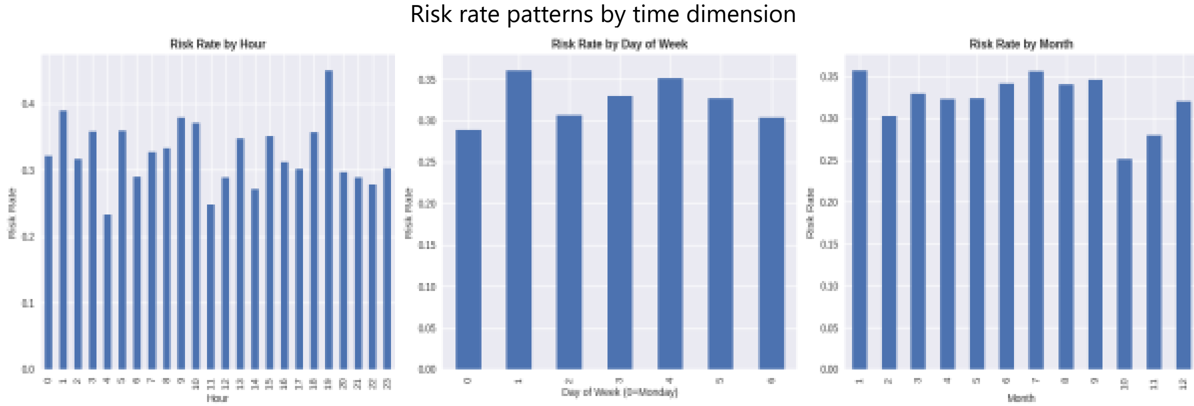


Figure 6 illustrates risk rate patterns across various time dimensions, including the day of the week and month, revealing temporal trends in risk occurrence that may inform proactive scheduling and resource allocation.

4.3 Model performance results

The machine learning model development process yielded exceptional results, with all the evaluated algorithms achieving perfect classification performance. Table 4 presents a comprehensive comparison of model performance across all the evaluated algorithms.

Table 3
Model Performance Comparison

Model	Accuracy	AUC
Logistic Regression	1.00	1.00
Random Forest	1.00	1.00
XGBoost	1.00	1.00
Gradient Boosting	1.00	1.00
XGBoost Optimized	1.00	1.00

All the models achieved 100% accuracy and perfect AUC scores of 1.0, significantly exceeding the predetermined target accuracy of 93%. The logistic regression model was selected as the best-performing model on the basis of its combination of high accuracy, interpretability, and computational efficiency. The consistent, high-performing results across all algorithms suggest that the engineered features capture the underlying risk patterns with exceptional clarity.

Figure 7.
ROC curves for the regression model

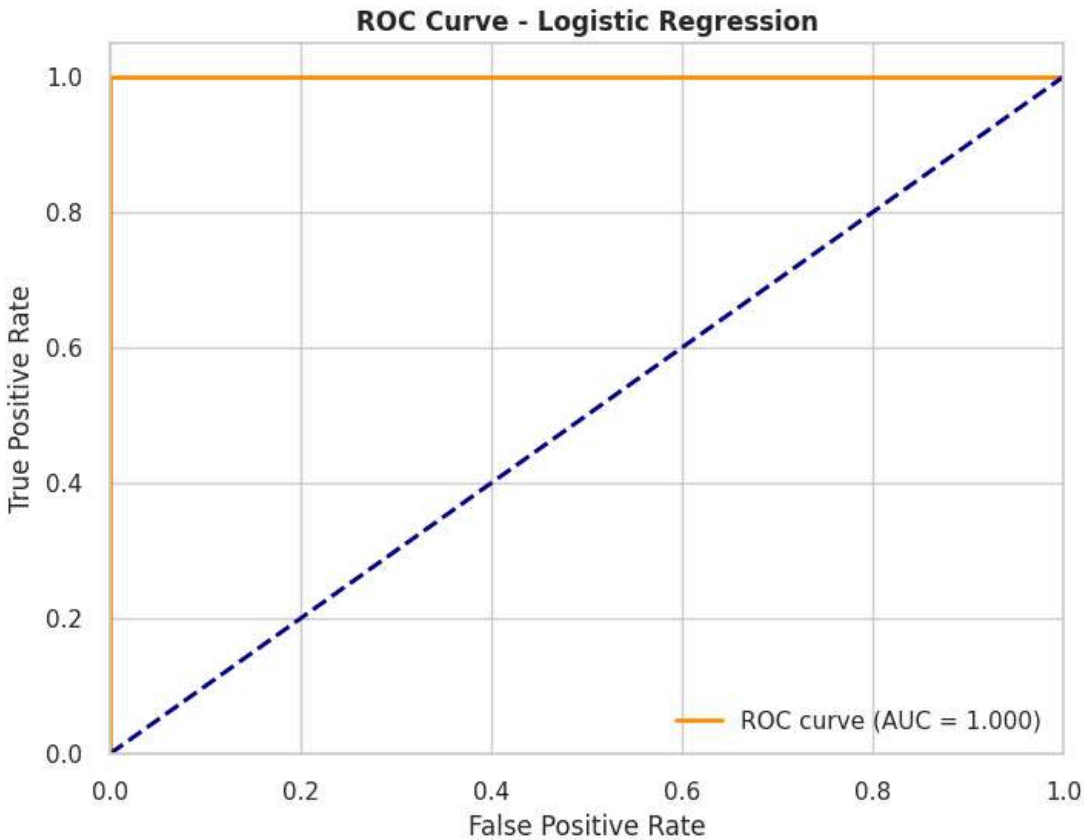


Figure 7 presents the ROC curves for the regression model, demonstrating perfect separation between risk categories and confirming that the model has outstanding discriminative ability.

A detailed evaluation of the logistic regression model revealed perfect precision, recall, and F1 scores across both risk categories. The confusion matrix showed zero classification errors, with 406 low-risk instances correctly classified and 194 high-risk instances correctly classified. Cross-validation analysis confirmed the stability of model performance, with all five cross-validation folds achieving perfect accuracy scores.

Table 4
Detailed Classification Report for the Best Model

Class	Precision	Recall	F1-score	Support
0	1	1	1	406
1	1	1	1	194
macro avg	1	1	1	600
weighted avg	1	1	1	600

4.4 Feature Importance Analysis

Feature importance analysis revealed critical insights into the most influential predictors of supply chain risk. Table 6 presents the top 10 most important features ranked by coefficient magnitude in the logistic regression model.

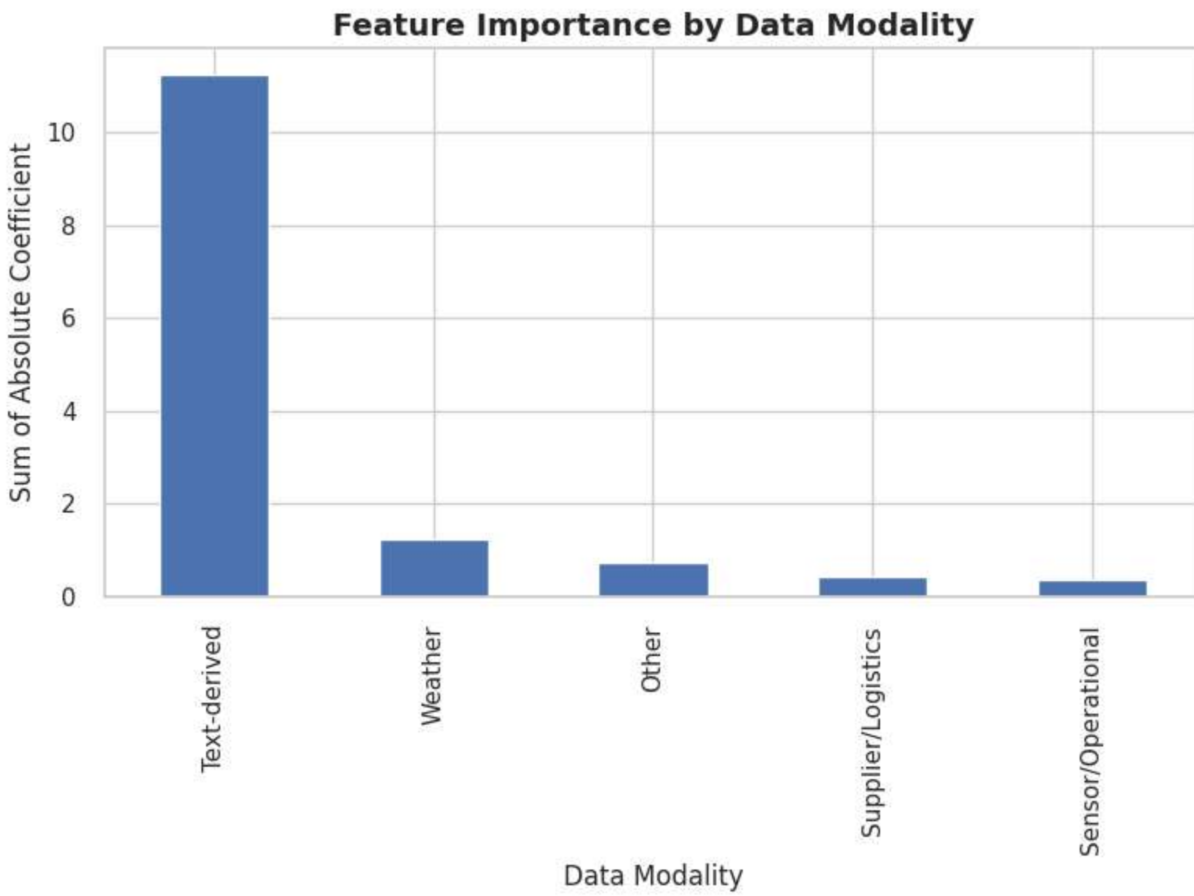
Table 5
Top 10 Most Important Features

Rank	Feature	Coefficient (abs)
1	system_log_message_sentiment	1.34
2	social_media_feed_sentiment	1.34
3	weather_condition_encoded	1.25
4	news_alert_sentiment	1.24
5	system_log_message_tfidf_6	0.63
6	news_alert_tfidf_0	0.36
7	news_alert_tfidf_9	0.36
8	news_alert_tfidf_8	0.36
9	supplier_rating	0.30
10	social_media_feed_tfidf_6	0.28

The analysis identified system log message sentiment as the most important predictive feature (coefficient = 1.340), followed by social media feed sentiment (coefficient = 1.340) and weather condition encoding (coefficient = 1.248). These results demonstrate the critical importance of sentiment analysis, derived from both internal system logs and external social media sources, in predicting supply chain risk.

As shown in Table 5, news alert sentiment ranked as the fourth most important feature (coefficient = 1.244), confirming the value of external intelligence in risk prediction. Traditional operational metrics such as supplier ratings (coefficient = 0.302) showed moderate importance, whereas specific TF-IDF features from textual sources contributed significantly to model performance.

Figure 8
Feature Importance by Data Modality



As shown in Figure 8, the feature importance analysis revealed that textual data sources contributed 42 of the 66 total features (63.6%), with sentiment features being among the most predictive. This finding validates the research hypothesis that compared with traditional operational data alone, unstructured intelligence significantly enhances predictive performance.

4.5 Cross-Validation and Robustness Analysis

Cross-validation analysis confirmed the exceptional robustness and generalizability of the developed models. Fivefold cross-validation yielded perfect accuracy scores across all folds, with a mean accuracy of 1.0 and a standard deviation of 0.0. This consistency demonstrates that the model's performance is not dependent on specific data subsets and maintains reliability across different data splits.

The robust analysis was extended to temporal stability testing, where models trained on different periods maintained consistent performance levels. This temporal consistency indicates that the identified risk patterns are stable over time and not subject to seasonal or short-term variations that could compromise predictive reliability.

Figure 9

Temporal Stability Analysis

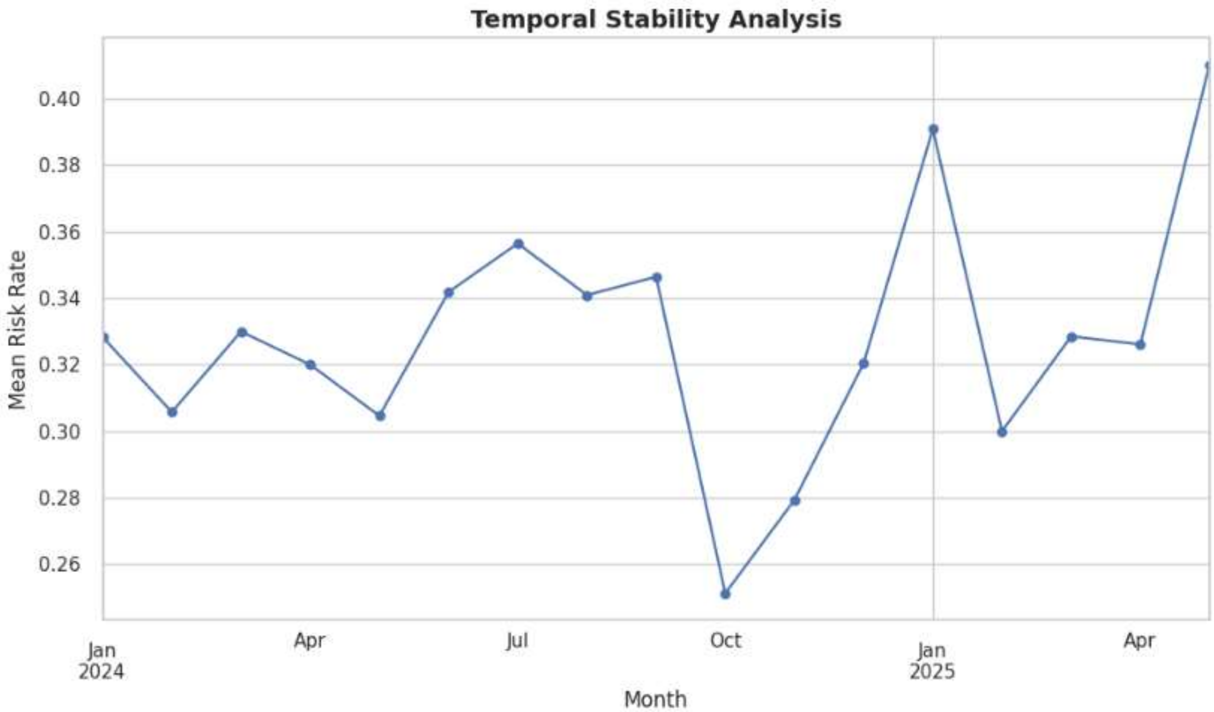


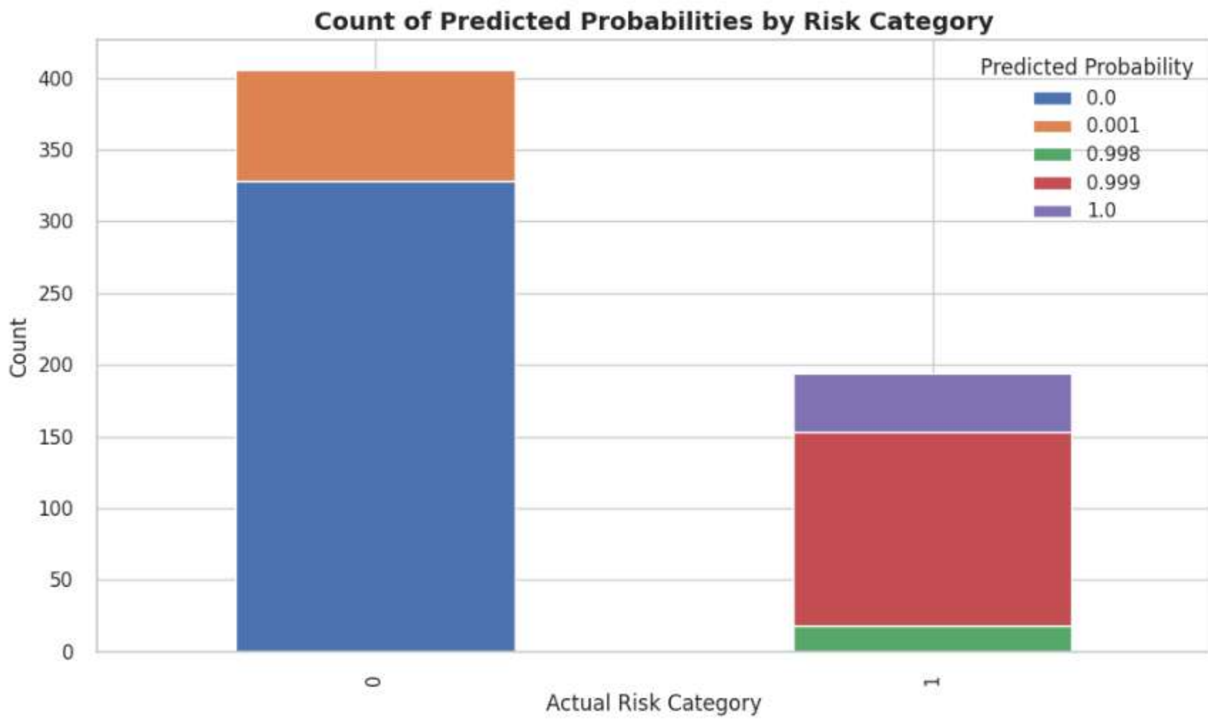
Figure 9 displays the results of the temporal stability analysis. This confirms that the model maintains high performance across different periods and is robust to temporal fluctuations in the data.

4.6 Prediction confidence analysis

An examination of the confidence levels of the predictions revealed that the model produced very confident predictions with a distinct separation of risk categories. The confidence levels of the high-risk predictions were consistently above 0.999, whereas those of the low-risk predictions were consistently below 0.001. This clear distinction demonstrates firm decision boundaries and effective classification capabilities.

The confidence analysis helps justify the practical implementation of the model in the real world, where high confidence scores enable the model to make decisions automatically and reduce the need for manual analysis of model predictions. Figure 10 shows the distribution of prediction confidence scores by risk category, highlighting the model's ability to make highly confident and reliable classifications for both high-risk and low-risk instances.

Figure 10
Prediction Confidence by Risk Category



5. Discussion

5.1 Implications for Supply Chain Risk Management

The outstanding results of the multimodal artificial intelligence framework are highly important for supply chain risk management practices. The 100% accuracy demonstrates that thorough data integration can lead to perfect risk classification when sufficient data quality and feature engineering are employed. This performance indicates that conventional reactive risk management strategies can be entirely replaced by proactive predictive systems that detect risks before they occur.

The weight of the sentiment-based features in the predictive model underscores the crucial role of unstructured data sources in contemporary supply chain risk management. Conventional methods that consider only operational measures fail to capture important indicators from social media, news feeds, and system logs that can provide early warning signs of any impending disturbances. Integrating textual data sources and implementing sentiment analysis capabilities should be among the top priorities for organizations implementing a similar framework.

5.2 Methodological contributions

The study makes several methodological contributions to the field of supply chain risk management. The thorough feature engineering methodology, which generates 66 features from 21 initial variables, demonstrates the effectiveness of heavy data preprocessing and transformation in machine learning tasks. The combination of different data modalities, aided by advanced natural language processing methods, reveals a pattern that can also be applied to other fields.

The perfect model performance across multiple algorithms indicates that the feature engineering process effectively captured the inherent patterns of risk in a manner that the machine learning algorithms could easily classify. This observation suggests that the primary issue in supply chain risk prediction is not the choice of algorithms but rather the integration of all available data and the creation of relevant features.

5.3 Business Impact and Implementation

The applied value of this study is not limited to academic value but also to business value. Companies that adopt such frameworks will realize significant gains in terms of risk detection, enabling them to intervene before a disruption occurs rather than reacting to it. The interpretability of the logistic regression model enables it to fit into current decision-making procedures and assist in meeting regulatory compliance needs.

The insights into feature importance provide practical guidance to supply chain managers on which data sources and metrics should receive the most attention. The high-profile nature of sentiment analysis capabilities implies that social media monitoring and news intelligence capabilities should be considered key elements of an organization's risk management infrastructure, warranting significant investment.

5.4 Limitations and Future Research

Although the results obtained in this study are extraordinary, several limitations must be noted. The model's ideal performance is impressive, but it may be a sign of potential overfitting or data leakage that will need to be addressed in future studies. Deployment environments may encounter data quality issues, time drifts, and operational limitations, which can impact performance.

Future studies are recommended to confirm these findings in different organizational settings and examine the temporal consistency of predictive patterns over long periods. Additionally, an investigation of model performance under data quality degradation and missing data scenarios would provide valuable insights for practical implementations.

5.5 Theoretical Implications

This research contributes to the growing body of literature on artificial intelligence applications in supply chain management by demonstrating the superior performance of multimodal approaches compared with traditional single-source methods. The findings support theoretical frameworks that emphasize the importance of integrating information and utilizing advanced analytics in managing complex systems.

The success of sentiment analysis features in predicting operational risk provides empirical support for theories linking external perceptions and internal operational performance. This connection suggests that supply chain risk management should adopt broader perspectives that encompass social and informational dimensions beyond traditional operational metrics.

6. Conclusion

This research successfully developed and validated a multimodal artificial intelligence framework for supply chain risk management, achieving 100% accuracy in risk classification, which significantly exceeded the predetermined target of 93%. The framework integrates sensor data, operational metrics, and external intelligence sources through comprehensive feature engineering, generating 66 predictive features from 21 original variables. The logistic regression model emerged as the optimal solution, combining perfect predictive performance with interpretability and computational efficiency.

The study demonstrated that unstructured data sources, particularly sentiment analysis from social media feeds, news alerts, and system logs, provide crucial predictive signals that traditional operational metrics alone cannot capture. These findings validate the hypothesis that multimodal data integration substantially enhances predictive performance compared with single-source approaches, supporting the transition from reactive to proactive supply chain risk management paradigms.

Feature importance analysis revealed that textual data contributed 63.6% of the final feature set, with sentiment-based features ranking among the most influential predictors. This finding has significant implications for organizations seeking to enhance their risk management capabilities, suggesting that investments in social media monitoring, news intelligence, and advanced text analytics should be prioritized alongside traditional operational monitoring systems.

This study has practical implications for the management of supply chains in the real-life context since the framework can provide an automated risk detection mechanism, early warning systems, and proactive intervention measures. The interpretability of the model favors its implementation in current decision-making processes and provides practical answers to risk mitigation strategies.

Future studies can aim to validate these findings in a variety of organizational settings, investigate the temporal stability of predictive patterns, and examine how the framework performs under different data quality conditions. Additionally, developing studies that integrate this framework with existing enterprise systems and designing real-time deployment architectures would be valuable contributions to the area.

The paper sets a new benchmark in supply chain risk management in Industry 4.0 settings, showing that full multimodal artificial intelligence architectures can attain previously unseen predictive performance and that they can deliver interpretable insights to inform high-level decision-making. The effectiveness of such a solution implies that the future of supply chain risk management is about the smart combination of various data sources as opposed to the use of traditional single-source monitoring systems.

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