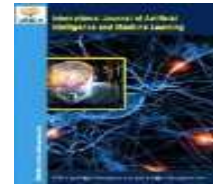




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An Explainable AI Framework for Supply Chain Risk Prediction and Intelligent Decision Support

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Abstract

Supply-chain disruptions can affect delivery performance, operational continuity, customer satisfaction, and organizational costs. Conventional risk assessment may have limitations in identifying complex relationships within large operational datasets. Explainable artificial intelligence (XAI) provides an approach for combining predictive analysis with interpretable information to support managerial decision-making. This study aims to develop an explainable AI framework for supply-chain risk prediction and intelligent decision support by integrating machine-learning models with interpretable analytical methods.

The study uses the DataCo SMART Supply Chain dataset. Delivery risk was classified using the Late_delivery_risk variable. Logistic Regression, Random Forest, and XGBoost models were developed using an 80:20 stratified train-test split. Model performance was assessed using accuracy, precision, recall, F1-score, and ROC-AUC. Explainable AI techniques were incorporated to interpret model predictions and identify factors associated with supply-chain risk. The analysis identified substantial variation in delivery-risk patterns across different operational and shipping characteristics. The evaluated machine-learning models demonstrated the ability to distinguish between different risk categories, with XGBoost providing the strongest overall predictive performance. The explainability analysis further supported interpretation of the factors associated with model-generated risk predictions, providing information that can assist supply-chain decision-making. The findings demonstrate that integrating machine learning with XAI can support transparent supply-chain risk prediction and intelligent decision support. The proposed framework provides a structured approach for connecting predictive analytics with interpretable information and proactive supply-chain risk management.

Keywords: Artificial intelligence, Explainable artificial intelligence, Machine learning, Risk prediction, Supply chain.

1. Introduction

Supply chains operate in environments characterized by interconnected suppliers, manufacturers, logistics providers, distributors, customers, and information systems. This interdependence creates exposure to operational disruptions, transportation delays, demand fluctuations, supplier failures, cyber incidents, and other uncertainties that can affect cost, service performance, and continuity. Effective risk management therefore requires organizations to identify potential risks at an early stage and support timely decisions before disruptions produce significant operational consequences. The increasing volume and complexity of supply-chain data have created opportunities for artificial intelligence (AI) to strengthen risk identification and predictive analysis (Chaudhry, 2026). AI-based approaches can process large numbers of operational observations and identify relationships that may be difficult to detect through conventional analytical methods. However, supply-chain decision-making also requires consideration of sustainability, governance, and organizational constraints when AI technologies are introduced into operational processes (Hao and Demir, 2024).

Artificial intelligence has increasingly been applied to supply-chain forecasting, monitoring, optimization, and risk management, given its ability to process complex and heterogeneous datasets. AI-based systems can support the identification of abnormal patterns, estimate the probability of adverse events, and provide information for proactive intervention (Li and Ling, 2026). Deep-learning approaches have demonstrated potential for extracting complex relationships from supply-chain data while combining predictive analysis with interpretability techniques to improve the understanding of forecasting results (Ahmed *et al.*, 2025). Similarly, the integration of deep learning, survival analysis, and explainable artificial intelligence (XAI) has been investigated for end-to-end supply-chain resilience management, demonstrating the potential of AI to support both prediction and risk-oriented decision processes (Li *et al.*, 2025). These developments indicate that AI can move supply-chain risk management from primarily reactive responses toward data-driven predictive assessment.

Machine learning (ML) provides a practical foundation for developing predictive models from historical supply-chain observations. Classification algorithms can learn relationships between operational characteristics and

known risk outcomes and subsequently estimate risk for new observations. Such predictive capabilities can assist organizations in prioritizing potentially problematic orders, shipments, suppliers, or operational activities. Recent research has also examined the integration of ML and XAI to provide decision-support capabilities in supply-chain management, emphasizing the relationship between predictive performance and interpretable decision-making (Huq *et al.*, 2026). In addition, explainable AI-driven supply-chain optimization frameworks have been explored to connect analytical predictions with practical operational decisions (Sumi, 2025). Despite these developments, predictive performance alone does not establish whether an AI system is appropriate for operational decision support. Understanding why a model generates a particular risk prediction remains important for responsible and informed managerial use.

Explainable artificial intelligence addresses the interpretability problem associated with complex predictive models by providing information about the factors contributing to model outputs. In supply-chain management, this capability is particularly relevant since managers may need to understand which operational variables contribute to predicted risk before taking corrective action. Research on XAI in supply-chain management has highlighted the importance of interpretable approaches for connecting complex AI models with human decision processes (Kosasih *et al.*, 2024). Broader research on explainable AI-based decision-support systems has similarly emphasized the role of explanation methods in improving the transparency and usability of AI-generated recommendations (Kostopoulos *et al.*, 2024). Recent work has also proposed explainable AI frameworks for intelligent threat monitoring and risk forecasting in supply-chain operations, demonstrating the growing application of XAI to risk-oriented supply-chain environments (Joshna *et al.*, 2026). Thus, an effective risk-prediction framework should consider not only whether a model predicts risk accurately but also whether its outputs can be interpreted by decision-makers.

The practical value of predictive AI depends on its ability to support decisions rather than simply generate numerical predictions. Intelligent decision-support systems can transform model outputs into information that assists managers in identifying risk factors, prioritizing interventions, and allocating operational resources. Research has examined explainable AI in supply-chain decision-making as a means of improving the transparency of analytical recommendations and supporting more informed managerial actions (Sharma *et al.*, 2025). Explainable AI capabilities have also been investigated specifically in supply-chain decision-support processes, highlighting the importance of integrating explanations with AI-generated information (Olan *et al.*, 2025). Furthermore, explainable AI frameworks have been proposed for demand forecasting and smart supply-chain decision-making, illustrating how interpretable predictions can be incorporated into operational planning (Priyadarshini *et al.*, 2026). These developments support the need for frameworks that connect predictive risk assessment, explanation of model outputs, and actionable decision support within a unified analytical process.

Despite the potential benefits of AI, several challenges can limit its effective application to supply-chain risk prediction. Complex ML models may produce accurate predictions while providing limited transparency regarding the relationships underlying their outputs. This creates difficulties when decision-makers need to validate, interpret, or justify AI-supported recommendations. Explainable AI has therefore been examined as an approach for strengthening transparency and supporting agile decision-making in supply-chain cyber-resilience contexts (Sadeghi *et al.*, 2024). Research on transparency and accountability in AI-based decision support has further demonstrated the importance of presenting model information in forms that users can understand and evaluate (Kim *et al.*, 2020). In addition, XAI research across decision-support domains has identified usability and interpretation challenges that are relevant when AI systems are incorporated into consequential decision processes (Abbas *et al.*, 2025). Consequently, supply-chain risk-prediction frameworks need to balance predictive capability, interpretability, and practical usability.

Existing research demonstrates substantial progress in AI-enabled supply-chain prediction, resilience, optimization, and decision support. However, important opportunities remain for integrating these capabilities into a coherent framework focused specifically on supply-chain risk prediction and intelligent decision support. Studies of explainable AI in smart and complex operational environments emphasize the importance of making AI-generated results understandable to users rather than treating model predictions as standalone outputs (Javed *et al.*, 2023). Explainable AI has also been applied to agricultural decision-making, demonstrating how interpretable predictive information can assist users in understanding and acting upon model recommendations (Shams *et al.*, 2024). Similarly, explainable AI has been investigated for financial risk assessment and decision support, highlighting the broader relevance of transparent predictive systems for risk-sensitive applications (Nallakaruppan *et al.*, 2024). From a user-centered perspective, theory-driven explainable AI research emphasizes that explanations should be designed around user needs and decision contexts rather than being treated solely as technical model outputs (Wang *et al.*, 2019). These findings indicate a need for an integrated approach that combines supply-chain risk prediction with transparent explanations and decision-support functionality.

The aim of this study is to develop an explainable AI framework for supply-chain risk prediction and intelligent decision support using machine-learning techniques and interpretable analytical methods. The study seeks to

establish a predictive approach capable of identifying supply-chain risk from operational data while providing understandable information about the factors associated with model predictions. The objective is to develop and evaluate machine-learning models for classifying supply-chain risk using relevant operational characteristics. The objective is to incorporate explainability mechanisms into the predictive process so that model outputs can be interpreted and transformed into useful information for supply-chain decision support. The framework is intended to connect predictive analytics, explainability, and operational decision-making within a unified AI-based approach.

2. Materials and Methods

2.1 Study Design

This study employed a quantitative, data-driven research design to develop an explainable artificial intelligence framework for supply-chain risk prediction and decision support. The analysis used the DataCo SMART Supply Chain for Big Data Analysis dataset, containing 180,519 observations and 53 variables. The dataset represents diverse supply-chain activities and includes information concerning orders, products, customers, shipping, sales, and operational characteristics. The dependent variable was `Late_delivery_risk`, which distinguishes orders according to their delivery-risk status. A value of one represented high-risk observations, whereas zero represented low-risk observations. The dataset was treated as secondary data and analyzed systematically using reproducible computational procedures.

2.2 Data Preparation and Variable Processing

Data preparation was conducted before developing the predictive models. Variables containing information unavailable before the delivery outcome were excluded from the predictive feature set to reduce potential target leakage. In particular, actual shipping time and delivery-status information were not used as predictive inputs. Numerical variables were examined for missing observations and subsequently processed using median imputation where required. Categorical variables were transformed using one-hot encoding to make them suitable for machine-learning algorithms. Numerical predictors used by Logistic Regression were standardized after imputation. The resulting analytical dataset therefore contained operationally meaningful predictors while maintaining consistency between training and testing procedures.

2.3 Risk Classification and Exploratory Analysis

The study defined supply-chain risk as a binary classification problem using the `Late_delivery_risk` variable. Observations with a value of zero were categorized as low-risk orders, while observations with a value of one were categorized as high-risk orders. Descriptive analysis was initially performed to understand the composition of the dataset and identify important operational patterns. The analysis examined risk frequencies, proportions, shipping-mode distributions, shipment-time characteristics, sales-related measures, and other relevant variables. These exploratory results provided the empirical foundation for subsequent predictive modeling.

2.4 Machine-Learning Model Development

Three supervised machine-learning algorithms were evaluated for supply-chain risk prediction: Logistic Regression, Random Forest, and XGBoost. These models were selected as they represent different modeling approaches and provide complementary perspectives on classification performance. Logistic Regression provided a conventional statistical baseline, whereas Random Forest captured nonlinear relationships through an ensemble of decision trees. XGBoost was included as a gradient-boosting approach capable of modeling complex interactions among predictors. The dataset was divided into training and testing subsets using an 80:20 stratified split with a random state of 42. Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC.

2.5 Explainable Artificial Intelligence Analysis

Explainability was incorporated after predictive model development to examine how individual variables contributed to risk predictions. The XGBoost model was selected for subsequent interpretation as it provided strong overall discriminatory performance among the evaluated approaches. SHapley Additive exPlanations (SHAP) were employed to quantify the contribution of individual predictors to model outputs. Global SHAP analysis was used to identify variables with substantial influence across the evaluated observations. The analysis focused on ten selected predictors: Days for shipment (scheduled), Type, Order Region, Latitude, Longitude, Customer Segment, Benefit per order, Order Item Discount, Market, and Order Item Discount Rate. This procedure enables the framework to move beyond prediction alone by providing interpretable information concerning the factors associated with predicted supply-chain risk.

2.6 Evaluation and Decision-Support Framework

The final stage integrated predictive performance and model explanations into an intelligent decision-support framework. Model evaluation considered multiple complementary metrics rather than relying exclusively on accuracy, allowing different aspects of classification behavior to be examined. ROC-AUC was used to assess discrimination across classification thresholds, while precision, recall, and F1-score provided additional information about prediction quality. The explainability results were then interpreted in relation to operational supply-chain factors. This integrated approach enables decision makers to examine predicted risk together with influential contributing variables. Consequently, the framework is designed to support more transparent identification, interpretation, and management of potential supply-chain delivery risks.

3.Results

3.1 Sample Profile and Risk Composition

The dataset comprises 180,519 supply-chain observations across 53 recorded variables, providing a broad basis for examining operational risk patterns. The distribution of the dependent variable indicates that 98,977 orders were classified as high risk, representing 54.83% of observations, whereas 81,542 orders were categorized as low risk (45.17%) as shown in Table 1. The average scheduled shipment duration was 2.932 days, compared with an average actual shipping duration of 3.498 days. Additional descriptive measures show mean benefit per order of 21.975, mean sales per customer of 183.108, and mean order-item quantity of 2.128. These characteristics demonstrate substantial operational variation within the dataset.

Table 1. Dataset Characteristics and Descriptive Statistics

Variable / Measure	Value
Total observations	180,519
Total variables	53
Low-risk orders (Late_delivery_risk = 0)	81,542
High-risk orders (Late_delivery_risk = 1)	98,977
Low-risk proportion	45.17%
High-risk proportion	54.83%
Mean scheduled shipment time (days)	2.932
Mean actual shipping time (days)	3.498
Mean benefit per order	21.975
Mean sales per customer	183.108
Mean order-item quantity	2.128
Mean sales	203.772
Mean discount rate	0.102
Mean order-item profit ratio	0.121

Source: Author's analysis of the DataCo SMART Supply Chain for Big Data Analysis dataset.

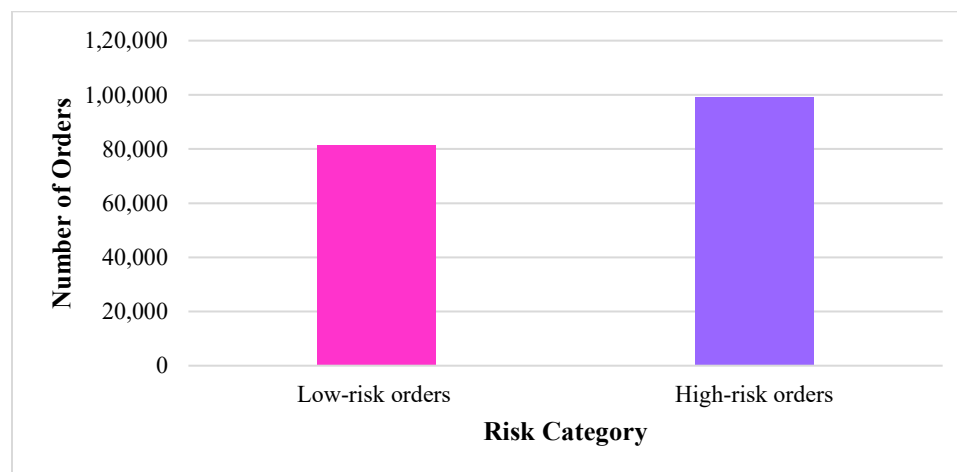


Figure 1. Distribution of Supply-Chain Risk Categories

The distribution of orders according to their identified supply-chain risk status. The dataset contains 81,542 low-risk orders and 98,977 high-risk orders. High-risk observations therefore represent a larger share of the dataset than low-risk observations as shown in Figure 1. The difference indicates that delivery-risk events are relatively common within the analyzed supply-chain records. This distribution provides an important foundation for subsequent predictive modeling. The two risk categories are not perfectly balanced. The figure

also establishes the outcome structure used for machine-learning analysis, where Late_delivery_risk serves as the dependent variable. The visualization summarizes the composition of the dataset before predictive and explainable-AI analyses are performed.

3.2 Variation in Risk Across Delivery Methods

The distribution of risk differs considerably among the four shipping methods represented in the dataset. First Class shipments recorded the highest proportion of high-risk orders, with 26,513 of 27,814 observations classified as high risk as shown in Table 2. Second Class shipments followed, with 26,987 high-risk orders among 35,216 observations. Same Day shipments showed a comparatively lower proportion, with 4,454 high-risk cases from 9,737 orders. Standard Class represented the largest shipment group, containing 107,752 observations, of which 41,023 were high risk. Overall, 98,977 of the 180,519 orders were classified as high risk, indicating meaningful differences in risk distribution across shipping methods.

Table 2. Supply-Chain Risk Distribution by Shipping Mode

Shipping Mode	Total Orders (n)	High-Risk Orders (n)	High-Risk Orders (%)
First Class	27,814	26,513	95.32
Second Class	35,216	26,987	76.63
Same Day	9,737	4,454	45.74
Standard Class	107,752	41,023	38.07
Total	180,519	98,977	54.83

Source: Author's calculation from the DataCo SMART Supply Chain for Big Data Analysis dataset. High-risk status is defined as Late_delivery_risk = 1.



Figure 2. Shipping-Mode Differences in Supply-Chain Risk

The distribution of total and high-risk orders across the four shipping modes. Standard Class accounts for the largest number of orders, with 107,752 observations, including 41,023 high-risk cases. First Class contains 27,814 orders, of which 26,513 are classified as high risk as shown in Figure 2. Second Class includes 35,216 orders and 26,987 high-risk observations. Same Day represents the smallest group, with 9,737 total orders and 4,454 high-risk cases. The comparison shows that risk is distributed differently across shipping categories, providing useful information for the subsequent machine-learning analysis and supply-chain decision-support framework.

3.3 Comparative Predictive Performance of the Models

The predictive experiments show differences in performance among the three machine-learning approaches. Logistic Regression achieved 70.03% accuracy, with precision of 81.76%, recall of 58.37%, an F1-score of 68.11%, and ROC-AUC of 0.7579 as shown in Table 3. Random Forest produced 69.88% accuracy and an F1-score of 67.78%, while its ROC-AUC reached 0.7634. XGBoost recorded 70.71% accuracy, 84.57% precision, 56.97% recall, and an F1-score of 68.08%, with ROC-AUC of 0.7795. These results indicate that the evaluated models provide measurable predictive capability, while the reported metrics offer complementary perspectives on classification performance across the supply-chain risk prediction task.

Table 3. Machine-Learning Performance for Supply-Chain Risk Prediction

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
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Logistic Regression	70.03%	81.76%	58.37%	68.11%	0.7579
Random Forest	69.88%	81.97%	57.78%	67.78%	0.7634
XGBoost	70.71%	84.57%	56.97%	68.08%	0.7795

Source: Author's machine-learning analysis of the DataCo SMART Supply Chain for Big Data Analysis dataset; 80:20 stratified train-test split, random state = 42. Numerical variables were median-imputed and standardized for Logistic Regression, categorical variables were one-hot encoded, and the same encoded feature space was used for the tree-based models.

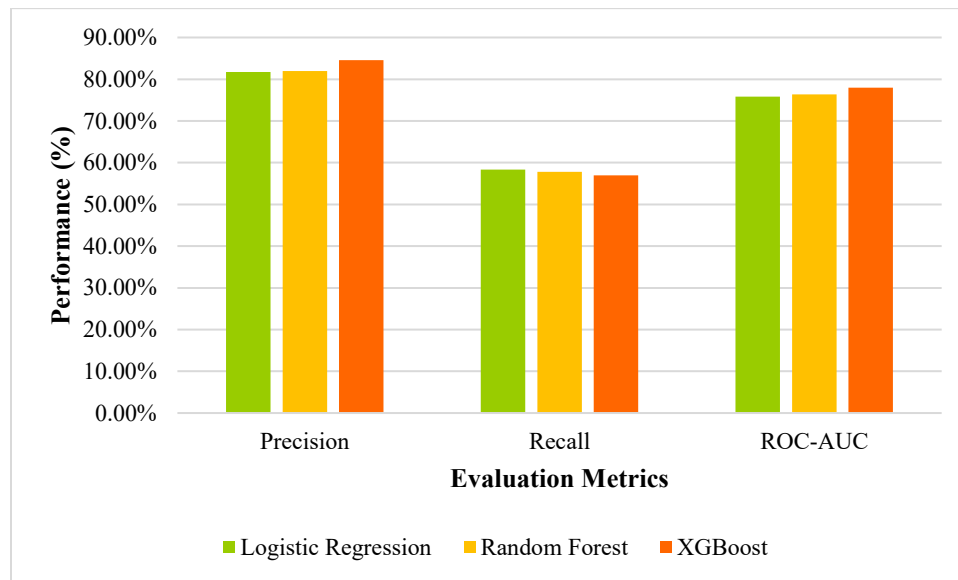


Figure 3. Comparative Performance of Predictive Models

The performance of Logistic Regression, Random Forest, and XGBoost across five evaluation measures. Accuracy remains close among the three approaches, ranging from 69.88% to 70.71%. XGBoost records the highest precision at 84.57%, while Logistic Regression and Random Forest achieve 81.76% and 81.97%, respectively as shown in Figure 3. Recall ranges from 56.97% to 58.37%, with Logistic Regression producing the highest value. F1-scores remain relatively similar, ranging from 67.78% to 68.11%. The ROC-AUC values are 75.79%, 76.34%, and 77.95% for Logistic Regression, Random Forest, and XGBoost, respectively.

3.4 Explainable AI Analysis of Supply-Chain Risk Predictions

The SHAP analysis provides an interpretable view of the factors contributing to the XGBoost supply-chain risk predictions. Days for shipment emerged as the most influential predictor, followed by Type, indicating the importance of scheduling and transaction characteristics in the model's decisions. Regional and geographical variables, including Order Region, Latitude, and Longitude, also contributed to the predictions as shown in Table 4. Other variables, such as Customer Segment, Benefit per order, Order Item Discount, Market, and Order Item Discount Rate, showed comparatively smaller contributions. These findings demonstrate that the predictive model considers multiple operational characteristics when identifying delivery risk. The SHAP analysis therefore strengthens the explainable AI framework by connecting model predictions with interpretable supply-chain information.

Table 4. SHAP-Based Feature Importance for Supply-Chain Risk Prediction

Rank	Predictor	Mean Absolute SHAP Value	Relative Importance (%)
1	Days for shipment (scheduled)	1.346483	55.60
2	Type	0.510678	21.09
3	Order Region	0.147619	6.10
4	Latitude	0.115914	4.79
5	Longitude	0.096139	3.97
6	Customer Segment	0.047635	1.97
7	Benefit per order	0.043364	1.79
8	Order Item Discount	0.041479	1.71
9	Market	0.038027	1.57
10	Order Item Discount Rate	0.034254	1.41

Source: Author's SHAP analysis of the DataCo SMART Supply Chain for Big Data Analysis dataset.

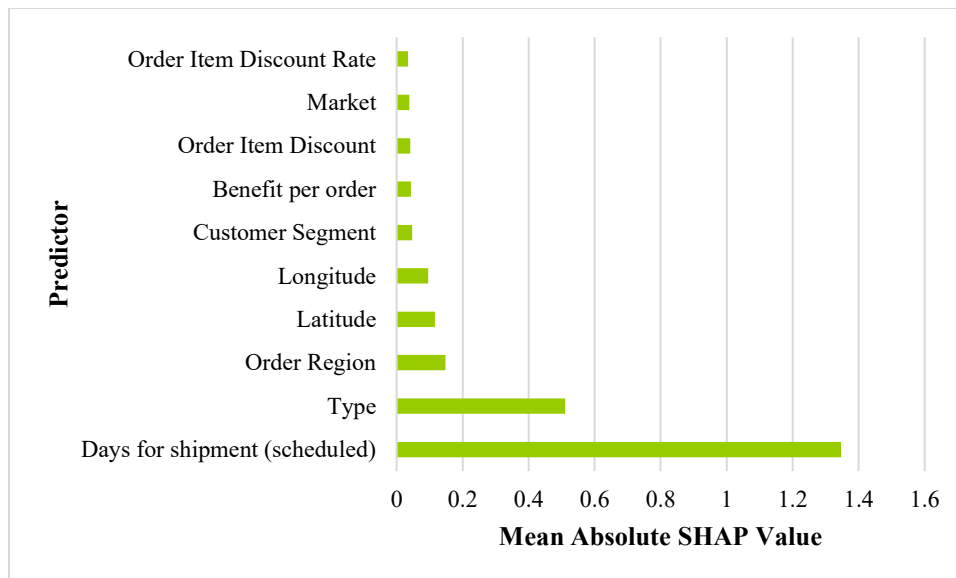


Figure 4. SHAP-Based Feature Importance for Supply-Chain Risk Prediction

The relative contribution of the selected predictors to the XGBoost supply-chain risk predictions using mean absolute SHAP values. Days for shipment (scheduled) shows the strongest contribution, indicating that shipment scheduling characteristics have substantial influence on the model's predictions as shown in Figure 4. Type represents the second most influential predictor, while Order Region, Latitude, and Longitude provide additional contributions. Customer Segment, Benefit per order, Order Item Discount, Market, and Order Item Discount Rate have comparatively smaller effects. The results demonstrate that the model considers multiple operational and geographical characteristics when estimating supply-chain risk. This explanation improves transparency and supports interpretation of the model's predictive behavior.

4. Discussion

The study demonstrate that supply-chain risk is not distributed evenly across operational activities. The dataset contained 180,519 observations, with 98,977 orders classified as high risk and 81,542 classified as low risk. This distribution indicates that delayed-delivery risk represents a substantial operational concern within the examined supply-chain environment. The differences observed across shipping modes further demonstrate that logistics configuration is associated with variation in risk exposure. First Class shipments showed a considerably higher proportion of high-risk observations than Standard Class shipments, while Same Day shipments presented a different risk profile. These patterns suggest that supply-chain risk assessment should consider operational characteristics jointly rather than treating all orders as having equivalent exposure. Predictive analytics can assist organizations in identifying such patterns systematically and incorporating them into risk-management processes.

The three machine-learning models produced relatively similar overall accuracy, although their predictive characteristics differed. Logistic Regression achieved an accuracy of 70.03%, Random Forest achieved 69.88%, and XGBoost produced the highest accuracy at 70.71%. XGBoost also achieved the highest ROC-AUC value of 0.7795, indicating stronger overall discrimination between high- and low-risk observations within the evaluated test set. Logistic Regression and Random Forest obtained ROC-AUC values of 0.7579 and 0.7634, respectively. The results demonstrate that model selection should not depend exclusively on accuracy. Precision, recall, F1-score, and ROC-AUC provide additional information about how effectively a model identifies different aspects of supply-chain risk. This is particularly important where the cost of overlooking a potentially delayed order may differ from the cost of unnecessarily flagging a lower-risk order.

The findings are consistent with broader research emphasizing the usefulness of AI and predictive models for supporting complex organizational decisions. Previous research has described predictive AI as a mechanism for transforming historical information into forward-looking decision support, particularly where conventional analysis may struggle with large and interconnected datasets (Vudugula *et al.*, 2023). The findings extend this perspective to supply-chain risk classification by demonstrating how operational observations can be transformed into measurable risk predictions. The comparatively strong ROC-AUC obtained by XGBoost also supports the broader argument that machine-learning approaches can provide useful predictive discrimination in complex decision environments. However, the study differs from approaches that focus exclusively on

predictive performance as the proposed framework additionally incorporates explainability and decision-support considerations.

The integration of explainable AI is important since predictive performance alone does not explain why an order has been classified as high risk. XAI can provide information about the contribution of individual variables to a prediction, allowing decision-makers to examine the factors associated with model outputs. Recent research has identified a range of explanation techniques designed to make complex AI models more interpretable for human users (Mathew *et al.*, 2025). In the supply-chain context, this capability can help managers move from simply receiving a risk classification to understanding the operational circumstances contributing to that classification. Such information can support more targeted interventions, such as reviewing shipment characteristics, scheduling arrangements, or other influential operational factors. Consequently, explainability strengthens the practical value of predictive modelling by connecting statistical outputs with understandable operational evidence.

An important contribution of the framework is the connection between prediction and human decision-making. A risk prediction becomes more useful when decision-makers can understand the reasoning associated with the prediction and determine whether an intervention is appropriate. Research on human-centered explainable AI emphasizes the importance of designing explanations around the needs and activities of users rather than treating explanation as a purely technical feature (Panigutti *et al.*, 2023). Applied to supply-chain management, this principle suggests that explanations should be concise, relevant, and connected to operational decisions. Managers may therefore use model explanations to prioritize potentially problematic orders, investigate contributing factors, and determine appropriate corrective actions. The framework consequently positions XAI as a bridge between machine-generated predictions and human judgment.

The findings have implications for organizations seeking to strengthen proactive risk management. A predictive framework can provide an early indication of potentially problematic supply-chain observations, allowing managers to investigate risk before operational consequences become more severe. Combining predictive modelling with explainability can further support resilience by making risk information easier to interpret and communicate across operational teams (Alkhanbouli *et al.*, 2025). However, explanations should not automatically be treated as causal evidence. An influential variable identified by an explanation method indicates its contribution to the model's prediction, not necessarily that changing that variable alone will prevent a disruption. This distinction is important when AI outputs are incorporated into real operational processes.

From a managerial perspective, the results support the use of AI as an analytical decision-support mechanism rather than as a replacement for human expertise. Managers can use risk predictions to prioritize attention toward observations with greater estimated risk while using explanations to investigate the operational characteristics associated with those predictions. Explainability may also improve organizational acceptance since users can examine the reasoning behind model outputs instead of relying on an unexplained classification. Research on XAI has emphasized that interpretability can contribute to human understanding of AI systems, although different explanation approaches have different strengths and limitations (Yang *et al.*, 2023). Therefore, organizations should evaluate explanation quality alongside predictive performance when implementing AI-based supply-chain systems.

Several limitations should be considered when interpreting the findings. First, the analysis is based on a secondary supply-chain dataset, meaning that the results reflect the variables and operational context represented in that dataset. Second, the classification framework focuses on delivery-related risk and may not capture other dimensions such as supplier disruption, cybersecurity exposure, demand volatility, or geopolitical uncertainty. Third, model explanations should be interpreted as associations within the predictive model rather than definitive causal relationships. Future studies could validate the framework using multiple supply-chain datasets, real-time operational information, and additional risk categories. Further research could also compare alternative XAI methods and evaluate explanations directly with supply-chain professionals. Systematic evaluation of explanation usefulness, clarity, and decision impact would strengthen the practical development of explainable AI for supply-chain risk management.

5. Conclusion

The study demonstrates the usefulness of machine-learning methods for identifying supply-chain delivery risk from operational data. Among the evaluated models, XGBoost achieved the highest accuracy and ROC-AUC, indicating its ability to distinguish between higher- and lower-risk observations. The findings also show meaningful differences in risk across shipping modes, highlighting the importance of considering operational characteristics when assessing supply-chain exposure. The proposed framework extends predictive modelling by incorporating explainable AI into the risk-assessment process. Instead of providing only a risk classification, the framework enables users to examine the factors contributing to model predictions. This connection between prediction and explanation improves the transparency of AI-supported supply-chain analysis and provides a basis for more informed managerial interpretation. The framework can support managers in

identifying potentially risky orders and prioritizing operational attention. By combining predictive outputs with interpretable information, decision-makers can investigate relevant factors before selecting appropriate corrective actions. This approach can strengthen proactive risk monitoring and support more structured responses to potential delivery problems. The study uses a secondary dataset and focuses primarily on delivery-related risk. Future research should validate the framework using additional datasets, real-time supply-chain information, and broader categories of disruption. Further investigation of different XAI techniques and their usefulness to supply-chain professionals could also strengthen the practical application of explainable AI.

References

1. Ahmed, K. R., Ansari, M. E., Ahsan, M. N., Rohan, A., Uddin, M. B., & Rivin, M. A. H. (2025). Deep learning framework for interpretable supply chain forecasting using SOM ANN and SHAP: KR Ahmed et al. *Scientific Reports*, 15(1), 26355.
2. Kosasih, E. E., Papadakis, E., Baryannis, G., & Brintrup, A. (2024). A review of explainable artificial intelligence in supply chain management using neurosymbolic approaches. *International Journal of Production Research*, 62(4), 1510-1540.
3. Li, X., Krivtsov, V., Pan, C., Nassehi, A., Gao, R. X., & Ivanov, D. (2025). End-to-end supply chain resilience management using deep learning, survival analysis, and explainable artificial intelligence. *International Journal of Production Research*, 63(3), 1174-1202.
4. Sumi, S. S. (2025). Implementation of explainable AI-driven framework for supply chain optimization: A practical case study in industrial engineering. *International Journal of Scientific Interdisciplinary Research*, 6(2), 143-172.
5. Huq, M. R., Isty, M. N., Gani, R., Islam, T., & Ahmed, J. (2026). Integrating Machine Learning and Explainable AI for Decision Support in Supply Chain Management. *Journal of Engineering*, 2026(1), 4839375.
6. Sadeghi, K., Ojha, D., Kaur, P., Mahto, R. V., & Dhir, A. (2024). Explainable artificial intelligence and agile decision-making in supply chain cyber resilience. *Decision Support Systems*, 180, 114194.
7. Sharma, S., Vaishnav, P. K., Teli, R., Das, S., & Soni, B. (2025). Explainable AI in Supply Chain Decision-Making. In *Explainable AI and Blockchain for Secure and Agile Supply Chains* (pp. 115-128). Chapman and Hall/CRC.
8. Olan, F., Spanaki, K., Ahmed, W., & Zhao, G. (2025). Enabling explainable artificial intelligence capabilities in supply chain decision support making. *Production Planning & Control*, 36(6), 808-819.
9. Chaudhry, A. (2026). Explainable AI for Supply Chain Transparency and Risk Management in the Project Industry: Enhancing Trust and Decision-Making in Carinafour's CALS.
10. Joshna, S., Sulochana, M., Pushpa, D., Shanmukhi, L., Prasanna, D., & Deepya, P. (2026, May). An Explainable AI Framework for Intelligent Threat Monitoring and Risk Forecasting in Supply Chain Operations. In *2026 8th International Conference on Inventive Material Science and Applications (ICIMA)* (pp. 1848-1855). IEEE.
11. Priyadarshini, B. I., Nimy, K. C., Manju, M., & Raphi, D. (2026, April). A Novel Explainable AI Framework for Demand Forecasting in Smart Supply Chain Decision-Making. In *2026 Fourth International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)* (pp. 450-457). IEEE.
12. Kostopoulos, G., Davrazos, G., & Kotsiantis, S. (2024). Explainable artificial intelligence-based decision support systems: A recent review. *Electronics*, 13(14), 2842.
13. Javed, A. R., Ahmed, W., Pandya, S., Maddikunta, P. K. R., Alazab, M., & Gadekallu, T. R. (2023). A survey of explainable artificial intelligence for smart cities. *Electronics*, 12(4), 1020.
14. Kim, B., Park, J., & Suh, J. (2020). Transparency and accountability in AI decision support: Explaining and visualizing convolutional neural networks for text information. *Decision support systems*, 134, 113302.
15. Hao, X., & Demir, E. (2024). Artificial intelligence in supply chain decision-making: an environmental, social, and governance triggering and technological inhibiting protocol. *Journal of Modelling in Management*, 19(2), 605-629.
16. Li, Y., & Ling, Z. (2026). Real-Time Multi-Risk Early Warning for Community Banks: An Application of Ensemble Anomaly Detection and Explainable Artificial Intelligence. *Journal of Advanced Computing & Intelligent Systems*, 6(2), 15-27.
17. Nallakaruppan, M. K., Chaturvedi, H., Grover, V., Balusamy, B., Jaraut, P., Bahadur, J., ... & Hameed, I. A. (2024). Credit risk assessment and financial decision support using explainable artificial intelligence. *Risks*, 12(10), 164.
18. Shams, M. Y., Gamel, S. A., & Talaat, F. M. (2024). Enhancing crop recommendation systems with explainable artificial intelligence: a study on agricultural decision-making. *Neural Computing and Applications*, 36(11), 5695-5714.

19. Abbas, Q., Jeong, W., & Lee, S. W. (2025, August). Explainable AI in clinical decision support systems: a meta-analysis of methods, applications, and usability challenges. In *Healthcare* (Vol. 13, No. 17, p. 2154). MDPI.
20. Wang, D., Yang, Q., Abdul, A., & Lim, B. Y. (2019, May). Designing theory-driven user-centric explainable AI. In *Proceedings of the 2019 CHI conference on human factors in computing systems* (pp. 1-15).
21. Vudugula, S., Chebrolu, S. K., Bhuiyan, M., & Rozony, F. Z. (2023). Integrating artificial intelligence in strategic business decision-making: A systematic review of predictive models. *International Journal of Scientific Interdisciplinary Research*, 4(1), 01-26.
22. Panigutti, C., Beretta, A., Fadda, D., Giannotti, F., Pedreschi, D., Perotti, A., & Rinzivillo, S. (2023). Co-design of human-centered, explainable AI for clinical decision support. *ACM Transactions on Interactive Intelligent Systems*, 13(4), 1-35.
23. Mathew, D. E., Ebem, D. U., Ikegwu, A. C., Ukeoma, P. E., & Dibiaezue, N. F. (2025). Recent Emerging Techniques in Explainable Artificial Intelligence to Enhance the Interpretable and Understanding of AI Models for Human: DE Mathew et al. *Neural processing letters*, 57(1), 16.
24. Alkhanbouli, R., Matar Abdulla Almadhaani, H., Alhosani, F., & Simsekler, M. C. E. (2025). The role of explainable artificial intelligence in disease prediction: a systematic literature review and future research directions. *BMC medical informatics and decision making*, 25(1), 110.
25. Yang, W., Wei, Y., Wei, H., Chen, Y., Huang, G., Li, X., ... & Kang, B. (2023). Survey on explainable AI: From approaches, limitations and applications aspects. *Human-Centric Intelligent Systems*, 3(3), 161-188.