https://doi.org/10.22306/al.v11i3.523 Received: 10 Jan. 2024; Revised: 17 Mar. 2024; Accepted: 11 May 2024

Integrating machine learning and deep learning for enhanced supplier risk prediction

Nisrine Rezki
Hassan First University of Settat, National School of Applied Sciences, Systems Analysis and Modeling and Decision Support Laboratory, BP 218, 26100, Berrechid, Morocco, n.rezki@uhp.ac.ma (corresponding author)
Mohamed Mansouri
Hassan First University of Settat, National School of Applied Sciences, Systems Analysis and Modeling and Decision Support Laboratory, BP 218, 26100, Berrechid, Morocco, mohamansouri@gmail.com

Keywords: supply chain risk management, machine learning, deep learning, risk prediction, supply chain.
Abstract: The importance of anticipating and preventing disruptions is underscored by the increased operational complexity and vulnerability caused by advancements in supply chain management (SCM). This has spurred interest in integrating machine learning (ML) and deep learning (DL) into supply chain risk management (SCRM). In this paper, we introduce a tailored method using ML and DL to improve SCRM by predicting supplier failures, thus boosting efficiency and resilience in SC operations. Our method involves five phases focused on classifying and predicting supplier failures in non-conforming deliveries. This involves forecasting failure quantities and estimating total disruption costs. Initially, data from an automotive company is selected, and appropriate potential features and algorithms are selected, performance metric aligns with case study objectives, facilitating method evaluation are used such as: Precision, recall, F1-score, and accuracy metrics assess classification models, while Mean Squared Error (MSE) is used for regression tasks. Finally, an experimental design optimizes models, assessing success rates of various algorithms and their parameters within the chosen feature space. Experimental results underscore the success of our methodology in model development. In the classification task, the Random Forest (RF) classifier achieved 86% accuracy. When combined with the Gradient Boosting classifier, the ensemble exhibited enhanced accuracy, highlighting the complementary strengths of both algorithms and their synergistic impact, surpassing the performance of RF, Support Vector Regression (SVR), k-Nearest Neighbors (KNN), and Artificial Neural Network (ANN). Noteworthy is the performance in regression tasks, where Linear Regression, ANN, and RF Regressor displayed exceptionally low MSE compared to other models.

1 Introduction

To meet delivery deadlines and customer expectations, it becomes crucial for manufacturing companies to predict potential disruptions in their upstream SC caused by non-conforming deliveries. this proactive approach ensures that the assembly process commences as scheduled, ultimately preventing higher production and operational costs.

In essence, non-quality products can trigger a cascade of negative effects, ranging from financial losses and operational challenges for manufacturers to safety risks and dissatisfaction for customers. The increasing intricacy and fragility of SCs underscore the need for enhanced monitoring of SC performance.

Quality issues within the supplier chain can trigger a chain reaction, disrupting the entire SC. This disruption can impede the manufacturer's capacity to source essential components, leading to production schedule disruptions, delays in product delivery, and the potential to compromise customer commitments. manufacturers may find themselves bearing the burden of additional expenses incurred in reworking or scrapping defective products, significantly impacting profitability. Additionally, non-quality products often result in customer dissatisfaction, manifesting as complaints, product returns, and unfavourable reviews.

With the growing accumulation of data and heightened engagement in communication with primary and upper-tier suppliers, it becomes feasible to anticipate and alleviate potential disruptions at a more localized level in the SC. This is particularly relevant given the increasing emphasis on leveraging Big Data (BD) and ML in SCM to gain additional insights into SC operations, ultimately enhancing overall performance and reducing risks [1-6].

Emerging digitalization technologies, including the Internet of Things (IOT) and artificial intelligence (AI), offer new prospects for predicting disruptions in SCM [7-9]. Conducting empirical and sophisticated research is crucial for a deeper exploration of the potential of ML in forecasting and mitigating risks arising from supplier disruptions. Our contribution involves an extensive case study that demonstrates the application of AI techniques in SCM for predicting disruptions. This study specifically concentrates on implementing ML and DL to predict disruptions related to materials from suppliers, with a specific focus on non-quality products. The research emphasis is encapsulated in the following research questions:

Failure Prediction RQ 1: Can we predict which supplier issues are likely to occur in the near future based on historical data, and if so, how can we use this information to prevent them?

Number of Issues Prediction RQ 2: Can we predict how many issues of the same type will occur for a specific failure, which could help in resource allocation and planning?

Total Cost Prediction RQ 3: Given information about a supplier issue, can we predict the total cost incurred by the failure, which would be valuable for cost estimation and budget planning?

These goals and questions establish a robust foundation for our research paper. By concentrating research efforts on quality issues causing SC disruptions, we can significantly reduce risk propagation and its impact on the SC operations. This proactive approach may help in improving supplier performance and maintaining a more resilient and efficient SC.

Each of these prediction questions addresses a specific facet of SC issue management. By homing in on these questions and leveraging AI models, we can offer valuable contributions to the following key areas:

SC risk identification and assessment: ML models enable the prediction and early detection of potential suppliers issues that may occur in the future, aiding in the identification of potential risks that may affect the SC.

Cost Estimation: Drawing from historical data, ML models estimate the cost of supplier issues, providing valuable insights for budget planning.

The structure of the paper is as follows: Section 2 provides a review to the recent progress in predictive data analytics within SCM. Section 3 provides the methodology adopted in accordance with ML and DL models, providing an overview of the case study dataset detailing the chosen algorithms along with their outcomes. Moreover, an evaluation of the performance of our models is conducted. To conclude, a conclusion is presented in the last section.

2 Literature review

Several authors highlight the increasing complexity and global nature of SCs, underscoring the growing significance of anticipating and preparing for disruptions [10,11]. Scholarly discussions have suggested the potential use of predictive algorithms in SCRM [2,12,13] to diminish the influence of a disturbance, there are generally two choices available. The initial choice involves reducing the likelihood of its happening, while the second option aims to establish a robust SC that swiftly reverts to its initial state following a disruption. these alternatives are the focal points of two distinct sectors within SCM, namely, SCRM and SC resilience. within both the broader scope of SCM and its associated fields, data analytics remains a fundamental and integral tool in operations [14]. Data analytics in SCM is characterized by the application of various quantitative and qualitative methods in combination with SCM theory. Its purpose is to address pertinent SCM issues, predict outcomes, and consider factors such as data quality and availability. Additionally, they categorize predictive analytics as a segment of data analytics, specifically focused on enhancing SCs and reducing risks by forecasting potential future occurrences. Conversely, [15] and [16] categorize the existing methods into descriptive, predictive, and prescriptive analytics. descriptive analytics within SCM focuses on comprehending past events [11-13].

Recent research predominantly emphasizes prescriptive analytics over descriptive and predictive analytics within these three categories [4]. However, in line with the standard practice of data analytics, not limited to SCM, the efficacy of prescriptive models is dependent on descriptive and predictive models [3,4]. Consequently, the previously mentioned review papers advocate for further exploration in descriptive and predictive analytics within SCM. Thus, we enhance the current body of knowledge by introducing a case study that highlights the significance of predictive analytics within the field of SCM.

[17-20] emphasize the fundamental role and application of BD and AI plays a crucial role in the procurement process's digital evolution, viewed as a pivotal element for enhancing the competitive edge, effectiveness, and financial success of organizations' SCs. The ever-expanding access to a more extensive range of data in terms of volume, speed, and diversity presents new prospects to transform the influence of data analytics methods [21].Within the broader spectrum of SCM, ML and various data mining methodologies are regularly employed for multiple purposes. These include demand forecasting [22-24] establishing retail prices in SCs and managing financial transactions [25-29]. In the particular realms of procurement and logistics, prior studies primarily focuses on selecting potential suppliers for particular products [30,31]. However, the area of missing materials due to delayed deliveries remains an overlooked aspect of research [32] there is a scarcity of models dedicated to predicting suppliers quality issue. [33] introduced a ML based approach designed to forecast delays in supplier deliveries, the primary focus was on ensuring interpretability to aid decision-making based on the predictions. Utilizing an actual dataset from a multi-tier aerospace manufacturing SC, they conducted a comparison between The effectiveness and clarity of SVM and decision trees (DT) Despite slightly inferior performance metrics, the authors advocated for the use of DT as the preferred ML algorithm, emphasizing their interpretability over performance. [34] conducted a study in an original equipment manufacturer (OEM), where they forecasted delays in deliveries from Tier 1 suppliers by analyzing historical product data. By comparing five ML algorithms, they determined that the RF algorithm demonstrated superior performance when compared to SVM, logistic regression, linear regression, and the KNN algorithm.

Similar to the findings of [33] more sophisticated ML algorithms such as ANN might have demonstrated superior performance but were not explored. Although we acknowledge the importance of incorporating more interpretable ML approaches in SCM, we assert that it is equally crucial to investigate other algorithms like ensemble algorithms or ANN, even if they may pose challenges in terms of interpretability. This exploration is

Acta logistica - International Scientific Journal about Logistics
Volume: 11 2024 Issue: 3 Pages: 387-396 ISSN 1339-5629

essential to provide decision-makers with a comprehensive array of options.

Numerous approaches center around data analytics in SCM. However, the exploration of predictive analytics within SCM remains an area that has not received sufficient attention. A particular aspect requiring further investigation is the precise identification and quantification of non-conform deliveries with potential impact for both manufacturers and customers. Existing methodologies in issues related to late and non-conform deliveries face limitations.

Therefore, our contribution to the existing literature comes in the form of a case study in predictive analytics within SCM, employing ML and DL algorithms. Specifically, our focus lies in predicting non conform deliveries from suppliers, employing a supervised learning approach and utilizing an authentic dataset from an automotive manufacturer. In this study, we contrast straightforward ML and DL algorithms such as Random Forest Classifier and Regressor, SVM, SVR, Linear Regression, KNN, and ANN.

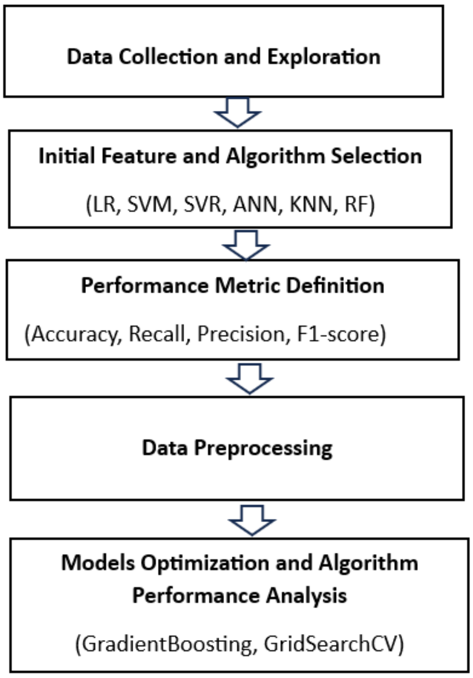

Figure 1 Methodology for predicting supplier risks utilizing ML and DL techniques

3 Methodology

3.1 *Case study*

The case under study involves a manufacturing company specializing in producing wiring harnesses for numerous OEMs. This company extensively sources millions of components from global suppliers, operating across varied production scales, encompassing both high and low volumes. While individual disruptions, delays, and quality issues remain relatively minor, their cumulative impact can escalate, creating a substantial number of disruptions that demand immediate handling to prevent further propagation.

Consequently, the objective is to establish a predictive system capable of preemptively categorizing potential disruptions and risk before their occurrence. This will facilitate proactive measures for risk mitigation and robust contingency planning, ensuring a proactive and resilient approach to managing and averting potential disruptions.

The focus of our investigation is on pinpointing suppliers most prone to SC vulnerabilities, specifically in terms of delivering bad product quality. As quality issues is a critical area for research. Understanding the impact of these quality issues and their correlation with SC disruptions is key to mitigating risks and ensuring a smoother operational flow. Our principal objective is to identify potential failures originating from suppliers impacted by vulnerabilities, thereby causing disruptions within the SC. We seek to estimate the overall costs associated with inferior-quality products resulting from various disruptions, which include line stoppages, delivery delays, as well as addressing customer concerns and dissatisfaction.

In the pursuit of addressing the complex challenges outlined in our case study, our methodology, in Figure 1, unfolds through a series of designed steps, each contributing to our overarching objective of establishing a predictive system for preemptively categorizing potential disruptions and risks in the SC.

3.2 *Data collection and exploration*

To comprehend the nuances of disruptions, caused by quality issues within our manufacturing company, we initiated the process with extensive data collection. This involved sourcing historical data from the manufacturer's Enterprise Resource Planning (ERP) system, The data covers supplier quality performance concerning 314 of purchased products over a period of seven years,incorporating assessments from 429 suppliers across 20 manufacturing plants worldwide. key variables within the dataset are outlined in Table 1, that comprising multiple columns containing information relevant to tracking and managing supplier issues. Additionally, each column is accompanied by a specific data format and description, providing insights into the type of information available within the dataset.

The dataset comprises records of 20,000 quality issues associated with distinct products. Among these issues, 53.5% were attributed to suppliers responsible for non-conforming products, 11.46% were linked to suppliers.who refused to acknowledge failures, and 35.04% of issues were communicated to suppliers as information for them to consider and rectify in their future deliveries.

3.3 *Initial feature and algorithm selection*

Identifying suppliers most prone to vulnerabilities, especially in delivering subpar product quality, was the focal point of our investigation. To translate this focus into actionable insights, we meticulously selected features that offer critical information about supplier performance, such as supplier name, failure description, issue gravity, number of issue per gravity, and total cost. To elaborate further on our approach, we utilized RF Classifier, SVM, KNN, and ANN for classification tasks, distinguishing and predicting failure descriptions. These models, renowned for their robustness, were instrumental in leveraging historical data to foresee potential disruptions. Concurrently, for regression tasks, specifically predicting the number of issues and total cost, we employed RF Regressor, SVR, Linear Regression and ANN.

As summarized in Table 2. These regression models excel in estimating numerical values, providing valuable insights into the expected quantity of failures and associated costs.

3.4 Performance metric definition

The incorporation of performance metrics is essential in evaluating the effectiveness of our models in addressing supplier quality concerns. In line with the case study's overarching goal of estimating failures, their numbers, and associated total costs, we have defined key performance metrics. These metrics (1), (2), (3), (4), (5), provide a comprehensive assessment of the models' predictive capabilities and their ability to contribute meaningful insights to SCM.

Table 1 Overview of the data

Data	Format	Description
ID number	Alphanumeric	Unique code describing supplier issue
Final Customer	Text	Short description of the final customer
Supplier PN	Alphanumeric	Unique supplier product number
Supplier Name	Text	Short description of the supplier's name
Failure Description	Text	Short description of the failure
Issue Gravity	Alphanumeric	Indicating where the product is detected as non-conform. It has three possible values: • C1: At the final customer • C2: At the manufacturer's plant production process • C3: At the manufacturer's plant in their incoming inspection
Number of issue per gravity	Number	How many issues from same failure were occurred
Supplier Acceptance	Binary	Indicating the acceptance of the supplier for the claimed failure (1 for "Accepted," 0 for "Not accepted")
Plant Location Number	Number	Number of the plant where the failure was detected
City	Text	Representing the city where the plant is located
NOK parts number	Number	Indicating the number of non-conform parts
Creation date	Date	When the failure was detected in the manufacturer's plant
NOK parts replacement	Binary	Representing whether the supplier ensured the replacement of non-conform parts (1 for "Yes," 0 for "No").
Replacement time	Number	Indicating how long the replacement process takes
Recurrent Issue	Binary	Did the issue have been occurred before (1 for "recurrent," 0 for "Not recurrent").
Total Cost (Euros)	Number	Representing the disruption cost incurred by the failure
Invoice Payment	Binary	Indicating if the supplier takes charge of the invoice payment (1 for "Yes," 0 for "No")
Response time	Binary	Indicating if the payment is made in time or not (1 for "Yes," 0 for "No").
Additional Time	Number	Indicating how long the payment takes in delay.

Table 2 ML and DL algorithms selection for regression and classification tasks

Machine Learning /Deep learning Algorithms	Random Forest Classifier	Random Forest Regressor	Support Vector Machine (SVM)	Support Vector Regression (SVR)	Linear Regression	KNN	ANN
Regression (for Number of issue prediction and Total cost)		x		x	x		x
Classification (for Failure prediction)	x		x			x	x

Precision (1): reflects the accuracy of positive predictions made by the model. In the context of our case study, precision signifies the proportion of correctly identified supplier failures out of all predicted failures.

Acta logistica - International Scientific Journal about Logistics
Volume: 11 2024 Issue: 3 Pages: 387-396 ISSN 1339-5629

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{1}$$

Recall (2): also known as sensitivity measures the model's ability to identify all actual supplier failures. It highlights the proportion of correctly identified failures out of the total actual failures.

$$\text{Recall (Sensitivity)} = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{2}$$

F1-score (3): is the harmonic mean of precision and recall. It provides a balanced assessment of a model's performance by considering both false positives and false negatives.

$$F1\ Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{3}$$

Accuracy (4): represents the overall correctness of the model's predictions, defined as the ratio of correct predictions to the total number of predictions.

$$Accuracy = \frac{Total\ Number\ of\ Predictions}{Number\ of\ Correct\ Predictions} \tag{4}$$

Mean Squared Error (MSE) (5) metric for regression tasks : It measures the average squared difference between the predicted values $\hat{y}_i$ and the actual y_i.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \tag{5}$$

3.5 Data pre-processing

After gaining insights into the dataset, our next step involved refining it for our predictive models. Initially, we converted categorical data into a numerical format, a prerequisite for ML and DL models that commonly process numerical input. One-Hot-Encoding, a widely established technique, was employed for this purpose. Incorporating dates as input features in a supervised learning framework involves training the prediction model on historical dates along with other relevant features depending on the target variable that we want to predict. In an effort to optimize the model's effectiveness, interpretability, and efficiency, we carefully chose a subset of features from our dataset. The identification of features required an understanding of the influence, correlation, and connections between variables, offering insights into their interdependencies and potential impact on the target variables. To mitigate interdependencies among our input features, certain variables were excluded.

Furthermore, and in order to enhance the performance of ML and DL models by ensuring the data is well-suited for analysis and model training. In summary, we chose the following independent variables to serve as input features for our models: Number of issue per gravity, Total cost, Issue gravity, Failure description, and Creation date.

The pair plot highlights a robust positive correlation among number of issue per gravity, failure description, and total cost, suggesting that a greater frequency of reported issues in failure description (as depicted in Figure 2) is linked to higher total costs.

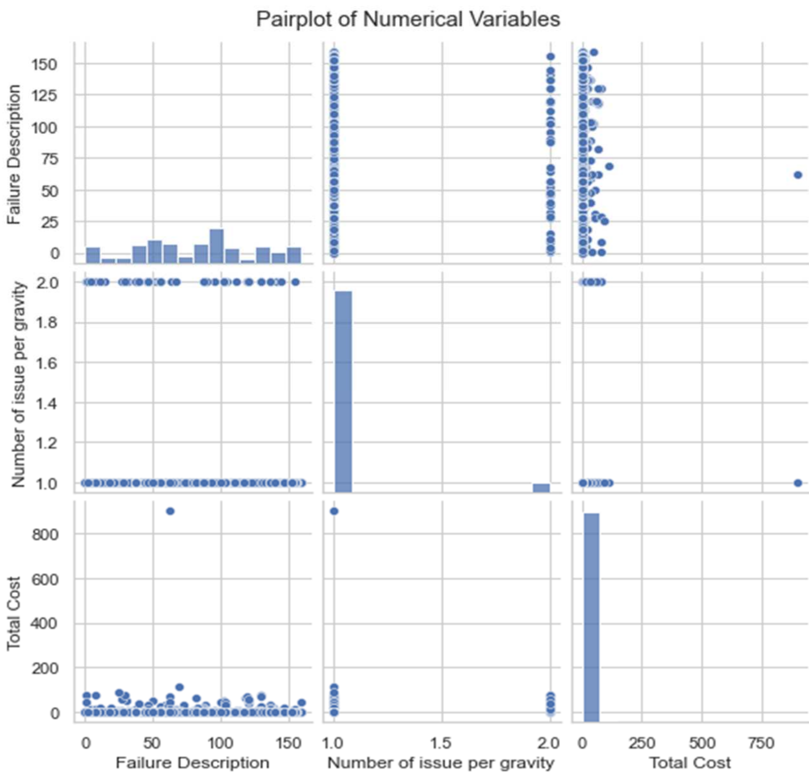

Figure 2 Analysis of issue frequency, failure description and total cost

Furthermore, the correlation observed between number of issue per gravity and total cost underscores that the gravity type occurring more frequently is associated with higher cost implications. This finding suggests that issues of this gravity type, identified by the end customer, are more likely to result in cost generation. Notably, these customer-detected failures, although occurring less frequently than C2-type issues, exhibit a heightened propensity to generate costs.

Following the specification of input features for various prediction models, the data preparation phase was successfully concluded. After understanding the available data and outlining the features for our models, we established an experimental plan consisted of two stages. The first stage focused on a classification task for predicting supplier failures description, where we can answer RQ 1. The second stage is focused on regression tasks for predicting the number of issues and total cost prediction and thus is designed to answer RQ 2 and RQ 3.

4 Result and discussion

This section unveils the findings of our investigation into predicting failure descriptions, a critical task for anticipating and managing potential disruptions in the SC. The accurate classification of failure scenarios holds the key to informed decision-making and proactive risk mitigation in SC operations. Our study delves into the performance of diverse ML and DL models, shedding light on their effectiveness in enhancing predictive capabilities.

4.1 Models optimization and algorithms performances analysis

4.1.1 Classification models optimization

After conducting an in-depth analysis, we explored hyperparameter tuning and feature engineering for both the KNN and SVM models. This rigorous exploration aimed to fine-tune the models and enhance their predictive capabilities.

Grid search is used to find the optimal hyperparameters, which are then used to train a final SVM model. The optimal settings for "C" (regularization parameter) and "kernel" are used to instantiate the SVM model. This improved SVM model is then used to generate predictions for cross-validation. By using an iterative procedure, the model's prediction accuracy and generalization ability are improved by training it with the most efficient hyperparameters found by grid search. As a result of these efforts in Table 3, the SVM model achieved a significant accuracy of 75%, showcasing the impact of parameter optimization.

As well, with hyperparameter optimization, the KNN model showed progress, with an accuracy of 60%. To optimize the KNN model, grid search is used, which entails examining a parameter grid that includes 'n_neighbors,' which is the number of neighbors taken into account for classification. Furthermore, a variety of weight functions ('weights') and distance metrics ('p') are methodically examined. Finding the ideal hyperparameter configuration to enhance classification accuracy is the goal of the grid search process. Five-fold cross-validation is used in conjunction with this optimization procedure to ensure strong assessment and reduce overfitting.

The combination of hyperparameter tuning and feature engineering contributes to a more refined and effective modeling approach, addressing specific characteristics of the dataset and improving overall models performance.

As well, we refined the neural network architecture employed in this task,this architecture consists of two hidden layers with ReLU activation functions, followed by dropout layers with rates of 0.5 and 0.3. The Adam optimizer is employed with default parameters, and training occurs over 100 epochs with a batch size of 32,strikes a balance between complexity and generalization performance, validated through empirical experimentation, providing us with an accuracy of 33%.

Applying advanced hyperparameter tuning techniques, we meticulously fine-tuned the RF to achieve superior performance. The initial RF model yielded an accuracy of 62%. Subsequently, we conducted an exhaustive hyperparameter search using GridSearchCV, exploring a parameter grid. This process resulted in a refined RF model with an enhanced accuracy of 64%, illustrating the significance of hyperparameter optimization.

In addition, we delved into the potential of Gradient Boosting to further boost model performance.

To find the ideal set of hyperparameters from the specified parameter distributions, RandomizedSearchCV is utilized. random sampling from the parameter distributions is done ten times.every possible combination of hyperparameters is assessed using 5-fold cross-validation.

The Gradient Boosting classifier exhibited exceptional accuracy, reaching an impressive 86%. This success highlights the effectiveness of Gradient Boosting in capturing intricate patterns within the data and maximizing predictive accuracy.

These detailed efforts in hyperparameter tuning, utilizing GridSearchCV for the RF model and configuring Gradient Boosting, showcase our commitment to optimizing model performance and uncovering the most effective configurations for the given classification task.

After the model is fitted, we carry out the validation set evaluation and cross-validation.Understanding the model's expected performance in real-world with unseen data. Using a 5-fold cross-validation, the cross-validation scores vary from 85.38% to 87.26%, with an accuracy of 86.39% on average and a standard deviation of 0.77%. The efficacy of the Gradient Boosting classifier in forecasting the failure descriptions within the dataset is exhibited by these outcomes.The model has strong performance on the validation set as well as in cross-validation, suggesting that it can generalize well to previously unseen data from the same distribution as the training data.

Table 3 Model evaluation metrics for classification task related to failures prediction

Model	Accuracy	Macro Avg Precision	Macro Avg Recall	Macro Avg F1-Score	Weighted Avg Precision	Weighted Avg Recall	Weighted Avg F1-Score
KNN	**60%**	**0.21**	**0.23**	**0.21**	**0.52**	**0.60**	**0.55**
SVM	**75%**	**0.35**	**0.35**	**0.34**	**0.75**	**0.75**	**0.75**
ANN	**33%**	**0.14**	**0.14**	**0.12**	**0.29**	**0.33**	**0.28**
RF classifier	**62%**	**0.26**	**0.30**	**0.27**	**0.54**	**0.62**	**0.56**
RF classifier with GridSearchCV	**64%**	**0.28**	**0.32**	**0.28**	**0.55**	**0.64**	**0.58**
RF classifier with Gradient Boosting classifier	**86%**	**0.58**	**0.59**	**0.58**	**0.78**	**0.82**	**0.79**

Table 4 Model evaluation metrics for regression task related to number of failures prediction

Regression (Metrics/Models)	ANN	Linear Regression	Random Forest Regressor	SVR
MSE 'Number of Failures'	**2.681293342490944e-16**	**1.87e-33**	**0.0001**	**0.05**

Table 5 Model evaluation metrics for regression task related to total cost prediction

Regression (Metrics/Models)	Linear Regression	Random Forest Regressor	ANN	SVR
MSE 'Total Cost'	**1.56e-28**	**0.023**	**0.17**	**0.88**

In addition, to assessing the performance metrics of our models, we conducted an in-depth analysis of feature importance to identify the input features that significantly influence the model's output. This exploration provides valuable insights into the variables driving the predictive capabilities of our models.

The results of our feature importance analysis underscore the pivotal role of specific variables in the prediction of failure descriptions. Notably, supplier name and failure description emerged as features with higher importance compared to others in the models for the initial stage. These variables exert a substantial influence on the accurate prediction of the failure description, aligning with the nuances of our SC disruption prediction task.

The identification of influential features enhances our understanding of the underlying dynamics of failure prediction. These insights can inform decision-makers in the SC, enabling them to focus on key variable for improved risk assessment and proactive mitigation strategies.

4.1.2 Regression models performance analysis

This part presents a detailed analysis of the performance metrics for the regression models employed in predicting the number of failures and total cost respectively in Table 4 and Table 5. The models considered include Linear Regression, SVR, RF Regressor, and ANN evaluated through MSE metric.

In our quest to predict the number of failures, Our analysis reveals noteworthy insights into the performance of various regression models. Linear Regression and the ANN stand out with unprecedented in conclusion, our research, which delves into the predictive capabilities of ML and DL models, significantly contributes to the proactive prevention of SC disruptions and the enhancement of supplier performance. By focusing on specific prediction questions, our study empowers decision-makers with valuable insights for issues prevention, risk control, and supplier management. The integration of predictive analytics and innovative methodologies, as explored in our research, empowers organizations to navigate the complexities of the modern SC landscape with heightened efficiency and effectiveness. This convergence of SCM with advanced technologies establishes a foundation for a more resilient and adaptive future in SC operations. By leveraging predictive capabilities, organizations can proactively respond to emerging challenges and uncertainties, ensuring a robust and future-ready SC.

However, it's essential to acknowledge the limitations of our study. Future research could explore additional industry-specific datasets and address potential biases in the selected data. Additionally, the ethical considerations of deploying advanced technologies in SCM, such as data privacy and algorithmic transparency, warrant continued attention as organizations embrace these predictive capabilities,predictive accuracy, boasting MSE values of 1.87e-33 and 2.681293342490944e-16, respectively. These exceptionally low errors underscore their remarkable precision in capturing the underlying patterns in the data. SVR demonstrates a commendable performance, striking a balance with an MSE of 0.05, indicative of solid predictive capabilities. Notably, the RF Regressor emerges as the top performer, showcasing an exceptionally low MSE of 0.0001. This outstanding result underscores its prowess in capturing intricate relationships within the data, making it a robust choice for regression tasks.

Furthermore, our detailed investigation into feature significance for our selected models, particularly the RF Regressor, identified gravity issue and number of issues per gravity as key variables with notably elevated importance compared to others in the second-stage models. These findings emphasize the crucial roles of these variables in predicting the number of issues per gravity, highlighting their substantial importance in our SCM context.

To predict the total cost, Linear Regression continues to demonstrate an exceptionally low MSE of 1.56e-28 for predicting total cost. This indicates very high accuracy and precision in its predictions. The ANN model has an MSE of 0.17, indicating acceptable performance. While higher than the MSE for Linear Regression. The RF Regressor has an MSE of 0.023, which is higher than Linear Regression but lower than the ANN. SVR has the highest MSE among the models, with a value of 0.88. This indicates a higher level of prediction error compared to the other models.

[35] The authors employed a variety of regression models, including Simple Regression, Lasso Regression, Ridge Regression, Elastic Net, RF, Gradient Boosting Machine (GBM), and Neural Network, to predict the availability of products in the event of disruption. The results of their experiments showed that tree-based learning algorithms,RF and GBM in particular,performed better than other models in terms of test error.

Overall,the type of data used and the features chosen for the study have an impact on the models' performance. Regression models can exhibit variability in their responses to distinct data sets and feature types.Neural networks can perform very well in scenarios with enormous datasets or sophisticated feature interactions because of their great degree of flexibility and ability to understand complex patterns in data. Nevertheless, they may be more prone to overfitting and need careful hyperparameter adjustments, particularly in cases when the dataset is noisy or tiny.In conclusion, elements including the type of data, the attributes of the features, and the intricacy of the underlying relationships all have an impact on the model selection and performance.

5 Conclusions

In summary, our research underscores the pivotal role that ML and DL models play in transforming SCM.By delving into the predictive capabilities of these models, we contribute significantly to the proactive prevention of disruptions in the SC and the overall improvement of supplier performance.

Our study's value lies in its specific focus on prediction questions, providing decision-makers with actionable insights for preventing issues, controlling risks, and managing suppliers more effectively. Through the integration of predictive analytics and innovative methodologies, as explored in our research, automotive organizations gain the tools necessary to navigate the intricate landscape of modern SCs with heightened efficiency.

This convergence of SCM with advanced technologies establishes a robust foundation for a more resilient and adaptive future in SC operations. leveraging predictive capabilities empowers organizations to proactively respond to emerging challenges and uncertainties, ensuring a SC that is both robust and future-ready.

The specific automotive data provides several strengths, it allows for a deep understanding of the nuances and intricacies within the automotive SC. The models developed based on this data are likely to be highly tailored to the specific challenges and dynamics of the automotive industry. This specialization can lead to more accurate predictions and insights, particularly for disruptions related to non-quality products from suppliers. Despite its resilience, the dynamics, challenges and variables influencing disruptions in the automotive SC may be very different from those in other sectors.Compared to businesses like electronics or pharmaceuticals, the automobile sector could have different procurement procedures, product lifecycles, or regulatory needs. As a result, models created using data from the automobile industry might not be directly applicable or accurate in other SC scenarios or industries. It's essential to validate the models developed using data from different industries or SC contexts. This validation process may involve testing the models with data from companies in other sectors and making necessary adaptations or adjustments to ensure their effectiveness and accuracy. Furthermore,the research focus on predicting disruptions from non-quality products while excluding other types of disruptions such as logistical issues and geopolitical events. Logistical issues could involve problems with transportation, warehousing, or distribution, while geopolitical events could include trade disputes, political instability, or natural disasters impacting and changing SC dynamics that can be influenced by a wide range of factors the assumption of stationarity may no longer hold true.Changes in SC dynamics can alter the underlying patterns and relationships in the data used for modeling and forecasting.For instance,supplier performance may change, or new SC partners may be introduced. These changes can affect the model’s accuracy and the statistical properties of the data, making it more challenging to accurately predict future outcomes using traditional stationary models.

References

[1] WANG, G., GUNASEKARAN, A., NGAI, E.W.T., PAPADOPOULOS, T.: Big data analytics in logistics and supply chain management: Certain investigations for research and applications, *International Journal*

of Production Economics, Vol. 176, No. 3, pp. 98-110, 2016. https://doi.org/10.1016/j.ijpe.2016.03.014

[2] NGUYEN, T., ZHOU, L., SPIEGLER, P., IEROMONACHOU, LIN, Y.: Big data analytics in supply chain management: A state-of-the-art literature review, *Computers & Operations Research*, Vol. 98, No. October, pp. 254-264, 2018. https://doi.org/10.1016/j.cor.2017.07.004

[3] REZKI, N., MANSOURI, M.: Improving supply chain risk assessment with artificial neural network predictions, *Acta logistica*, Vol. 10, No. 4, pp. 645-658, 2023. https://doi.org/10.22306/al.v10i4.444

[4] YU, L., WANG, S., LAI, K.K.: Developing an SVM-based ensemble learning system for customer risk identification collaborating with customer relationship management, *Frontiers of Computer Science in China*, Vol. 4, No. 2, pp. 196-203, 2010. https://doi.org/10.1007/s11704-010-0508-2

[5] MANGORTEY, E., MONTEIRO, D., ACKLEY, J., GAO, Z., PURANIK, T.G., KIRBY, M., PINON-FISCHER, O.J., MAVRIS, D.N.: *Application of Machine Learning Techniques to Parameter Selection for Flight Risk Identification*, In: American Institute of Aeronautics and Astronautics, AIAA Scitech 2020 Forum, 6-10 January 2020, Orlando, Florida, 2020. https://doi.org/ doi: 10.2514/6.2020-1850

[6] VAN VOORN, G., HENGEVELD, G., VERHAGEN, J.: An agent-based model representation to assess resilience and efficiency of food supply chains, *PLOS ONE*, Vol. 15, No. 11, pp. 1-27, 2020. https://doi.org/10.1371/journal.pone.0242323

[7] SAZVAR, Z., TAFAKKORI, K., OLADZAD, N., NAYERI, S.: A capacity planning approach for sustainable resilient supply chain network design under uncertainty: A case study of vaccine supply chain, *Computers & Industrial Engineering*, Vol. 159, p. 107406, 2021. https://doi.org/10.1016/j.cie.2021.107406

[8] RAD, F.F.: Industry 4.0 and supply chain performance: A systematic literature review of the benefits, challenges, and critical success factors of 11 core technologies, *Industrial Marketing Management*, Vol. 105, pp. 268-293, 2022. https://doi.org/10.1016/j.indmarman.2022.06.009

[9] KATSALIAKI, K., GALETSI, P., KUMAR, S.: Supply chain disruptions and resilience: a major review and future research agenda, *Annals of Operations Research*, Vol. 319, No. 1, pp. 965-1002, 2022. https://doi.org/10.1007/s10479-020-03912-1

[10] SHEFFI, Y.: Preparing for the big one [supply chain management], *Manufacturing Engineer*, Vol. 84, No. 5, pp. 12-15, 2005. https://doi .org/10.1049/me:20050503

[11] RASHID, A., RASHEED, R., NGAH, A.H., PRADEEPA JAYARATNE, M.D.R., RAHI, S., TUNIO, M.N.: Role of information processing and digital supply chain in supply chain resilience through supply chain risk management, *Journal of Global Operations and Strategic Sourcing*, Vol. 17, No. 2, pp. 429-447, 2024. https://doi.org/10.1108/JGOSS-12-2023-0106

[12] ZHENG, G.: DRN: *A Deep Reinforcement Learning Framework for News Recommendation*, In: Proceedings of the 2018 World Wide Web Conference on World Wide Web (WWW ’18), Lyon, France, pp. 167-176, 2018. https://doi .org/10.1145/3178876.3185994

[13] MUKHERJEE, S., DE, A., ROY, S.: Supply chain risk prioritization: a multi-criteria based Intuitionistic Fuzzy TOPSIS approach, *International Journal of Quality & Reliability Management*, Vol. ahead-of-print, No. ahead-of-print., 2024. https://doi .org/10.1108/IJQRM-07-2023-0214

[14] WALLER, M.A.: Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management, *Journal of Business Logistics*, Vol. 34, No. 2, pp. 77-84, 2013. https://doi.org/10.1111/jbl.12010

[15] WANG, C., LI, X., ZHOU, X., WANG, A., NEDJAH, N.: Soft computing in big data intelligent transportation systems, *Applied Soft Computing*, Vol. 38, pp. 1099-1108, 2016. https://doi.org/10.1016/j.asoc.2015.06.006

[16] NGUYEN, N.T., CHBEIR, R., EXPOSITO, E., ANIORTÉ, P., TRAWIŃSKI, B. (Éd.): *Computational Collective Intelligence*, 11th International Conference, ICCCI 2019, September 4-6, Hendaye, France, Vol. 11683, 2019. https://doi.org/10.1007/978-3-030-28377-3

[17] SPREITZENBARTH, J.M., BODE, C., STUCKENSCHMIDT, H.: Artificial intelligence and machine learning in purchasing and supply management: A mixed-methods review of the state-of-the-art in literature and practice, *Journal of Purchasing and Supply Management*, Vol. 30, No. 1, pp. 1-21, 2024. https://doi.org/10.1016/j.pursup.2024.100896

[18] DALMARCO, G., BARROS, A.C.: *Adoption of Industry 4.0 Technologies in Supply Chains*, In: Moreira, A., Ferreira, L., Zimmermann, R. (eds) Innovation and Supply Chain Management, Contributions to Management Science, Springer, Cham., pp. 303-319, 2018. https://doi.org/10.1007/978-3-319-74304-2_14

[19] GHARAIBEH, L., ERIKSSON, K.M., LANTZ, B., MATARNEH, S., ELGHAISH, F.: Toward digital construction supply chain-based Industry 4.0 solutions: scientometric-thematic analysis, *Smart and Sustainable Built Environment*, Vol. 13, No. 1, pp. 42-62, 2024. https://doi.org/10.1108/SASBE-12-2021-0224

[20] DOSDOĞRU, A.T., BORU İPEK, A., GÖÇKEN, M.: A novel hybrid artificial intelligence-based decision support framework to predict lead time, *International Journal of Logistics Research and Applications*, Vol. 24, No. 3, pp. 261-279, 2021.

https://doi.org/10.1080/13675567.2020.1749249

[21] QUEIROZ, M.M., FOSSO WAMBA, S., MACHADO, M.C., TELLES, R.: Smart production systems drivers for business process management improvement: An integrative framework, *Business Process Management Journal*, Vol. 26, No. 5, pp. 1075-1092, 2020. https://doi.org/10.1108/BPMJ-03-2019-0134

[22] LIU, P., HENDALIANPOUR, A., RAZMI, J., SANGARI, M.S.: A solution algorithm for integrated production-inventory-routing of perishable goods with transshipment and uncertain demand, *Complex Intelligent Systems*, Vol. 7, No. 3, pp. 1349-1365, 2021. https://doi.org/10.1007/s40747-020-00264-y

[23] SARDAR, S.K., SARKAR, B., KIM, B.: Integrating Machine Learning, Radio Frequency Identification, and Consignment Policy for Reducing Unreliability, in Smart Supply Chain Management, *Processes*, Vol. 9, No. 2, pp. 1-16, 2021. https://doi.org/10.3390/pr9020247

[24] ZHU, X., NINH, A., ZHAO, H., LIU, Z.: Demand Forecasting with Supply-Chain Information and Machine Learning: Evidence in the Pharmaceutical Industry, *Production and Operations Management*, Vol. 30, No. 9, pp. 3231-3252, 2021. https://doi.org/10.1111/poms.13426

[25] GOTTLIEB, S., IVANOV, D., DAS, A.: *Case studies of the digital technology impacts on supply chain disruption risk management*, In: Logistik im Wandel der Zeit – Von der Produktionssteuerung zu vernetzten Supply Chains, M. Schröder et K. Wegner, Éd., Wiesbaden: Springer Fachmedien Wiesbaden, pp. 23-52, 2019. https://doi.org/10.1007/978-3-658-25412-4_2

[26] LIU, P., HENDALIANPOUR, A., HAMZEHLOU, M.: Pricing model of two-echelon supply chain for substitutable products based on double-interval grey-numbers, *International Journal of Fuzzy Systems*, Vol. 40, No. 5, pp. 8939-8961, 2021. https://doi.org/10.3233/JIFS-201206

[27] HENDALIANPOUR, A., HAMZEHLOU, M., FEYLIZADEH, M.R., XIE, N., SHAKERIZADEH, M.H.: Coordination and competition in two-echelon supply chain using grey revenue-sharing contracts, *Grey Systems*, Vol. 11, No. 4, pp. 681-706, 2021. https://doi.org/10.1108/GS-04-2020-0056

[28] CHOWDHURY, MD. T., SARKAR, A., PAUL, S.K., MOKTADIR, MD. A.: A case study on strategies to deal with the impacts of COVID-19 pandemic in the food and beverage industry, *Operations Management Research*, Vol. 15, No. 1-2, pp. 166-178, 2022. https://doi.org/10.1007/s12063-020-00166-9

[29] KUMAR, A., MANGLA, S.K., KUMAR, P.: Barriers for adoption of Industry 4.0 in sustainable food supply chain: a circular economy perspective, *International Journal of Productivity and Performance Management*, Vol. 73, No. 2, pp. 385-411, 2024. https://doi.org/10.1108/IJPPM-12-2020-0695

[30] SAHOO, S.K., GOSWAMI, S.S., HALDER, R.: Supplier Selection in the Age of Industry 4.0: A Review on MCDM Applications and Trends, *Decision Making Advances*, Vol. 2, No. 1, pp. 32-47, 2024. https://doi.org/10.31181/dma21202420

[31] KHAN, M.M., BASHAR, I., MINHAJ, G.M., WASI, A.I., HOSSAIN, N.U.I.: Resilient and sustainable supplier selection: an integration of SCOR 4.0 and machine learning approach, *Sustainable and Resilient Infrastructure*, Vol. 8, No. 5, pp. 453-469, 2023. https://doi.org/10.1080/23789689.2023.2165782

[32] WAGNER, J., BURGGRÄF, P., DANNAPFEL, M., FÖLLING, C.: Assembly Disruptions – Empirical Evidence in the Manufacturing Industry of Germany, Austria and Switzerland, *International Refereed Journal of Engineering and Science*, Vol. 6, No. 3, pp. 15-25. 2017.

[33] BARYANNIS, G., DANI, S., ANTONIOU, G.: Predicting supply chain risks using machine learning: The trade-off between performance and interpretability, *Future Generation Computer Systems*, Vol. 101, pp. 993-1004, 2019. https://doi.org/10.1016/j.future.2019.07.059

[34] BRINTRUP, A., PAK, P., RATINEY, D., PEARCE, T., WICHMANN, P., WOODALL, P., MCFARLANE, D.: Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing, *International Journal of Production Research*, Vol. 58, No 11, pp. 3330-3341, 2020. https://doi.org/10.1080/00207543.2019.1685705

[35] CAMUR, M.C., RAVI, S.K., SALEH, S.: Enhancing supply chain resilience: A machine learning approach for predicting product availability dates under disruption, *Expert Systems with Applications*, Vol. 247, p. 123226, 2024. https://doi.org/10.1016/j.eswa.2024.123226

Review process
Single-blind peer review process.