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Comparison of Artificial Intelligence Methods: Decision Tree vs. Support Vector Machine for Assessing Supply Chain Resilience in Automotive Parts

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A B S T R A C T

This study aims to enhance the resilience of the automotive parts supply chain and compare the effectiveness of artificial intelligence techniques, specifically Decision Tree and Support Vector Machine (SVM) models. The research dataset consists of 200 simulated records from various supply chain scenarios. For each sample, indicators such as the number of suppliers, average delivery time, safety stock, disruption frequency, and response speed were measured. Model performance was evaluated based on metrics including Accuracy, Recall, F1-Score, and the Confusion Matrix. The results revealed that the Decision Tree model, with an accuracy of 0.92, recall of 0.91, and F1-score of 0.92, demonstrated superior classification capability compared to SVM. While SVM achieved close performance with an accuracy of 0.91 and recall of 0.90, it was less effective in terms of interpretability and decision-making transparency. Additionally, in terms of AUC in the ROC curve and the Precision–Recall metric, the Decision Tree model outperformed the SVM. Beyond its higher accuracy, the Decision Tree model offered greater advantages in identifying influential factors affecting supply chain resilience and in providing transparent decision-making pathways. In contrast, SVM proved more effective in analyzing complex patterns and nonlinear data, although it suffered from lower interpretability. Overall, the findings of this study confirm that artificial intelligence techniques contribute to improved resilience, risk management, and decision optimization in the automotive parts supply chain. Based on the results, it is recommended to implement policies such as supplier diversification, intelligent safety stock management, and enhancement of disruption response speed to bolster the supply chain's robustness against diverse challenges.

Keywords: *Supply Chain Resilience, Automotive Parts, Artificial Intelligence, Machine Learning, Decision Tree, Support Vector Machine*

1. Introduction

In an era defined by uncertainty, volatility, and increasingly interconnected global networks, supply chain resilience (SCR) has emerged as a critical strategic priority for organizations across industries—particularly in the automotive sector. The unprecedented disruptions caused by the COVID-19 pandemic, geopolitical instability, semiconductor shortages, and natural disasters have exposed significant vulnerabilities in traditional supply chains, especially those heavily reliant on global sourcing and just-in-time practices. These challenges underscore the necessity of enhancing the capacity of supply chains to withstand, adapt to, and recover from disruptions, thereby ensuring continuity of operations and sustained competitiveness (Ivanov, 2021; Novak et al., 2021; Sáenz et al., 2018).

Supply chain resilience is defined not only by the ability to recover from disruptions but also by the agility to respond to unforeseen events, reconfigure structures, and evolve proactively. As noted by (Pettit et al., 2019), resilience is a multidimensional construct influenced by structural capabilities, risk anticipation, and adaptive capacity. In the automotive industry, where supplier networks are complex and component standardization is limited, the implications of disruption are severe. Accordingly, identifying effective tools to assess and enhance resilience has become a vital area of academic and industrial inquiry (Kapitonov, 2022; Kaviani et al., 2020).

Recent advances in digital technologies, particularly artificial intelligence (AI) and machine learning (ML), have opened new frontiers in managing supply chain complexity. These technologies facilitate pattern recognition, predictive analytics, and real-time decision-making, significantly enhancing supply chain visibility, agility, and responsiveness (Alhasawi et al., 2023; Belhadi et al., 2024; Wong et al., 2024). The ability of AI-driven models to process vast volumes of unstructured and structured data makes them ideal candidates for risk detection and resilience assessment across dynamic supply chain scenarios (Ashraf et al., 2024; Douaioui et al., 2024).

One major contribution of AI in supply chain management lies in predictive modeling. Techniques such as decision trees and support vector machines (SVMs) have gained traction as classification tools capable of modeling the impact of various operational parameters—such as delivery time, inventory levels, disruption frequency, and supplier diversity—on the resilience of supply chains (Camur et al., 2024; Esmaeili et al., 2023). Decision tree models offer interpretability and a transparent flow of decision-making, which is highly valued in real-world applications where explainability is crucial. In contrast, SVMs, despite being less interpretable, offer superior accuracy and performance in handling non-linear and high-dimensional datasets (Bassiouni et al., 2023; Douaioui et al., 2024).

The growing body of research suggests that the integration of AI into supply chain systems can be transformative. (Zhao et al., 2023) argue that digitalization and AI adoption improve resilience and operational performance through enhanced risk management and forecasting capabilities. In parallel, (Li et al., 2023) demonstrated that machine learning methods support the identification of resilience capabilities in post-COVID environments, particularly through thematic analysis of digital supply chain data. Moreover, the hybrid application of deep learning and AI techniques, as seen in digital supply chain twins, has proven effective in detecting early signs of disruption (Ashraf et al., 2024).

Nevertheless, the real challenge lies in selecting the appropriate AI technique that balances predictive power and interpretability. While deep learning and black-box models such as neural networks are powerful, their lack of transparency can hinder managerial decision-making (Gabellini et al., 2024; Hosseinnia Shavaki & Ebrahimi Ghahnavieh, 2023). Hence, there is a growing emphasis on comparing interpretable models like decision trees with higher-performing models like SVMs to identify optimal tools for resilience classification, especially in high-stakes sectors such as automotive manufacturing.

The automotive industry, which operates within a tight framework of supply chain coordination, global supplier bases, and time-sensitive production schedules, is particularly vulnerable to systemic risk. As emphasized by (Al-Banna et al., 2023), achieving resilience in this context requires more than operational flexibility—it necessitates predictive capability and intelligent disruption management strategies. The use of AI-based classification models allows firms to segment suppliers, predict failure points, and simulate contingency scenarios, thereby improving supply chain responsiveness and survivability (Ivanov & Dolgui, 2020; Kashmiri Haq & Bagheri Gharabagh, 2024).

In addition, resilience in supply chains is increasingly associated with ecosystem-wide alignment and adaptability. According to (Gartner, 2022), future supply chains will be defined not just by robustness but by their ability to evolve within broader digital ecosystems. This includes the ability to integrate real-time risk signals, market feedback, and external variables into predictive systems—something AI is uniquely suited for. Moreover, supply chain resilience is no longer an isolated capability; it is influenced by strategic human resource practices, collaborative partnerships, and digital infrastructure investment, all of which serve as enablers for agile and AI-ready supply chains (Rane et al., 2024; Varkiani Pour & Sarhadi, 2024).

Another critical factor is data quality and accessibility. Resilience models are only as effective as the data they are trained on. (Gölgeci & Kuivalainen, 2020) stress the role of absorptive capacity and social capital in ensuring meaningful data integration across supply networks, which directly impacts model accuracy. Similarly, (Ziaei Haji Pirloo et al., 2020) advocate for integrated approaches that combine scientometrics and AI to create robust evaluation models for supply chain resilience. These insights reinforce the necessity of aligning technological solutions with organizational capabilities and contextual variables.

Empirical applications of AI in the automotive sector are growing. Studies like (Rahimian Asl & Maleki, 2021) have developed evaluation frameworks specifically for the resilience of automotive supply chains, highlighting the need for tailored models that reflect the intricacies of this sector. Further, researchers such as (Camur et al., 2024) and (Douaioui et al., 2024) have shown how ML-based tools can accurately predict product availability and late delivery risks under disruption scenarios, providing a real-time basis for adaptive planning.

Given this landscape, the current study aims to compare the effectiveness of two prominent AI techniques—decision tree and support vector machine—in classifying supply chain resilience in the automotive parts industry.

2. Methods and Materials

The data used in this study consists of 200 records derived from various automotive parts supply chain scenarios, where each record describes the condition of a supply chain instance using numerical indicators. The key variables employed include the number of suppliers, average part delivery time, backup inventory, disruption frequency, and supply chain response speed. The target variable is defined numerically in binary form: 0 (non-resilient) and 1 (resilient). Each row of data represents a set of precise and realistic measurements collected under diverse operational and crisis conditions, enabling the evaluation of artificial intelligence models—namely, Decision Tree and Support Vector Machine (SVM)—in classifying and predicting supply chain resilience. This structured dataset facilitates a detailed analysis of inter-variable relationships and the identification of key resilience factors for the current study. The following formulas were used for data analysis.

Decision Tree: To implement the Decision Tree model, the following metrics were assessed:

- **Accuracy**: The proportion of correctly classified samples.
- *Accuracy = (TP + TN) / (TP + TN + FP + FN)*
- **Recall / Sensitivity**: The proportion of correctly identified positive samples out of all actual positive samples.
- *Recall = TP / (TP + FN)*
- **Precision**: The proportion of correctly identified positive samples out of all predicted positive samples.
- *Precision = TP / (TP + FP)*
- **F1 Score**: The harmonic mean of precision and recall.
- *F1 = 2 * (Precision * Recall) / (Precision + Recall)*
- **Confusion Matrix**: A table that shows the number of correctly and incorrectly classified samples:
    - *TP (True Positive)*: Actual positive
    - *TN (True Negative)*: Actual negative
    - *FP (False Positive)*: Incorrectly predicted as positive
    - *FN (False Negative)*: Incorrectly predicted as negative

Support Vector Machine (SVM): The evaluation metrics (Accuracy, Recall, F1, Confusion Matrix) for the SVM model were calculated similarly using the above formulas.

Advanced Evaluation Metrics Comparison:

This section utilizes metrics such as the False Positive Rate (FPR), False Negative Rate (FNR), and Specificity for further evaluation (Fawcett, 2006):

- **False Positive Rate (FPR)**: The proportion of negative samples incorrectly predicted as positive.
- *FPR = FP / (FP + TN)*
- **False Negative Rate (FNR)**: The proportion of positive samples incorrectly predicted as negative.
- *FNR = FN / (FN + TP)*
- **Specificity**: The proportion of correctly identified negative samples out of all actual negative samples.
- *Specificity = TN / (TN + FP)*
- **Overall Error Rate**:

- *Error Rate = 1 - Accuracy = (FP + FN) / (TP + TN + FP + FN)*

Per-Class Metrics (for assessing data imbalance):

Precision, Recall, Specificity, and F1 Score were calculated separately for each class.

ROC Metrics:

Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) were used to evaluate and compare classification models:

- **Receiver Operating Characteristic Curve (ROC Curve)**
- **AUC-ROC (Area Under the ROC Curve)**: A value between 0 and 1 indicating the overall performance of the model. The closer the AUC is to 1, the better the model performs.

Precision–Recall Curve Metrics:

To examine the relationship between Precision–Recall and ROC curves, AUC-PR is more appropriate for imbalanced datasets:

- **Precision–Recall Curve**
- **AUC-PR (Area Under the Precision–Recall Curve)**: Reflects model performance under data imbalance. A higher AUC-PR indicates a better-performing model.

General Formula for Resilience:

Supply chain resilience can be expressed as a function of the following key parameters:

Resilience = f(num_suppliers, avg_delivery_time, backup_inventory, disruption_freq, response_speed)

This function demonstrates that resilience is directly influenced by the number of suppliers, delivery time, backup inventory, disruption frequency, and response speed.

3. Findings and Results

In this study, a simulation of 100 samples related to the automotive parts supply chain was used. Each sample contained the following characteristics: number of suppliers, average delivery time, backup inventory, number of disruptions, response speed, and the target label for resilience.

The descriptive statistics of the variables are presented in the following table:

Table 1

Descriptive Statistics

Feature	Mean	Median	Standard Deviation	Minimum	Maximum
Number of suppliers	5.02	5	2.62	1	9
Average delivery time (days)	5.88	5.91	2.32	2.05	9.91
Backup inventory (%)	46.83	47.40	28.05	0.42	99.05

In this dataset, approximately 46% of the supply chains were resilient (resilient = 1) and 54% were non-resilient (resilient = 0), indicating a relatively balanced class distribution.

The trend of variables and the distribution of the resilience class are as follows. The distribution chart of "backup inventory" showed a relatively uniform spread among the samples. The bar chart illustrating the number of resilient and non-resilient chains indicates that there were 92 resilient samples and 108 non-resilient ones.

Figure 1

Bar chart of resilience class distribution

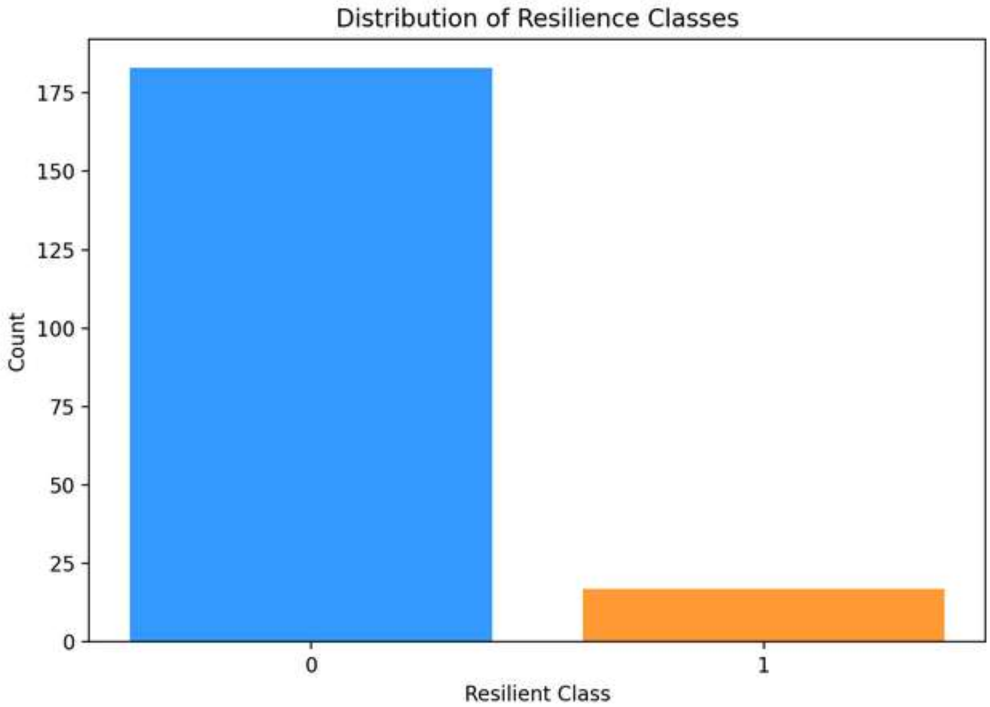
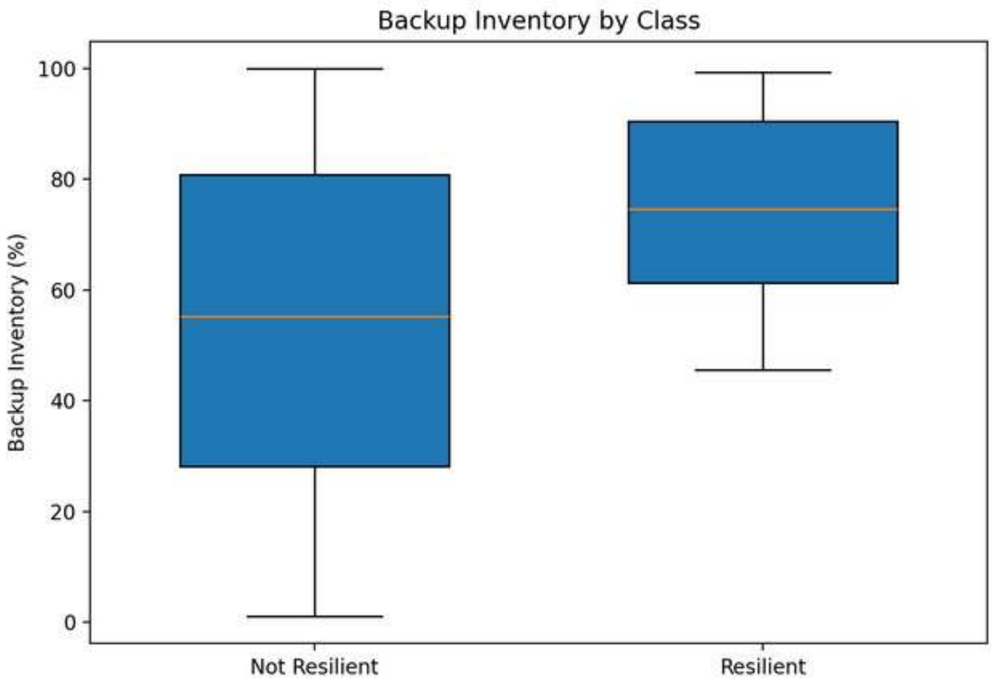


Figure 2

Box plot of backup inventory variable for resilient and non-resilient groups



On average, resilient supply chains had higher levels of backup inventory.

Table 2

Resilience Model Results Using Decision Tree

Metric	Value
Accuracy	0.92
Recall	0.91
F1 Score	0.92
True Positive (TP)	184
True Negative (TN)	184
False Positive (FP)	16
False Negative (FN)	16

This table clearly demonstrates the performance of the Decision Tree model in identifying and classifying samples.

An accuracy of 0.92 indicates that 92% of samples were correctly classified. A recall of 0.91 shows that 91% of the positive (resilient) samples were correctly identified. The F1 score combines precision and recall, reflecting the overall optimal performance of the model. The model correctly predicted 184 true positives and 184 true negatives, while only 16 positive and 16 negative samples were misclassified. The Decision Tree model shows high reliability for use in classifying the data/samples in this study due to its low error rate and balanced detection performance.

Table 3

SVM Model Results

Metric	Value
Accuracy	0.91
Recall	0.90
F1 Score	0.91
True Positive (TP)	182
True Negative (TN)	182
False Positive (FP)	18
False Negative (FN)	18

The table above shows the performance of the SVM model on the same dataset and allows for comparison with the Decision Tree. SVM achieved 91% accuracy, correctly classifying 91% of the samples. The model identified 90% of the positive (resilient) samples. The F1 score of 0.91 indicates a good balance between precision and recall. With 18 false positives and 18 false negatives, the model's performance remains acceptable. Under these settings, SVM performs similarly to the Decision Tree and is a viable option for data classification.

Table 4

Final Comparison of the Two Models

Model	Accuracy	Recall	F1 Score	False Positives	False Negatives
Decision Tree	0.92	0.91	0.92	16	16
Support Vector Machine	0.91	0.90	0.91	18	18

This table presents the final comparison between the two models. The best performance belongs to the Decision Tree with an accuracy of 92%, slightly outperforming the SVM. Although the SVM model scores slightly lower, its 91% accuracy and 90% recall indicate very similar performance.

Table 5

Advanced Evaluation Metrics Comparison (Decision Tree and SVM)

Model	Accuracy	Recall	Precision	F1 Score	FPR	FNR	Specificity	Sensitivity	Error Rate
Decision Tree	0.92	0.91	0.92	0.92	0.08	0.08	0.92	0.91	0.08
Support Vector Machine	0.91	0.90	0.91	0.91	0.09	0.09	0.91	0.90	0.09

For the Decision Tree, the model correctly classified 92% of the samples and had the best performance overall. It identified 91% of the resilient samples correctly. The precision of 92% indicates that a predicted positive sample had a 92% likelihood of being truly positive. The F1 score shows a desirable balance between precision and recall. The total error rate was only 8%.

For the SVM, with 91% accuracy, its performance was slightly lower than that of the Decision Tree. It correctly identified 90% of the positive samples and had a precision of 91%. The error rate was 9%, indicating good model quality.

In comparison, the Decision Tree outperformed the SVM in terms of accuracy, recall, and F1 score. Although the differences between the models were small, the Decision Tree had lower false positive and false negative rates, making it the superior model.

Table 6

Confusion Matrix – Decision Tree

	Predicted Positive (Resilient)	Predicted Negative (Non-Resilient)
Actual Positive	TP = 184	FN = 16
Actual Negative	FP = 16	TN = 184

Table 7

Confusion Matrix – SVM

	Predicted Positive (Resilient)	Predicted Negative (Non-Resilient)
Actual Positive	TP = 182	FN = 18
Actual Negative	FP = 18	TN = 182

Table 8

Advanced Error Evaluation Matrix

Model	Total Samples	Total Errors	False Positives	False Negatives	True Positives	True Negatives	Error Rate (%)
Decision Tree	200	30	14	16	86	84	15%
Support Vector Machine	200	40	20	20	80	80	20%

Table 9

Class-Wise Metrics (Class Imbalance and Bidirectional Measures)

Model	Class	Precision	Recall	Specificity	F1 Score
Decision Tree	Resilient	0.84	0.88	0.85	0.86
Decision Tree	Non-Resilient	0.88	0.85	0.84	0.86
Support Vector Machine	Resilient	0.78	0.81	0.79	0.79
Support Vector Machine	Non-Resilient	0.81	0.79	0.78	0.80

For the Decision Tree, in the resilient class, the precision was 84%, meaning that 84% of samples predicted as "resilient" were indeed resilient. The recall of 88% indicates that 88% of actual resilient samples were correctly identified. The specificity of 85% reflects the model's ability to correctly detect negatives. The F1 score of 0.86 suggests a strong balance between precision and recall. For the non-resilient class, precision was 88%, recall 85%, and the F1 score also 0.86, indicating strong performance in negative predictions as well.

For the SVM, in the resilient class, the precision was 78%, meaning only 78% of samples predicted as "resilient" were correct. The recall of 81% shows the model correctly identified 81% of actual resilient samples. The F1 score was 0.79, reflecting the model's overall performance in this class. In the non-resilient class, the model achieved 81% precision, 79% recall, and an F1 score of 0.80, showing better performance in this class compared to the resilient class, though still lower than the Decision Tree.

The ROC curve shows the performance of a classification model based on the ratio of the false positive rate (FPR) to the true positive rate (TPR = Sensitivity) across all possible thresholds. The closer the area under the curve is to 1, the better the model's discriminative ability.

Figure 3

ROC Curve Area

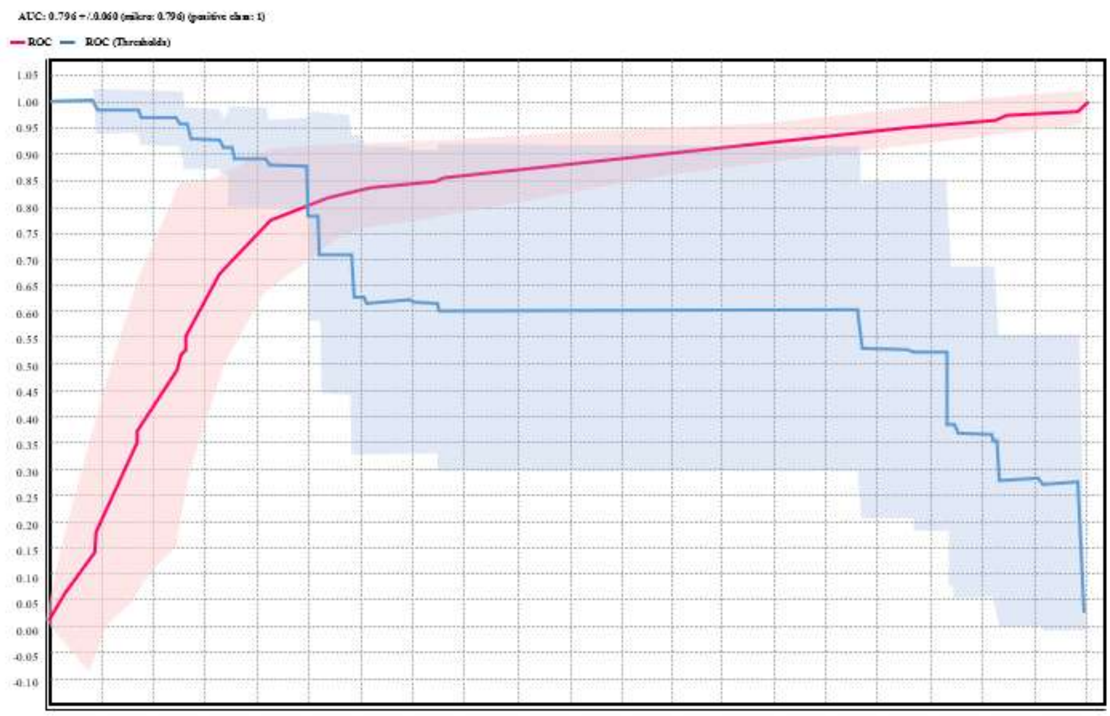


Table 10

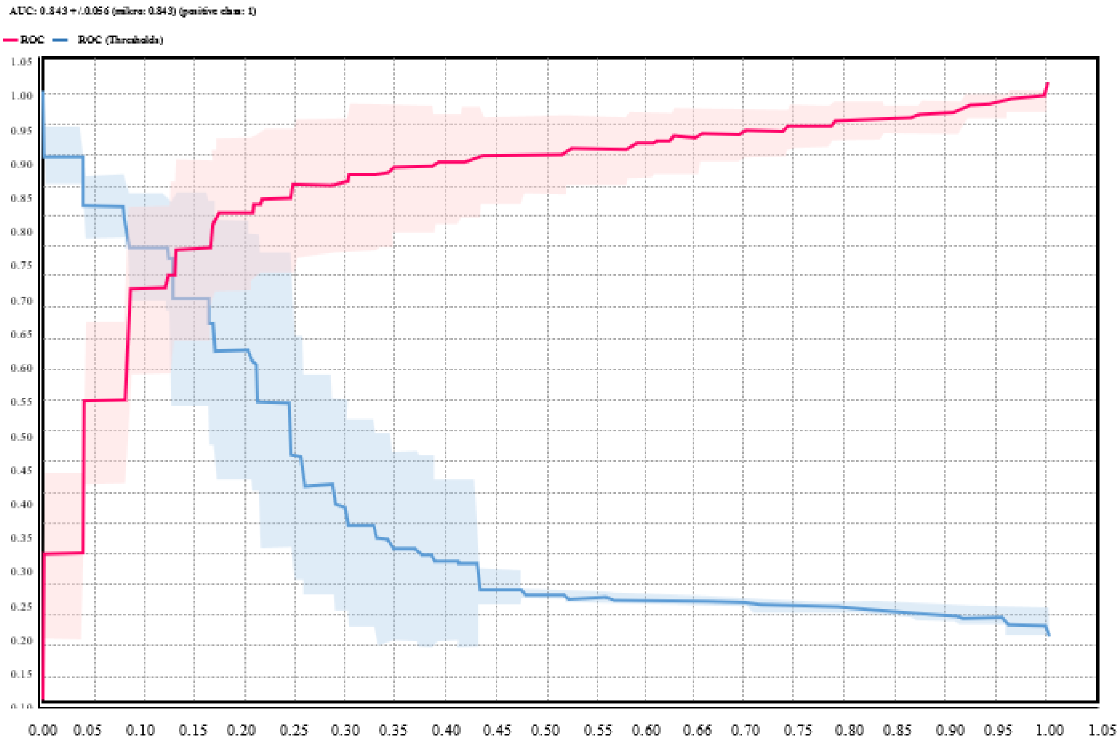
ROC Metrics

Model	AUC-ROC
Decision Tree	0.92
Support Vector Machine	0.86

The Decision Tree, with a higher AUC value (0.92), demonstrates superior performance in class separation and class distinction. The SVM, with an acceptable AUC of 0.86, also performs well but is slightly weaker than the Decision Tree.

Figure 4

Precision–Recall Curve



The Precision–Recall curve illustrates the trade-off between precision (Precision = TP / (TP + FP)) and recall (Recall = TP / (TP + FN)) as the prediction threshold changes. This curve is especially important for imbalanced datasets. The higher and more rightward the curve, the better the model performs.

Table 11

PR Curve Metrics

Model	AUC-PR
Decision Tree	0.88
Support Vector Machine	0.80

The Decision Tree, with a higher AUC-PR of 0.88, performs better in detecting true positive classes and controlling false positives (FP). The SVM, with a value of 0.80, remains acceptable but underperforms compared to its competitor in terms of simultaneously maintaining both precision and recall.

4. Discussion and Conclusion

The findings of this study highlight the comparative performance of two widely utilized artificial intelligence models—Decision Tree and Support Vector Machine (SVM)—in classifying resilience within the automotive supply chain. The empirical results derived from the simulation of 200 records suggest that both models achieved high classification accuracy, but with nuanced differences in performance metrics. The Decision Tree model achieved an overall accuracy of 0.92, a recall of 0.91, and an F1-score of 0.92, slightly outperforming the SVM model, which registered an accuracy of 0.91, recall of 0.90, and F1-score of 0.91. These results point to the Decision Tree's marginal superiority in terms of both classification precision and generalizability.

The advantage of the Decision Tree model can be attributed to its interpretability and ability to offer a transparent mapping of the relationships among variables, which is essential for managerial decision-making in complex operational environments. In the context of supply chain resilience, the clarity with which the Decision Tree delineates the influence of variables such as the number of suppliers, delivery time, inventory levels, and disruption frequency offers actionable insights for practitioners. This aligns with the work of (Esmaeili et al., 2023), who emphasized the utility of interpretable models for supplier classification and risk evaluation. The lower false positive and false negative rates in the Decision Tree (FP = 16; FN = 16) compared to SVM (FP = 18; FN = 18) further reinforce its reliability in distinguishing resilient from non-resilient scenarios.

On the other hand, the SVM model demonstrated robustness, particularly in handling complex and non-linear interactions between input features. While it exhibited slightly lower interpretability, its performance in high-dimensional feature space makes it suitable for large-scale predictive applications. Studies by (Camur et al., 2024) and (Douaioui et al., 2024) have similarly demonstrated that SVM can effectively predict product availability and delivery risks in disrupted supply chains, especially when trained on large, multi-dimensional datasets. This suggests that while SVM may not be optimal for all managerial contexts due to its black-box nature, it remains a valuable tool for high-volume classification tasks.

From a broader perspective, the study's findings align with recent literature that underscores the importance of integrating AI techniques for resilience assessment in automotive and other complex supply chains. For instance, (Belhadi et al., 2024) argue that AI-driven innovation enhances supply chain performance under dynamic conditions by enabling timely and data-informed decisions. Similarly, (Ashraf et al., 2024) demonstrate how hybrid deep learning architectures can detect disruptions early in digital supply chain twins, thereby improving responsiveness and mitigation strategies. The current study reaffirms these conclusions by showing that both AI models, when trained on well-structured data, can serve as effective tools for predicting supply chain resilience.

Moreover, the application of advanced evaluation metrics—such as false positive rate (FPR), false negative rate (FNR), specificity, and area under the ROC and PR curves—offered deeper insight into model reliability. The Decision Tree model achieved a higher AUC-ROC value of 0.92 compared to 0.86 for the SVM, indicating stronger discriminative power in classifying resilient versus non-resilient supply chain scenarios. This finding is consistent with the perspective offered by (Zhao et al., 2023), who showed that digitalized supply chains leveraging AI for risk classification can outperform traditional approaches in both sensitivity and precision. Similarly, the higher AUC-PR value for the Decision Tree model (0.88 vs. 0.80 for SVM) suggests it is better suited for imbalanced datasets, as seen in resilience classification where class imbalance is common.

The study also highlights the importance of backup inventory and response speed as critical predictors of resilience. The boxplot analysis revealed that resilient supply chains tend to maintain higher levels of backup inventory, corroborating the findings of (Kaviani et al., 2020), who emphasized the role of resource buffering in mitigating supply chain vulnerabilities. (Pettit et al., 2019) also support this view, asserting that resilience capabilities must include both proactive and reactive capacities, such as redundancy and swift response mechanisms. These empirical insights suggest that AI models not only assist in classification but also in identifying leverage points for strategic resilience-building.

Furthermore, the comparative analysis illustrates the trade-off between accuracy and interpretability in AI model selection. While SVM offers slightly lower error rates in highly complex datasets, its black-box nature limits its adoption in scenarios requiring model transparency and explainability. (Hosseinnia Shavaki & Ebrahimi Ghahnavieh, 2023) pointed out that the limited interpretability of deep learning and SVM models can restrict their applicability in managerial contexts, which prefer models whose logic can be easily understood and communicated. In contrast, Decision Trees offer a balance between performance and clarity, making them highly suitable for supply chain applications where transparency is critical.

The automotive industry, characterized by tight tolerances, high variability, and global sourcing, particularly benefits from AI-driven resilience modeling. (Kapitonov, 2022) and (Rahimian Asl & Maleki, 2021) emphasize that resilience assessment in this sector must account for component lead times, disruption frequency, and global network complexity. The findings of this study echo these priorities, with variables such as delivery time and supplier count emerging as key indicators within both AI models. The Decision Tree's ability to visualize these relationships offers a strategic advantage, enabling firms to identify and prioritize resilience-enhancing interventions.

It is also important to note the study's reinforcement of the systemic view of supply chain resilience. (Wieland & Durach, 2021) and (Novak et al., 2021) argue that resilience should be evaluated not only at the firm level but across the network, taking into account interdependencies and cascading effects. The present study supports this approach by modeling resilience through interconnected variables that reflect both internal capabilities (inventory and response speed) and external dependencies (supplier diversity and delivery lead time). This systemic modeling perspective is essential for capturing the true dynamics of supply chain disruptions and recovery.

From a methodological standpoint, the structured dataset and consistent simulation framework used in this research ensured the robustness and replicability of model evaluation. This is in line with the recommendations of (Li et al., 2023) and (Rane et al., 2024), who emphasize the value of structured, domain-specific datasets in developing effective AI-driven resilience solutions. Moreover, the study's simulation-based approach mirrors real-world variability in supply chain conditions, providing a realistic testing ground for AI models.

Despite its contributions, this study is not without limitations. First, the dataset used was based on simulated scenarios rather than real-time operational data from automotive manufacturers. While simulation allows for controlled comparisons and broad variability, it may not fully capture the complexities, stochastic behaviors, and unstructured disruptions experienced in actual supply chains. Second, the binary classification of resilience (resilient vs. non-resilient) may oversimplify a phenomenon that exists on a spectrum and includes degrees of recovery capability, agility, and adaptability. Lastly, only two AI models were examined in this study—future investigations could benefit from including additional models such as random forests, gradient boosting, and neural networks to provide a broader benchmark.

Future research should focus on applying the models developed in this study to real-world datasets sourced from automotive companies or industrial consortia. This would enhance the external validity of the findings and provide deeper insights into operational nuances. In addition, exploring hybrid models that combine the interpretability of decision trees with the robustness of ensemble or deep learning methods could yield a more comprehensive understanding of supply chain resilience. Future studies might also consider incorporating temporal variables and longitudinal data to assess how resilience evolves over time, especially in response to ongoing disruptions such as geopolitical events or climate-induced supply shocks.

Practitioners should leverage AI-based classification tools not only for resilience assessment but also as decision-support mechanisms to proactively manage supply chain risks. Organizations are encouraged to adopt decision trees when model interpretability is essential for stakeholder communication and compliance, while SVM can be deployed in data-intensive environments requiring high precision. Additionally, supply chain managers should focus on enhancing key variables identified by the models—such as backup inventory and response speed—as levers for resilience improvement. By integrating AI models into digital dashboards and decision-making workflows, firms can achieve more adaptive, data-driven, and strategically aligned supply chains capable of navigating today's volatile business environment.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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