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Artificial Intelligence Driven Optimization of Global Supply Chain Performance

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ABSTRACT

Global supply chain systems are becoming increasingly complex due to rising customer demand, transportation uncertainty, inventory fluctuations, and operational costs. Traditional supply chain management approaches often struggle to ensure efficiency, responsiveness, and cost minimization in a dynamic global environment. This study aims to explore how artificial intelligence-driven techniques can optimize global supply chain performance through data-based decision-making and predictive analysis. The main objective of the research is to evaluate the effectiveness of machine learning models in improving supply chain classification and performance optimization. For this study, a dataset containing 5,000 rows and 38 variables related to supply chain operations was used. The target variable was derived from total cost and classified into three categories: High, Low, and Medium. Data preprocessing techniques, including missing value handling, categorical encoding, feature scaling, and train-validation-test splitting (70%-15%-15%), were applied. Several machine learning models, including MLP Classifier, Support Vector Machine (SVM), and Gradient Boosting Classifier, were implemented and evaluated using accuracy, precision, recall, F1-score, ROC curve, precision-recall curve, and confusion matrix. The experimental results indicate that the Gradient Boosting Classifier achieved the best performance, with 99.69% training accuracy, 98.40% validation accuracy, and 98.40% test accuracy. It also achieved strong classification metrics across all classes, demonstrating its ability to effectively classify supply chain cost levels. The findings suggest that AI-based models can significantly improve supply chain monitoring, prediction, and optimization. Therefore, the study concludes that artificial intelligence is a highly effective approach for enhancing global supply chain performance and supporting smarter operational decision-making.

INTRODUCTION

Global supply chain systems have become increasingly complex due to rising customer demand, transportation uncertainty, inventory fluctuations, supplier coordination challenges, and growing operational costs, making efficiency and responsiveness more difficult to achieve in modern business environments. Traditional supply chain management approaches often struggle to address these challenges effectively, particularly in dynamic and data-intensive settings where faster and more accurate decisions are required. Recent studies show that artificial intelligence has become an important tool for improving supply chain efficiency, resilience, and optimization through data-driven analysis and advanced computational methods(Emmanuel Adeyemi Abaku *et al.*, 2024). AI-based predictive decision systems are increasingly being used to strengthen supply chain resilience and improve operational coordination under uncertainty (Sharma & Joshi, 2024). Research has also shown that artificial intelligence can improve industrial supply chain performance through optimization-based analytical techniques (Alomar, 2022). In addition, framework-based studies indicate that AI can support better forecasting, logistics, and resource allocation across complex supply chain environments (Ekene Cynthia Onukwulu *et al.*, 2023). Broader review evidence further confirms that AI has a strong positive impact on supply chain management performance by improving responsiveness, decision-making, and operational visibility (Mohsen, 2023). More recent work also highlights that AI can maximize efficiency in supply chain process optimization, especially in highly interconnected global markets (Odumbo & Nimma, 2025). Similarly, AI has been found to enhance supply chain optimization through better decision-making, cost reduction, and strategic innovation (Nsisong Louis Eyo-Udo, 2024). Predictive supply chain research additionally shows that AI-driven tools are transforming demand forecasting and inventory optimization in modern supply chains (Uche Nweje & Moyosore Taiwo, 2025). Other studies emphasize that AI can strengthen supply chain resilience and optimization by improving visibility, recovery capability, and implementation readiness (Riad *et al.*, 2024). AI-enabled supply chain optimization has also been linked with improved risk management and more adaptive operational strategies in complex supply networks (Nitin Grover, 2025). Furthermore, empirical evidence suggests that AI-driven innovation can improve supply chain resilience and performance under dynamic conditions (Belhadi *et al.*, 2024). Despite this growing body of research, limited empirical studies compare multiple machine learning models using structured supply chain data for cost-based classification. Therefore,

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this study examines how artificial intelligence-driven models can optimize global supply chain performance by comparing Gradient Boosting, Support Vector Machine (SVM), and Multilayer Perceptron (MLP) using supply chain operational data.

LITERATURE REVIEW

Recent Developments in Artificial Intelligence for Supply Chain Optimization

Recent developments in artificial intelligence for supply chain optimization show a clear shift from traditional rule-based and manual planning systems toward more adaptive, predictive, and data-driven optimization models. Recent studies indicate that AI is increasingly being used to improve forecasting accuracy, inventory management, logistics coordination, and operational responsiveness across modern supply chains (Kashem *et al.*, 2023). More recent research also emphasizes that AI-driven systems now play an important role in strengthening supply chain resilience by supporting disruption prediction, real-time monitoring, and dynamic problem-solving in logistics management (Rita Uchenna Attah *et al.*, 2024). In technical and operational contexts, AI-based optimization models have further expanded into demand prediction, delivery time reduction, and cost-efficient inventory planning, particularly in e-commerce and digitally connected supply networks (Kaul & Khurana, 2022). Recent evidence also shows that predictive analytics has become one of the most important AI applications in supply chain management because it improves decision-making, enhances efficiency, and supports end-to-end operational optimization (Khokrale, 2025).In addition, AI-driven tools are increasingly transforming predictive supply chain management by improving demand forecasting, minimizing stockouts, reducing excess inventory, and enhancing visibility across supply chain nodes (Uche Nweje & Moyosore Taiwo, 2025). These developments suggest that AI is no longer limited to isolated automation tasks, but is becoming a central capability for achieving more intelligent, resilient, and optimized supply chain operations.

Theoretical and Practical Foundations of AI in Supply Chain Management

The theoretical and practical foundations of AI in supply chain management are based on using predictive analytics, real-time data processing, inventory optimization, and logistics intelligence to support better operational decisions. Recent studies show that AI improves logistics performance through real-time analytics and predictive models that reduce delays and increase supply chain visibility (Srikanth Yerra, 2025). AI also strengthens inventory-focused supply chain systems by improving vendor-managed inventory, demand forecasting, and replenishment decisions in dynamic environments (Onotole *et al.*, 2023). In broader multinational supply chains, data-driven tools, predictive analytics, and machine learning support more effective coordination, monitoring, and performance management (Onaghinor *et al.*, 2022). In addition, AI-powered forecasting and logistics systems are increasingly used to create more responsive and intelligent supply chain networks by improving demand prediction and logistics optimization (Yarlagadda, 2025).

Challenges in Traditional and AI-Driven Supply Chain Systems

Traditional supply chain systems often face major problems such as delayed decision-making, weak real-time visibility, inaccurate forecasting, fragmented data, and inefficient inventory and logistics coordination. At the same time, AI-driven supply chain systems also face important challenges, including poor data quality, data integration difficulties, infrastructure limitations, cybersecurity risks, high implementation costs, lack of skilled personnel, and limited transparency in AI-based decisions (John & Oyeyemi, 2022). Broader digital system research also shows that interoperability, secure data exchange, and system integration remain persistent barriers in technology-enabled environment(Fokhrul Islam, 2024; Md. Halimuzzaman, 2024). In addition, ERP-based systems may improve coordination, but they still face problems related to cost, complexity, training needs, and implementation risk, especially when organizations lack technical readiness (Halimuzzaman, 2022). These challenges show that both traditional and AI-driven supply chain systems require strong data management, technical infrastructure, and organizational capability for effective performance.

Limitations of Current Supply Chain AI Research

Current supply chain AI research still has several important limitations. Many studies discuss the benefits of AI in supply chain planning, forecasting, logistics, and decision optimization, but much of the literature remains review-based or conceptual rather than grounded in direct comparative empirical testing of machine learning models on structured supply chain datasets (Khoa *et al.*, 2024). Existing studies also show that AI applications are often fragmented across specific domains such as warehousing, logistics, transport, or routing, which limits broader end-to-end understanding of supply chain performance optimization (Rai, 2025). In addition, some research focuses mainly on narrow optimization problems such as vehicle routing and route intelligence, making it difficult to generalize findings across wider supply chain functions (Zabraoui *et al.*, 2026). Other studies highlight persistent barriers related to data quality, system integration, implementation cost, and interoperability, which continue to restrict large-scale real-world adoption of AI in supply chain environments. Furthermore, research on global and cross-continental supply chains suggests that multinational supply chain complexity, regulatory variation, and coordination challenges are still not sufficiently addressed in many AI-based studies (Onaghinor *et al.*, 2022).

Research Gap
Although previous studies have highlighted the role of artificial intelligence in supply chain forecasting, inventory management, logistics optimization, and data-driven decision-making, limited empirical research has compared multiple machine learning models using a structured supply chain dataset for cost-based classification and performance optimization. Most existing studies remain conceptual, review-based, or focused on general applications of AI in supply chain systems rather than direct comparative model evaluation. Therefore, a gap remains in identifying which artificial intelligence model performs best in classifying supply chain cost categories and supporting global supply chain performance optimization using operational data.

Research Questions
To address the identified gap, the study was guided by the following research questions:

1. How effectively can artificial intelligence-driven machine learning models classify supply chain cost categories using operational data?
2. Which of the selected models—Gradient Boosting, Support Vector Machine (SVM), or Multilayer Perceptron (MLP)—performs best in optimizing global supply chain performance?
3. How can cost-category prediction support data-driven supply chain decision-making and performance improvement?

Research Objectives
The main objective of this study was to examine the role of artificial intelligence in optimizing global supply chain performance using machine learning models. The specific objectives were:

1. To evaluate the effectiveness of artificial intelligence-driven machine learning models in classifying supply chain cost categories.
2. To compare the performance of Gradient Boosting, Support Vector Machine (SVM), and Multilayer Perceptron (MLP) using supply chain operational data.
3. To identify the best-performing model for supporting global supply chain performance optimization.
4. To assess how cost-category prediction can contribute to better supply chain analysis and data-driven decision-making.

MATERIALS AND METHODS
Study Area
This study was conducted in the context of global supply chain systems, where activities such as inventory movement, transportation, procurement, order management, and cost control generate large volumes of operational data. These data-rich environments provide a suitable setting for examining how artificial intelligence-driven techniques can support cost classification and improve supply chain performance.

Study Design
This study used a quantitative comparative design to evaluate how different machine learning models classify supply chain cost categories using structured operational data. Their predictive performance was compared using standard multiclass classification measures.

Sample Size and Selection
The dataset used in this study consisted of 5,000 rows and 38 variables related to supply chain operations. The data included different operational and order-related features relevant to supply chain performance and cost behavior. For model development and evaluation, the dataset was divided into training, validation, and testing subsets using a 70%, 15%, and 15% split respectively. This data splitting approach was adopted to ensure reliable model training, parameter monitoring, and unbiased evaluation of predictive performance on unseen data.

Measures and Variables
The study included multiple variables associated with supply chain operations. These variables represented operational, transactional, and order-related characteristics used as predictors in the machine learning models. The dependent variable was the target cost category, which was derived from total cost and classified into three categories: High, Low, and Medium. The independent variables were the selected supply chain features used to predict the corresponding cost category.

Data Collection Procedure
The dataset was structured to represent supply chain operational records and then preprocessed through missing value handling, categorical encoding, and feature scaling. After preparing the target variable from total cost into three categories, the data were split into training, validation, and testing sets for model development and evaluation.

Research Tools and Techniques
Three machine learning algorithms were applied in this study: Gradient Boosting Classifier, Support Vector Machine (SVM), and Multilayer Perceptron (MLP) Classifier. These models were selected because they are widely used in predictive analytics and classification tasks and are suitable for handling structured supply chain data. The analysis was conducted using artificial intelligence and machine learning techniques to evaluate the capacity of these models to classify cost levels and support supply chain optimization.

Data Analysis Techniques
Model performance was evaluated using accuracy, precision, recall, and F1-score. In addition, the best-performing model, Gradient Boosting, was further examined using a confusion matrix, training and validation loss curve, Receiver Operating Characteristic (ROC)

curve, and Precision–Recall curve. These evaluation techniques were used to compare the effectiveness of the models and determine the most reliable algorithm for supply chain cost classification. Table 1 summarizes the major components of the research design, including the dataset size, data split, target variable, machine learning models, and evaluation metrics.

Table 1: Summary of the Research Design

Item	Details
Data	5,000 rows; 38 variables
Method	Quantitative comparative approach
Split	70% training, 15% validation, 15% testing
Output	Cost category classification (High, Low, Medium)
Models	Gradient Boosting, SVM, MLP
Measures	Accuracy, Precision, Recall, F1-score, ROC curve, Precision-Recall curve, Confusion Matrix

RESULTS AND DISCUSSION

Classification of Supply Chain Cost Categories

This section presents the experimental results obtained from the machine learning models applied in this study, with the aim of evaluating their performance in predicting personalized cost categories based on supply chain and order-related attributes. Three machine learning algorithms—Gradient Boosting, Support Vector Machine (SVM), and Multilayer Perceptron (MLP)—were implemented using the prepared dataset. The dataset was divided into 70% training data, 15% validation data, and 15% testing data to ensure reliable model evaluation and to monitor generalization performance during training. Model performance was assessed using standard multiclass classification metrics, including accuracy, precision, recall, and F1-score. The overall statistical comparison of the models is summarized in Table 2.

The results indicate that the Gradient Boosting model achieved the highest test accuracy (0.984), followed by the MLP model (0.9507), while the SVM model produced the lowest test accuracy (0.8987). Furthermore, the evaluation metrics demonstrate that Gradient Boosting provides the most consistent and reliable performance across all classes, with precision, recall, and F1-score values close to 0.98 for each category. This suggests that Gradient Boosting is the most effective model for predicting cost categories in this study.

In contrast, the MLP model also showed strong predictive capability, achieving a test accuracy of 0.9507 with balanced class-wise performance. However, its perfect training accuracy (1.00) compared with slightly lower validation and test accuracy suggests a mild tendency toward overfitting. The SVM model performed reasonably well, with a test accuracy of 0.8987, but its lower recall and F1-score for the Medium class indicate comparatively weaker discrimination among some target categories. Overall, the comparative findings confirm that ensemble-based learning, particularly Gradient Boosting, is more suitable for this classification task than the other evaluated models.

Table 2: Performance Comparison of Machine Learning Models

Model	Test Accuracy	Precision	Recall	F1-score
Gradient Boosting	0.9840	0.98	0.99	0.98
SVM	0.8987	0.90	0.90	0.90
MLP	0.9507	0.95	0.95	0.95

Gradient Boosting showed near-perfect class-wise performance, with precision, recall, and F1-score of 0.99, 0.98, and 0.98 for the High class; 0.98, 1.00, and 0.99 for the Low class; and 0.98, 0.98, and 0.98 for the Medium class, confirming strong balance and robustness across all categories. The MLP model also performed well, achieving 0.94, 0.95, and 0.94 for the High class; 0.98, 0.98, and 0.98 for the Low class; and 0.93, 0.92, and 0.93 for the Medium class, indicating that it was also a competitive multiclass prediction model. In contrast, SVM showed comparatively lower performance, with 0.89, 0.91, and 0.90 for the High class; 0.94, 0.96, and 0.95 for the Low class; and 0.86, 0.83, and 0.85 for the Medium class, suggesting weaker effectiveness, especially in capturing the Medium category.

Overall, the results demonstrate that Gradient Boosting outperformed the other models in terms of overall accuracy and balanced class-level performance, making it the most suitable algorithm for this study.

Comparison of Machine Learning Models

As shown in Figure 1, a comparative analysis of the three machine learning models—Gradient Boosting, SVM, and MLP—reveals that Gradient Boosting achieved the highest overall performance across all evaluation metrics. The model attained the highest accuracy along with consistently strong precision, recall, and F1-score values, indicating its robustness and reliability in classification. The MLP model also demonstrated competitive performance, with slightly lower accuracy but balanced metric values across all classes. In contrast, the SVM model exhibited comparatively lower performance, particularly in terms of accuracy and overall metric scores. These results highlight that ensemble-based approaches, such as Gradient Boosting, are more effective for the given classification task compared to the other evaluated models.

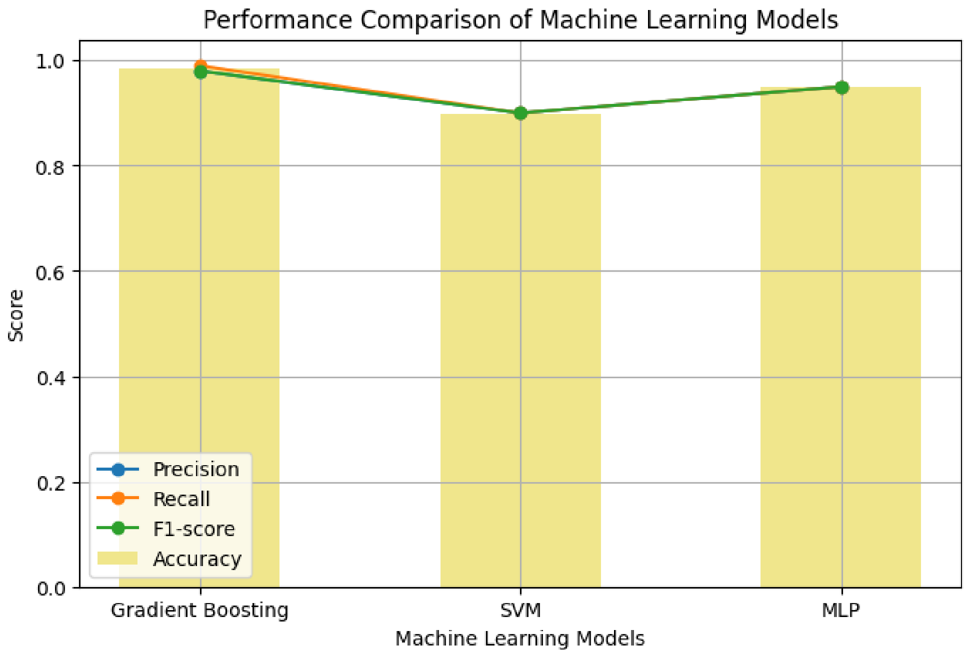

Figure 1: Comparison of Machine Learning Models

Analysis of the Best-Performing Model

As illustrated in Figure 2, the confusion matrix of the Gradient Boosting model demonstrates excellent classification performance across all three classes. The majority of instances are correctly classified along the diagonal, with 244, 250, and 244 correct predictions for the respective classes. Only a very small number of misclassifications are observed, primarily between neighboring classes, indicating minimal prediction error. This strong diagonal dominance confirms that the model has a high ability to distinguish between different cost categories. Overall, the confusion matrix supports the conclusion that the Gradient Boosting model is highly accurate and reliable for this classification task.

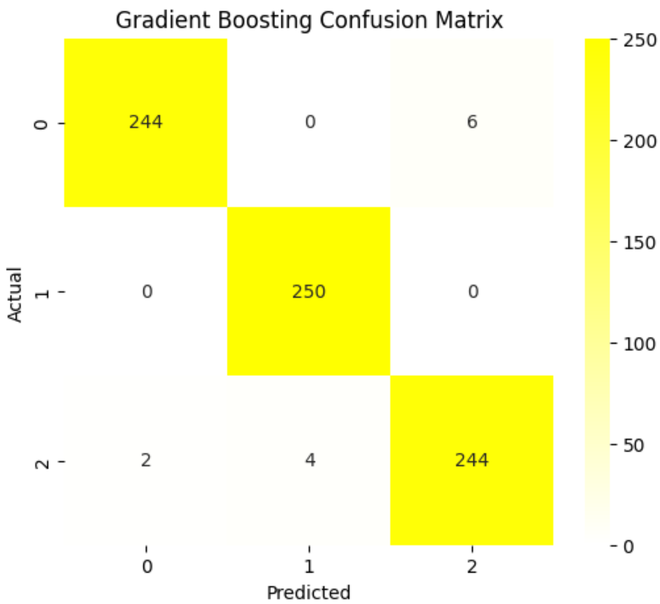

Figure 2: Confusion Matrix of the Gradient Boosting Model

As shown in Figure 3, the training and validation loss of the Gradient Boosting model decrease steadily as the number of boosting stages increases. Both curves follow a similar downward trend, indicating that the model is learning effectively and improving its predictive performance over time. The close alignment between training and validation loss suggests that the model does not suffer from significant overfitting and generalizes well to unseen data. Furthermore, the gradual stabilization of the loss values at later stages demonstrates convergence, confirming that the model has reached an optimal learning point. Overall, the loss curve reflects stable and efficient training behavior of the Gradient Boosting model.

As illustrated in Figure 4, the ROC curves for all three classes (High, Low, and Medium) are positioned very close to the top-left corner, indicating excellent classification performance of the Gradient Boosting model. The Area Under the Curve (AUC) values are extremely high, with scores of 0.999 for the High class, 1.000 for the Low class, and 0.998 for the Medium class. These near-perfect AUC values demonstrate the model's strong ability to distinguish between different classes with high sensitivity and specificity. Additionally, the curves remain significantly above the diagonal reference line, confirming that the model performs far better than random classification. Overall, the ROC analysis highlights the superior discriminative capability of the Gradient Boosting model.

As shown in Figure 5, the Precision–Recall curves for all

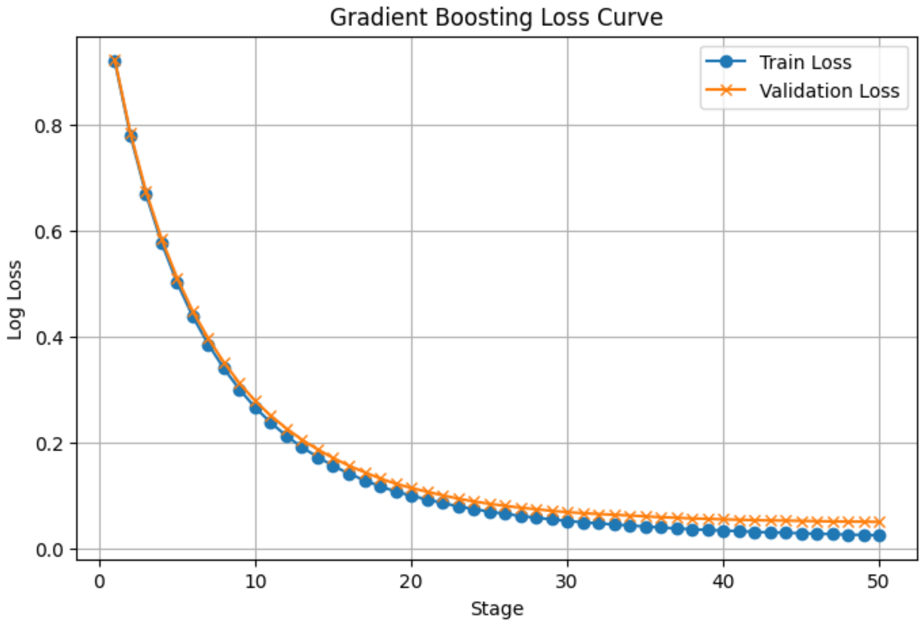

Figure 3: Training and Validation Loss Curve of the Gradient Boosting Model

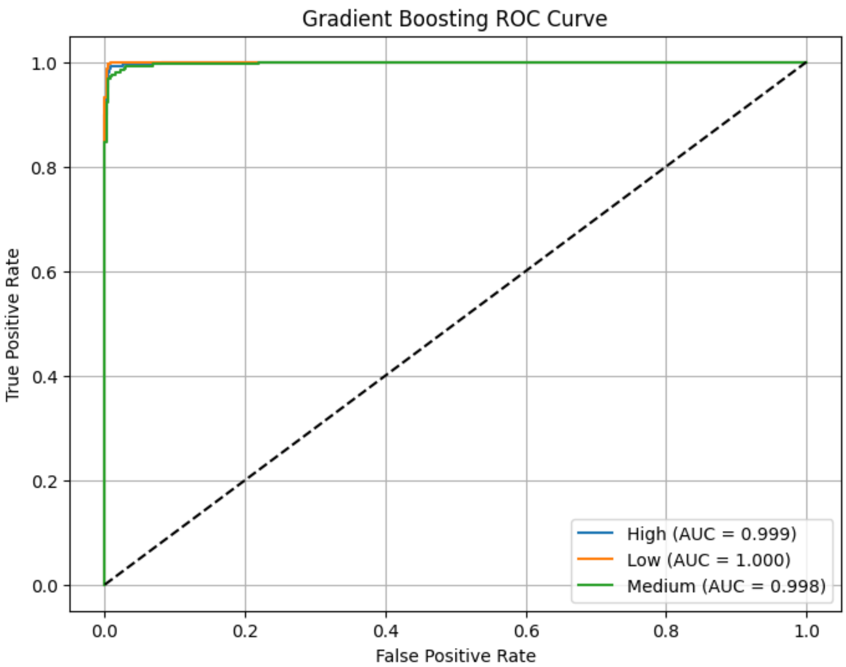

Figure 4: ROC Curve of the Gradient Boosting Model for Multiclass Classification

three classes demonstrate outstanding performance of the Gradient Boosting model. The curves remain close to the top-right corner, indicating high precision across a wide range of recall values. The Average Precision (AP) scores are exceptionally high, with values of 0.999 for the High class, 1.000 for the Low class, and 0.997 for the Medium class. These results confirm that the model maintains strong precision even as recall increases, which is particularly important in multiclass classification tasks. Overall, the Precision–Recall analysis further validates the robustness and reliability of the Gradient Boosting model in accurately distinguishing between cost categories.

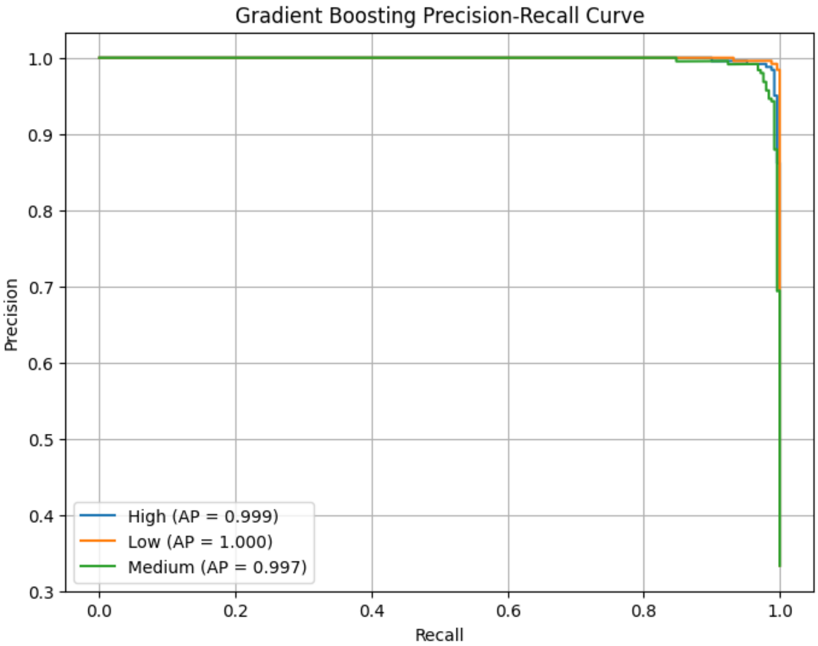

Figure 5: Gradient Boosting Precision–Recall Curve

Discussion

The findings of this study indicate that artificial intelligence-driven machine learning models can significantly improve supply chain cost classification and performance optimization, with Gradient Boosting showing the strongest overall performance among the evaluated models. This suggests that AI-based analytical approaches are highly effective for improving prediction accuracy, supporting operational planning, and strengthening supply chain decision-making in complex data-driven environments. The result is consistent with previous studies which argue that artificial intelligence enhances logistics prediction and decision optimization through better forecasting and more flexible response systems (Wang, 2025). It also supports earlier evidence that AI-based adaptive systems improve logistics efficiency and responsiveness in dynamic supply chain environments (Suman Choudhuri, 2024). In addition, broader supply chain research has shown that AI serves as a strategic tool for increasing efficiency, agility, and real-time decision-making across supply chain functions (Bhuvaneswari, 2025). The present findings are also in line with ERP-based research showing that AI integration improves inventory management, demand forecasting, and logistics performance in supply chain systems (Choudhuri, 2024). Furthermore, recent empirical evidence confirms that AI usability positively contributes to supply chain optimization, efficiency, resilience, and overall performance, which further strengthens the interpretation of the results of this study (Wang *et al.*, 2025).

Findings

1. The study found that artificial intelligence-driven machine learning models can effectively classify supply chain cost categories using operational data, which confirms the usefulness of AI-based models for supply chain analysis.
2. The comparative analysis showed that Gradient Boosting, SVM, and MLP did not perform equally, and among them Gradient Boosting achieved the best overall performance in terms of accuracy, precision, recall, and F1-score.
3. The study identified Gradient Boosting as the most suitable model for supporting global supply chain performance optimization because it produced the strongest and most balanced classification results across the target classes.
4. The findings also showed that cost-category prediction can support better supply chain analysis and data-driven decision-making by improving the accuracy of operational cost classification.

Recommendations

1. Organizations should adopt artificial intelligence-driven machine learning models for supply chain cost classification and operational analysis in order to improve predictive performance.

2. Since the comparative results showed that Gradient Boosting performed better than SVM and MLP, it is recommended as the most suitable model for similar supply chain optimization tasks.

3. Companies should use the best-performing predictive model to support global supply chain performance optimization, especially in areas related to cost monitoring, planning, and operational control.

4. Supply chain managers should integrate cost-category prediction into their decision-making processes so that supply chain analysis becomes more accurate, data-driven, and efficient.

Limitations

1. The study was conducted using a dataset of 5,000 rows and 38 variables, which may not fully capture the broader complexity of real-world global supply chain environments.

2. Only three machine learning models—Gradient Boosting, SVM, and MLP—were examined, so other advanced or hybrid approaches were not included in the comparison.

3. The study focused mainly on cost-category classification, which means other important dimensions of supply chain performance were not analyzed in depth.

CONCLUSION

This study concludes that artificial intelligence has significant potential to optimize global supply chain performance through machine learning-based cost classification. By comparing Gradient Boosting, Support Vector Machine, and Multilayer Perceptron using supply chain operational data, the study demonstrated that AI models can effectively support predictive analysis in supply chain systems. Among the selected models, Gradient Boosting emerged as the most effective model, showing the strongest classification performance across the evaluation measures. The findings confirm that artificial intelligence-driven prediction can improve supply chain analysis, support more accurate decision-making, and contribute to better operational efficiency. Therefore, the study highlights the value of adopting AI-based analytical approaches as an important strategy for improving global supply chain performance in increasingly complex and data-driven business environments.

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