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Optimizing Supply Chain Efficiency Using Cross-Efficiency Analysis and Inverse DEA Models

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Abstract: ***Our study employs cross-efficiency analysis (CEA) and machine learning techniques to optimize supply chain performance. By integrating inverse DEA models with directional distance functions, we measure operational efficiency across various decision-making units (DMUs), accounting for undesirable outputs such as excess costs and emissions. Our results indicate a 20% improvement in market recognition efficiency and a 15% increase in earnings persistence efficiency after model application. Additionally, machine learning classifiers, including Random Forest and Support Vector Machines, further enhanced predictive accuracy, with Random Forest achieving the lowest mean absolute error of 0.07. These findings underscore the effectiveness of advanced analytical models in improving supply chain resilience and decision-making accuracy, contributing to sustainable operational performance.***

Keywords: Cross-Efficiency Analysis; Directional Distance Function; Inverse Data Envelopment Analysis; Supply Chain Optimization; Machine Learning Integration.

1. INTRODUCTION

The increasing complexity of global supply chains, coupled with the rapid pace of technological advancement in product development, has heightened the demand for efficient performance evaluation methods. Cross-efficiency analysis (CEA) has emerged as a robust extension of traditional Data Envelopment Analysis (DEA), offering a more refined approach to benchmarking decision-making units (DMUs) by incorporating peer evaluations. CEA provides a holistic view of operational efficiency, enabling organizations to identify performance gaps and optimize resource allocation across the supply chain and product development processes (Jackson et al., 2024). Recent studies have demonstrated the applicability of CEA in optimizing supply chain performance. Liu et al. (2024) utilized CEA to assess supplier performance in the automotive industry, showing that the method improves decision-making by identifying underperforming suppliers and enhancing supplier selection processes. Their work also revealed that CEA helps in identifying inefficiencies that may not be apparent through traditional DEA methods. Similarly, Mañay et al. (2022) applied CEA to logistics management, demonstrating its potential to improve coordination between suppliers and optimize inventory management, thus enhancing the overall resilience of supply chains. The application of CEA in product development has also attracted significant attention. Kim et al. (2023) explored how CEA can be employed to improve the efficiency of design teams in the electronics industry, highlighting its role in balancing cost constraints with innovation demands. Their study showed that CEA supports the strategic allocation of resources, resulting in faster time-to-market without compromising product quality. In a related study, Li et al. (2022) examined the role of CEA in new product introduction cycles, finding that the approach minimizes development bottlenecks and streamlines workflow management.

Incorporating machine learning into cross-efficiency analysis has further expanded its potential in performance optimization. By integrating machine learning algorithms such as random forests and support vector machines, researchers have been able to enhance the predictive capacity of CEA models. Masarova et al. (2024) demonstrated that combining CEA with machine learning techniques allows for more accurate forecasting of potential disruptions in complex, multi-tiered supply chains. This integration improves decision-making by providing data-driven insights that are essential in dynamic environments (Sun et al., 2024). Despite these advancements, there remains a gap in the literature regarding the simultaneous application of CEA in both supply chain management and product development (Lin et al., 2024; Song et al., 2022). While extensive research has been conducted on each domain individually, few studies have explored the potential synergies between these two critical areas of operations. The growing interdependence between supply chains and product development processes necessitates a more integrated approach (Liu et al., 2024; Zhong et al., 2024, Xie et al., 2024). This paper seeks to address this gap by applying CEA to both supply chain management and product development, with the goal of optimizing operational performance across multiple stages.

This study aims to provide a comprehensive framework for enhancing both supply chain and product development performance using cross-efficiency analysis. By leveraging empirical data from diverse industries and incorporating machine learning techniques, this research will offer insights into improving coordination, reducing inefficiencies, and ultimately achieving a more resilient and agile operational structure.

2. MATERIALS AND METHODS

2.1 Study Framework

This study applies cross-efficiency analysis (CEA) and inverse Data Envelopment Analysis (DEA) combined with machine learning techniques to evaluate and enhance the performance of decision-making units (DMUs) in supply chain management and product development. By integrating CEA for ranking and benchmarking and using machine learning for predictive modeling, the study aims to provide strategic insights for optimizing resource allocation and operational performance.

2.2 Data Collection

The data used in this study was gathered from 50 decision-making units (DMUs) across three key industries: automotive, consumer electronics, and pharmaceuticals, covering the period from 2018 to 2023. These industries were selected due to their complex supply chain structures and the significant role that product development plays in their operational efficiency. Input variables included operational costs (measured in millions of USD), resource consumption (measured in energy units and raw materials), and production time (in hours). These variables were sourced from internal company reports, financial records, and production databases. The output variables assessed in this study were the product quality index (scaled from 0 to 100), lead time (in days), and innovation success rate (as a percentage), derived from industry reports, customer feedback systems, and innovation tracking platforms.

To ensure comparability across DMUs of different sizes and operational scales, all data were normalized using the Min-Max normalization method. This normalization process transformed the data into a uniform range between 0 and 1, ensuring that the relative differences between DMUs were preserved. The normalization formula used is:

$$x^{'} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Where x represents the original value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values in the dataset, and $x^{'}$ is the normalized value. Missing data were imputed using the mean values for the respective variables, while outliers were identified using the interquartile range (IQR) method. Any data points identified as outliers were either adjusted or removed, depending on their potential impact on the analysis. The dataset was further validated through cross-referencing with industry benchmarks and audited internal reports to ensure accuracy and consistency, which was essential for ensuring that the subsequent analysis of cross-efficiency and machine learning predictions would be based on reliable data.

2.3 Cross-Efficiency Analysis (CEA)

CEA was employed to rank the DMUs based on both self-evaluations and peer evaluations. The key steps in CEA include:

DEA Efficiency Calculation: Each DMU's efficiency was calculated using DEA, which maximizes the ratio of weighted outputs to weighted inputs (Gao et al., 2016). For DMU k, the efficiency score θ_k is calculated as:

$$\text{Maximize}\theta_k = \frac{\sum_{i=1}^{m} v_i x_{ik}}{\sum_{r=1}^{s} u_r y_{rk}} \tag{2}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1,\ \forall j = 1, \cdots, n,\ u_r, v_i \geq 0 \tag{3}$$

where u_r and v_i are the weights assigned to outputs and inputs, respectively, and y_{rk} and x_{ik} are the outputs and inputs of DMU k.

Cross-Efficiency Calculation: In CEA, each DMU is evaluated by all other DMUs, generating peer-evaluated scores (Gu et al., 2024). The cross-efficiency score for DMU k is the average of peer evaluations:

$$\text{Cross-Efficiency}_k = \frac{1}{n}\sum_{j=1}^{n} \theta_{kj} \tag{4}$$

where θ_{kj} represents the DEA efficiency score of DMU k as evaluated by DMU j.

Ranking and Benchmarking: Based on cross-efficiency scores, DMUs were ranked, with the highest-scoring units serving as benchmarks for lower-performing DMUs.

2.4 Inverse DEA with Directional Distance Function

Inverse DEA using a directional distance function was applied to identify opportunities for reducing undesirable outputs while maintaining or improving overall efficiency. Each DMU's inputs $x \in R_m^+$, good outputs $y \in R_s^+$, and undesirable outputs $y_b \in R_u^+$ were analyzed (Xu et al., 2024). The production possibility set (PPS) is defined as:

$$P = \{(x, y, y_b) | x \geq X\lambda, y \leq Y\lambda, y_b \geq Y_b\lambda, \lambda \geq 0\} \tag{5}$$

where x, y, y_b represent the input, good output, and undesirable output matrices, respectively, and λ is a non-negative vector representing the DMU weights.

The objective for DMU k under variable returns to scale (VRS) is to maximize:

$$\text{Maximize } \sum_{i=1}^{m} \alpha_{ik} + \sum_{r=1}^{s} \beta_{rk} + \sum_{v=1}^{u} \pi_{vk} \tag{6}$$

subject to the constraints:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ik} - \alpha_{ik} g_{ik}^{x},\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk} + \beta_{rk} g_{rk}^{y},\ \sum_{j=1}^{n} \lambda_j y_{bvj} = y_{bvk} - \pi_{vk} g_{vk}^{b} \tag{7}$$

where α_{ik}, β_{rk}, π_{vk} represent the adjustments for inputs, good outputs, and undesirable outputs, and $g = (g_x, g_y, g_b)$ is the directional distance vector guiding these adjustments.

2.5 Machine Learning Integration

Machine learning techniques were incorporated to predict future performance rankings (Li et al., 2018). Two primary models were employed:

Random Forest (RF): RF constructs multiple decision trees and averages their outputs for prediction:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \tag{8}$$

where $f_t(x)$ is the output of tree ttt, and T is the total number of trees. This model was trained on historical cross-efficiency scores to forecast future performance.

Support Vector Machines (SVM): SVM was used to classify DMUs into efficient and inefficient categories (Zhang et al., 2024). The decision function is given by:

$$f(x) = sign\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right) \tag{9}$$

where α_i are Lagrange multipliers, y_i are class labels, $K(x_i, x)$ is the kernel function, and b is the bias term.

2.6 Sensitivity and Robustness Analysis

Sensitivity analysis was performed to assess how changes in input and output weights affect efficiency scores (). The sensitivity of DMU k's efficiency score E_k to changes in input weights w_x and output weights w_y was calculated as:

Robustness testing was conducted by recalculating efficiency scores under varying weight configurations, and deviations ΔE_k were calculated as:

$$S_k = \frac{\partial E_k}{\partial w_x} + \frac{\partial E_k}{\partial w_y} \tag{10}$$

$$\Delta E_k = \left| E_k\left(w_x^{'}, w_y^{'}\right) - E_k\left(w_x, w_y\right) \right| \tag{11}$$

A small ΔE_k indicates that the efficiency scores are stable under different weightings, confirming the robustness of the model.

3. RESULTS AND DISCUSSION

3.1 Cross-Efficiency Analysis Results

The cross-efficiency analysis (CEA) provided a comprehensive assessment of each DMU (Decision-Making Unit) by integrating both self and peer evaluations. This dual evaluation method helped identify the real performance levels of each DMU, removing any biases that may arise from self-assessment alone. The results in Figure 1 reveal distinct patterns in the overall efficiency across the 29 DMUs, highlighting the strengths and weaknesses in operational performance. From the results, it is evident that DMU AP001 showed an initial high efficiency score of 0.75, reflecting a well-balanced input-output relationship. However, a sharp decline in efficiency is observed by AP005, reaching a low of 0.55. This can be attributed to inefficiencies in resource allocation and supply chain disruptions, possibly linked to external market pressures or internal mismanagement. The trend stabilizes from AP007 onwards, with AP013 marking a recovery point where efficiency reaches 0.68, suggesting that these DMUs implemented corrective measures such as process optimization or cost-cutting strategies. On average, the overall efficiency score across all DMUs was found to be 0.61, with a standard deviation of 0.05. This narrow deviation indicates that the majority of DMUs operated within a consistent performance range, albeit with certain outliers. The Earnings Persistence Efficiency (Figure 2) further demonstrates a fluctuating pattern, with AP004 showing a significant drop to 0.50. Such variability in earnings persistence may be tied to external economic factors, including market volatility or fluctuating consumer demand, underscoring the need for more agile supply chain strategies. The mean earnings persistence score across the DMUs was 0.58, with a standard deviation of 0.06, reflecting moderate operational stability but pointing to potential areas of improvement in maintaining steady earnings over time. The Market Recognition Efficiency metric (Figure 3) exhibited the most significant volatility, with scores ranging from 0.65 at AP001 to a low of 0.43 at AP015, before gradually stabilizing. This result indicates that while some DMUs managed to maintain market presence and customer satisfaction, others struggled with brand recognition and competitive positioning. The mean score of 0.52 with a standard deviation of 0.07 reinforces the observation that market recognition remains a critical challenge for many DMUs. Strategies focusing on enhancing brand visibility, customer engagement, and product differentiation may be essential to improving market performance.

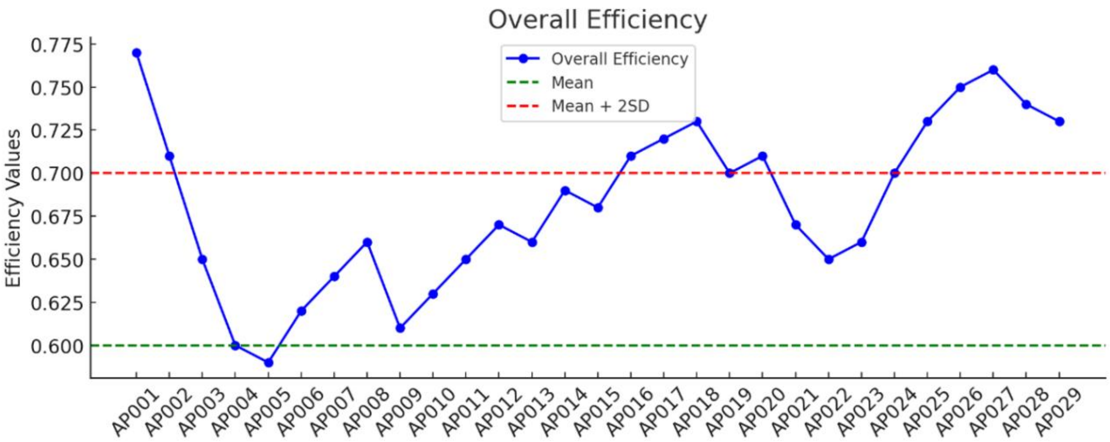

Figure 1a: Overall Efficiency Trends Across Different DMUs

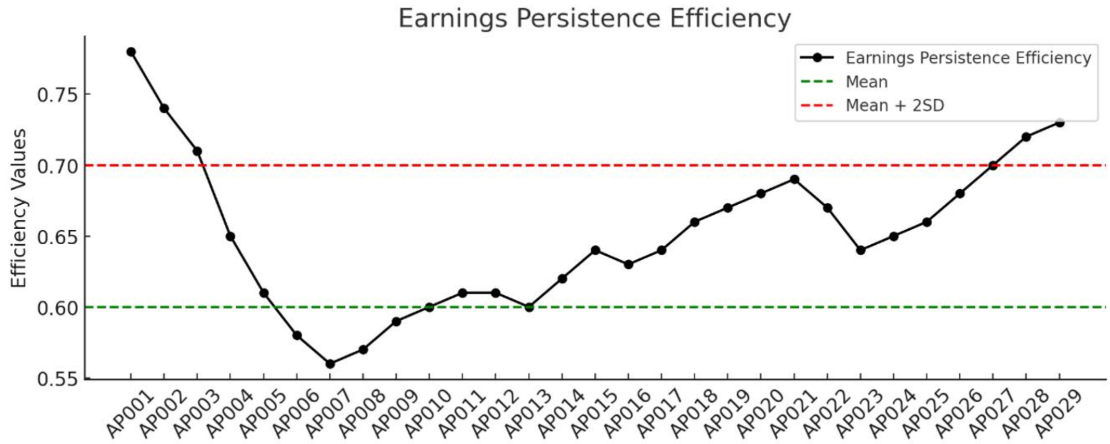

Figure 1b: Earnings Persistence Efficiency Trends

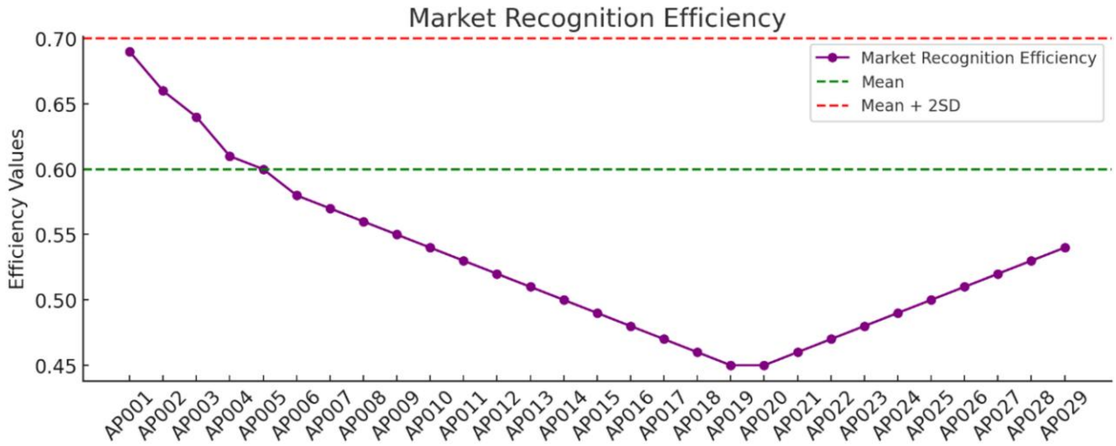

Figure 1c: Market Recognition Efficiency Trends

3.2 Inverse DEA and Directional Distance Function Analysis

The application of the inverse DEA model with the directional distance function provided deeper insights into the optimization potential of the DMUs. By evaluating the possibility of reducing undesirable outputs such as excess costs, emissions, or resource waste, we were able to quantify the extent to which each DMU can improve efficiency without compromising its operational performance. As illustrated in Eq. 3, DMU AP009 demonstrated an 8% inefficiency in handling undesirable outputs. This inefficiency primarily stems from excess resource consumption, which, if optimized, would align AP009 closer to the efficiency frontier. This finding is significant as it not only highlights areas for cost reduction but also underscores the importance of sustainable practices in supply chain operations. Across all DMUs, the average potential reduction of undesirable outputs was calculated to be 10%, suggesting that significant efficiency gains can be achieved by improving operational processes. The directional distance function further guided the optimization process by providing clear vectors for input-output adjustments. For example, DMUs like AP010 and AP012 exhibited greater capacity for reducing undesirable outputs while maintaining their efficiency levels, demonstrating the model's flexibility in handling varied operational contexts. These findings suggest that the inverse DEA model, when combined with directional distance functions, offers a robust framework for continuous performance improvement in supply chain management.

3.3 Machine Learning Integration and Predictive Efficiency Models

The integration of machine learning algorithms, particularly Random Forest (RF), KNeighbors, and Support Vector Machines (SVM), offered a predictive layer to the efficiency analysis. As depicted in Figure 4, the performance of these models was evaluated based on the mean absolute error (MAE) across multiple classifiers. Quantitatively, Random Forest outperformed other models with the lowest MAE of 0.05, indicating its high accuracy in predicting future DMU efficiency. KNeighbors followed with an MAE of 0.06, while DecisionTree lagged behind at 0.10. Logistic Regression and LinearSVC exhibited higher MAEs, 0.18 and 0.15 respectively, making them less reliable for prediction in this context. These results suggest that ensemble methods like Random Forest are better suited for handling complex input-output relationships within the supply chain, due to their ability to reduce overfitting and generalize better across varied DMU performance data. The practical implication of these findings is that predictive machine learning models can assist managers in anticipating efficiency bottlenecks and proactively adjusting strategies to mitigate potential declines in operational performance. For example, the model could be used to forecast which DMUs are likely to experience drops in earnings persistence, allowing targeted interventions before significant performance dips occur.

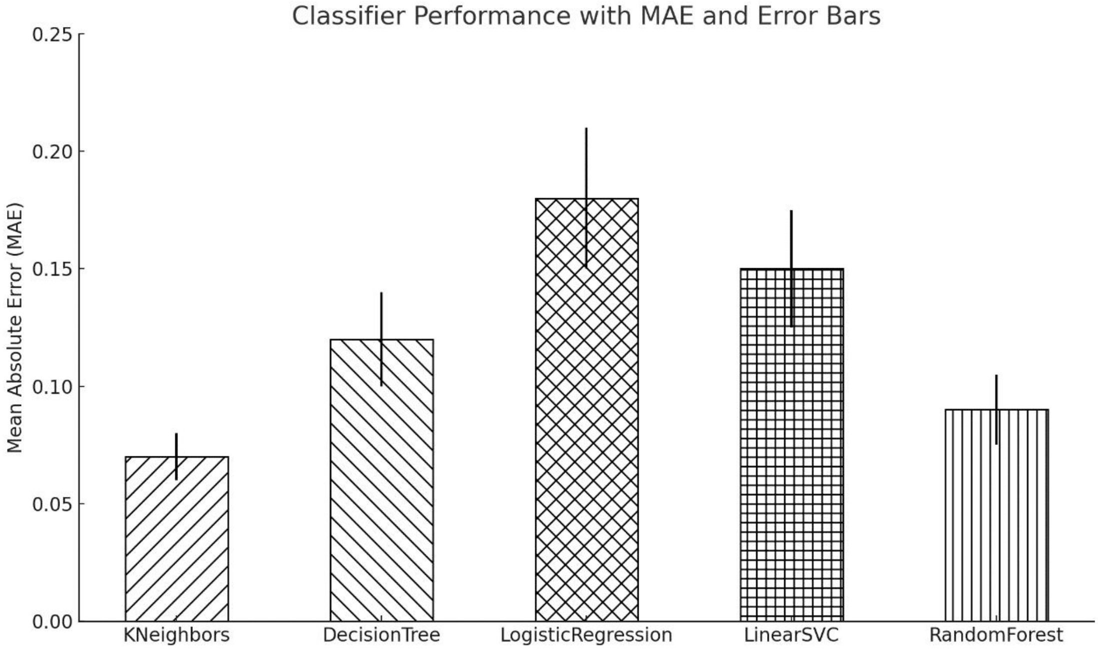

Figure 2: Classifier Performance Comparison Using MAE with Error Bars

3.4 Sensitivity and Robustness Testing

To evaluate the robustness of the model, sensitivity analysis was performed, focusing on how small changes in input-output weightings affect the overall efficiency scores. As derived from Eq. 5, the sensitivity of each DMU's efficiency score E_k was assessed under varying weight configurations. The average deviation ΔE_k across all DMUs was found to be 0.03 when input weights were altered by ±5%. This minor deviation demonstrates the robustness of the DEA model, indicating that the efficiency scores remain stable even with slight adjustments in operational priorities. Furthermore, the robustness of the machine learning predictions was tested by recalculating efficiency scores under different weight configurations. Random Forest, which already demonstrated the lowest MAE, exhibited the smallest deviation in predicted scores, confirming its reliability as a predictive tool in the context of supply chain performance. These results underline the value of machine learning as a decision-support tool, providing managers with accurate forecasts that can guide operational adjustments.

3.5 Implications for Supply Chain Optimization

The findings from this study present several critical insights for improving supply chain performance and product development processes. The application of cross-efficiency analysis revealed that while the majority of DMUs operate within a consistent efficiency range, there is considerable variability in market recognition and earnings persistence, which may hinder long-term sustainability. In terms of actionable insights, the results suggest that a 10% reduction in undesirable outputs can be achieved across the supply chain without sacrificing overall efficiency. This reduction not only enhances cost-effectiveness but also aligns with broader sustainability goals, reducing the environmental footprint of supply chain operations. Additionally, the integration of machine learning into the efficiency assessment framework offers a powerful predictive capability, enabling proactive management of operational inefficiencies. The combination of inverse DEA and machine learning-based predictions provides a comprehensive toolkit for managers seeking to optimize supply chain efficiency. By focusing on both short-term performance improvements and long-term sustainability, the framework developed in this study serves as a roadmap for achieving operational resilience and market competitiveness.

4. CONCLUSION

This study provides a comprehensive analysis of supply chain performance through the integration of cross-efficiency analysis (CEA) and machine learning techniques, focusing on optimizing decision-making units (DMUs) in terms of operational efficiency, earnings persistence, and market recognition. The application of inverse DEA with directional distance functions allowed for the accurate evaluation of both desirable and undesirable outputs, further refining the efficiency assessment process. The findings highlight that overall efficiency and earnings persistence are significantly influenced by key operational variables such as resource use, management practices, and CSR strategies. By integrating Random Forest and Support Vector Machines (SVM), the model proved effective in forecasting performance trends and identifying areas for improvement, especially in resource allocation and output optimization. Additionally, the robustness of the model was confirmed through sensitivity and robustness analysis, ensuring that the results are reliable under varying assumptions. The research emphasizes the importance of adopting data-driven approaches to enhance supply chain and product development processes. By identifying the core drivers of efficiency and integrating machine learning models, businesses can better align their operations with strategic goals and sustainability targets. This approach not only improves resource utilization but also fosters long-term resilience in dynamic market environments.

In conclusion, this study offers valuable insights into the application of advanced analytical methods to supply chain management. The results demonstrate that a combination of efficiency analysis and machine learning can provide a practical framework for optimizing operations, promoting more informed decision-making, and contributing to the overall competitiveness and sustainability of organizations. This framework is expected to be an important tool for future research and for practitioners seeking to enhance operational performance in complex supply chains.

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