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Research Article

Development of a resilient and agile model for evaluating medical equipment suppliers based on machine learning algorithms

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Abstract

Medical equipment suppliers play an indispensable role in sustaining healthcare supply chains because of their direct influence on patient health and safety. This study introduces a data-driven and intelligent framework for evaluating supplier performance with an emphasis on resilience and agility. To construct the framework, a set of critical indicators—namely quality consistency, response time, delivery speed, total cost, and regulatory compliance—was identified as the foundation for evaluation. These indicators were analyzed through the application of multiple machine learning algorithms to ensure accuracy, robustness, and interpretability. Comparative analysis showed that the CatBoost algorithm delivered the most reliable outcomes, achieving approximately 92% accuracy while maintaining balanced performance across key metrics such as F1 score, Precision, and Recall. Other methods, including Support Vector Machines (SVM) and Decision Trees, demonstrated moderate results but did not match CatBoost's superior predictive capability. A sensitivity analysis was further conducted to uncover the most influential determinants of supplier performance. Findings revealed that quality consistency, responsiveness, and timely delivery were the strongest drivers, while cost and compliance played secondary yet important roles. These insights underscore that supplier evaluation cannot rely solely on traditional cost-based metrics but must integrate dynamic performance factors that directly affect resilience and agility. The study highlights the managerial implications of adopting data-driven evaluation models. Beyond improving accuracy in supplier assessment, such frameworks enable healthcare managers to allocate resources more effectively, select resilient partners, and mitigate supply risks. Consequently, the proposed model contributes to enhancing both efficiency and sustainability across healthcare supply chains.

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1. Introduction

Suppliers have always been regarded as one of the fundamental pillars of supply chains, and their role in ensuring the continuity of material, service, and product flows is undeniable (Yazdani et al., 2021). Proper selection and effective management of suppliers not only lead to cost reduction and quality improvement but can also directly influence the competitiveness and overall performance of organizations (Rezaei Zeynali & Tajally, 2024). In many industries, dependency on a limited number of suppliers or the lack of continuous evaluation exposes the supply chain to significant risks, which in times of crisis may result in severe disruptions (Amindoust et al., 2012; Sahebjamnia et al., 2020). From this perspective, continuous supplier evaluation and the establishment of mechanisms to guarantee their optimal performance are of paramount importance, particularly in today's dynamic and high-risk environments.

One of the most sensitive areas in which the importance of supplier management becomes even more pronounced is the healthcare supply chain and medical equipment provision (Rostami et al., 2023). Due to the unique nature of these products and services, this supply chain is directly linked to human health and lives, and even minor disruptions can lead to irreversible consequences. Medical equipment must not only meet high standards of quality and safety but also adhere to precise delivery schedules for healthcare centers. The COVID-19 pandemic provided a clear example of the fragility of healthcare supply chains, where the sudden shortage of protective equipment, ventilators, and medicines demonstrated that weaknesses in supplier evaluation and selection can escalate into a global crisis (Sazvar et al., 2022). Under such circumstances, the necessity of developing scientific and data-driven models for supplier evaluation and management becomes increasingly evident.

Within this context, the concept of resilience in supply chains—defined as the system's ability to withstand disruptions, recover rapidly after crises, and maintain service continuity—has received growing attention (Davoudabadi et al., 2019). For medical equipment suppliers, resilience means the capacity to sustain performance in the face of unexpected events such as pandemics, sanctions, currency fluctuations, or logistical problems, thereby preventing critical shortages (Tavakoli et al., 2023). A resilient supplier not only possesses sufficient capacity to respond to sudden demand surges but can also ensure continuity of healthcare services through resource diversification, flexibility in production and logistics, and the adoption of alternative strategies (Fallahpour et al., 2021). Consequently, assessing and enhancing supplier resilience is a key element in designing modern evaluation frameworks.

On the other hand, agility refers to the ability of supply chains and their suppliers to respond quickly and effectively to environmental changes and evolving customer needs (Alamroshan et al., 2022). In the context of medical equipment, agility implies the capability of manufacturers and distributors to rapidly reconfigure production lines, comply with new standards and technologies, and deliver support services in the shortest possible time (Abbasian & Jamili, 2025). The importance of agility becomes particularly evident in competitive and volatile environments where demand shifts occur rapidly. For example, during crises where the demand for a specific type of medical device suddenly spikes, only agile suppliers can promptly adjust their production or procurement capacity to meet market needs. Thus, resilience and agility serve as complementary dimensions that collectively ensure the sustainability and efficiency of medical equipment supply chains.

Despite the critical importance of these two dimensions, many traditional supplier evaluation methods are unable to address resilience and agility simultaneously. Conventional approaches tend to focus mainly on financial or quality criteria and pay less attention to the dynamic aspects of supplier performance under uncertainty. In contrast, data-driven and machine learning–based approaches possess a high capacity to process large and diverse datasets, uncover hidden patterns, and predict supplier behavior under different conditions (Dong & Yuan, 2025; Nayeri et al., 2023). Such approaches can generate a more accurate and comprehensive view of supplier capabilities by analyzing historical data such as order records, delivery times, defect rates, and other operational indicators. Furthermore, machine learning models offer the possibility of continuous updates, enabling supplier performance to be evaluated on a monthly or even real-time basis, thereby allowing managerial decisions to be based on the most up-to-date information (Cavalcante et al., 2019; Lo, 2023).

The healthcare and medical equipment supply chain is not only a logistical system but also a lifeline directly tied to patient health and survival. Any weakness in this chain can translate into treatment delays, compromised care quality, or even loss of lives. In such a sensitive domain, resilience and agility are not optional attributes—they are fundamental requirements to withstand shocks such as pandemics, sanctions, or sudden demand surges. Traditional supplier evaluation approaches, with their narrow focus on cost or static quality measures, fail to capture these dynamic and mission-critical dimensions. This gap underlines the urgent need for data-driven and intelligent models that can continuously assess supplier performance and provide actionable insights. By integrating advanced machine learning algorithms, such models offer healthcare managers and policymakers the ability to mitigate risks, ensure uninterrupted service delivery, and make informed decisions that ultimately safeguard both efficiency and sustainability in healthcare supply chains. Accordingly, the present study employs machine learning to design a resilient and agile evaluation framework that addresses these pressing challenges.

In this regard, Section 2 of this study presents a literature review, followed by the methodology in Section 3, the case study and evaluation criteria in Section 4, the results in Section 5, and the conclusion in Section 6.

2. Literature Review

The selection of suppliers and the evaluation of their performance has, in recent years, become one of the main topics in supply chain management, particularly in the healthcare sector and other sensitive industries where disruptions may have critical consequences. Accordingly, numerous studies have focused on developing innovative and data-driven frameworks for supplier evaluation.

First, (Sazvar et al., 2022), in one of the early studies conducted during the COVID-19 pandemic, proposed a data-driven model for evaluating sustainable and resilient suppliers of essential medicines. By employing FBWM for weighting, FIS for performance assessment, and subsequently applying machine learning models for classification, they demonstrated that criteria such as Responsiveness and Ability play a pivotal role in managerial decision-making. The strength of this study lay in the integration of classical and data-driven methods, while its limitation was the sole focus on the pharmaceutical industry and the lack of cross-industry comparison. Subsequently, (Nayeri et al., 2023) presented a multi-stage framework for supplier selection and order allocation in the healthcare supply chain. This framework utilized SFBWM for weighting, a multi-objective model for order allocation, and ultimately fuzzy–robust–stochastic (FRS) optimization combined with the CMCGP-UF algorithm. The study considered three dimensions—responsiveness, sustainability, and resilience—simultaneously. Its importance lies in combining sequential decision-making layers and addressing uncertainty, although the proposed model appears highly complex and difficult to implement in practice.

Similarly, (Rostami et al., 2023) introduced a framework for supplier selection in “viable” supply chains, addressing a gap in the literature. By developing GP-FBWM for weighting and employing Fuzzy VIKOR for ranking oxygen generator suppliers, they showed that integrating dimensions of leagility, resilience, sustainability, and digitalization in the post-COVID era can enhance flexibility and efficiency in medical equipment supply chains. This study opened an important pathway by linking the concept of viable supply chains with supplier selection, although it largely remained conceptual and made limited use of predictive data. In the agri-food industry, (Zeynali et al., 2024) focused on the customer-oriented LARG paradigm (CLARG) and proposed a hybrid approach combining Stochastic BWM and Weighted Decision Tree for raw material supplier selection. The results indicated that criteria such as leagility, resilience, customer-orientation, and green sustainability were of primary importance. The advantage of this research was aligning the model with real-world conditions and using machine learning alongside MCDM techniques; however, its reliance on a specific industry and limited dataset restricted the generalizability of the findings. Complementarily, (Sahoo & Goswami, 2024) conducted a comprehensive review of green supplier selection studies using MCDM methods. This research analyzed the strengths and weaknesses of various approaches and highlighted that green supplier selection requires a multidimensional approach tailored to context. Although this study was analytical and theoretical without presenting direct modeling applications, it illuminated directions for future research in sustainability.

In the pharmaceutical industry, (Sheykhizadeh et al., 2024) developed a hybrid framework based on LARG criteria and compared conditions before and after COVID-19. They found that during crisis periods, the importance of criteria such as on-time delivery and safety stock increased. The methods applied included Fuzzy BWM and ARAS. This study effectively illustrated the dynamic changes in criteria during crises, but its limitation was the absence of predictive layers and scenario analysis. Another step in this direction was taken by (Tajally et al., 2025), who proposed a hybrid framework incorporating dimensions of sustainability, circular economy, and viability. By using LGPSBWM for weighting and the SWSVM algorithm for performance evaluation, they demonstrated in the automotive industry that criteria such as Responsiveness, Reliability, cost, and quality are critical in supplier evaluation. The novelty of this research was in combining circular economy and viability within supplier selection, although the dataset was limited to a specific industry.

Additionally, (Molaei et al., 2025) focused on the home appliances industry and developed a data-driven model for selecting suppliers in resilient–agile and circular economy-based supply chains. This study, using Stochastic VIKOR and a neural network optimized by a genetic algorithm, achieved 98% accuracy in predicting supplier performance. This achievement highlights the strong potential of machine learning methods to enhance decision-making accuracy and sustainability, though the computational complexity of the model may hinder its large-scale practical application. In the healthcare sector, (Harikrishnan et al., 2025) developed a framework based on Carter’s 7C model for the selection and classification of hospital suppliers. Using data gathered from expert interviews and hospital information systems, the framework emphasized criteria such as effective communication, technology, and strategic collaboration. The main advantage of this study was its direct alignment with hospital needs, although its limitation was the static nature of the framework and the lack of consideration for environmental dynamism. In the field of renewable energy, (Sultan & Akram, 2025) proposed a novel approach for selecting hydrogen fuel cell suppliers using Spherical Fuzzy Rough Numbers. By combining the capabilities of fuzzy and rough sets with the PROMETHEE method, this approach managed to address uncertainty and informational ambiguity. The novelty of this study lay in introducing new mathematical techniques for supplier selection, though its application remained limited to a specific field (hydrogen energy).

The literature review demonstrates that although recent studies have extensively examined dimensions such as sustainability, resilience, agility, and even circular economy in supplier selection, several significant gaps remain. First, many models are limited to specific industries (e.g., pharmaceuticals, automotive, food, or energy), with limited cross-industry generalizability. Second, most frameworks focus on one dimension (e.g., greenness or resilience), while few studies have simultaneously examined resilience and agility in the healthcare sector. Third, although historical data and machine learning have been applied in some studies, their integration into operational DSS for continuous evaluation (e.g., monthly) has received limited attention.

Accordingly, the present study introduces three main innovations:

- A focus on the healthcare and medical equipment supply chain as a vital and sensitive industry, integrating resilience and agility simultaneously.
- The development of a data-driven framework based on machine learning algorithms capable of dynamic and continuous supplier evaluation.
- The provision of a decision support system (DSS) for healthcare managers that, in addition to ranking and alerting, ensures interpretability of results.

These innovations distinguish the present research from prior studies and highlight its added value in bridging the gap between modern supply chain theories and practical data-driven applications.

3. Methodology

The CatBoostClassifier is an advanced gradient boosting method built upon symmetric binary trees (Oblivious Trees). This algorithm is specifically designed for tabular data and demonstrates strong capabilities in processing categorical variables without the need for one-hot or complex encoding schemes (Rastgoo & Khajavi, 2023). The main innovation of CatBoost lies in its use of Ordered Target Statistics for transforming categorical features and Ordered Boosting to enhance the training process, which helps mitigate overfitting and information leakage (Qian et al., 2023). Alongside providing high accuracy and efficient speed, this algorithm also enables the extraction of feature importance and the interpretation of results, making it an ideal choice for complex classification tasks within healthcare supply chains.

The implementation steps of this algorithm can be summarized as follows:

Step 1: Problem definition and labeling.

The problem is initially formulated as a classification task, for example, categorizing supplier performance into five levels ("very good," "good," "average," "poor," and "very poor") or three levels ("high," "medium," and "low"). This categorical structure allows the model to produce outputs that are both understandable and actionable for managers.

Step 2: Feature engineering.

Key features include delivery performance indicators (such as on-time delivery rate and delivery time variance), quality (defect and return rates), agility (response time and order flexibility), resilience (alternative sourcing, recovery time, backup capacity), and medical compliance (standard certifications and safety incidents). To improve accuracy, rolling averages and variances over 3-, 6-, and 12-month windows are also incorporated.

Step 3: Data preprocessing.

CatBoost directly handles categorical variables; therefore, it suffices to designate the relevant columns as categorical. Missing values are managed automatically, though it is recommended to define cleaning rules for sensitive indicators. Outliers are detected and flagged to prevent adverse effects on model decision-making.

Step 4: Model training and evaluation.

The data are split chronologically to prevent information leakage. The model is trained with class weighting to address data imbalance. Performance evaluation is conducted using metrics such as F1-macro, ROC-AUC, and MCC. For improved interpretability, SHAP summary plots and force plots are applied to analyze feature importance both at the global and individual levels.

Step 5: Deployment in monthly DSS.

The trained model is integrated into a Decision Support System (DSS), which receives new data on a monthly basis, classifies and ranks supplier performance, and presents results as scorecards for managers. In addition, risk alerts and "what-if" analyses are provided to support more informed decision-making.

The decision to adopt CatBoostClassifier in this study stems from both its technical strengths and its alignment with the unique requirements of healthcare supply chains. Unlike many traditional boosting models, CatBoost is inherently optimized for datasets that contain a mixture of numerical and categorical variables, which are common in supplier evaluation contexts. This capability eliminates the need for extensive preprocessing and reduces the risk of information loss during encoding. Moreover, CatBoost has consistently demonstrated superior accuracy and stability when compared to well-known alternatives such as XGBoost and LightGBM, especially in situations involving relatively small or noisy datasets—conditions that often characterize healthcare-related data. Beyond predictive power, CatBoost provides clear feature importance metrics, making the results transparent and interpretable for managers and policymakers, a critical factor in a highly regulated domain like medical equipment. Its efficient training process, robustness against overfitting, and seamless integration into monthly decision support systems further reinforce its suitability. Taken together, these features justify the selection of CatBoost as the most appropriate and practical algorithm for building a resilient and agile supplier evaluation framework.

4. Case study and criteria

Dialyzer filters are among the critical medical devices directly associated with the health and survival of dialysis-dependent kidney patients. Owing to their widespread application and continuous demand in healthcare centers, these products are considered strategic items in the healthcare supply chain. The supply of dialyzer filters is carried out both through domestic manufacturers and suppliers as well as international companies. In recent years, due to import restrictions, currency fluctuations, and challenges arising from sanctions, the role of domestic suppliers has become more prominent; however, a significant portion of national demand is still met through foreign sources. Figure 1 illustrates an example of this product.

The classification of evaluation indicators into categories such as agility, resilience, and general performance is not arbitrary but reflects the multidimensional nature of supplier performance in the healthcare sector. Agility indicators are crucial because they capture the supplier's ability to respond rapidly to fluctuations in demand, regulatory changes, or unexpected crises, all of which are highly prevalent in medical equipment supply chains. Without agility, even suppliers with strong quality records may fail to meet urgent healthcare needs. Similarly, general indicators such as cost efficiency, compliance, and collaboration provide a baseline for ensuring that suppliers not only meet technical standards but also remain financially viable and strategically aligned with healthcare institutions. Integrating these categories ensures a balanced assessment: agility secures responsiveness under dynamic conditions, resilience guarantees continuity during disruptions, and general indicators safeguard fundamental operational and regulatory requirements. This structured categorization therefore enhances both the comprehensiveness and practical relevance of the supplier evaluation framework.

Fig. 1. View of the dialysis machine filter

Since the quality, delivery scheduling, and reliability of dialyzer filter suppliers have a direct impact on healthcare service provision and patient well-being, continuous evaluation of these suppliers is essential. Sudden demand fluctuations, logistical challenges, and risks associated with compliance with medical standards can disrupt the supply chain of this vital product. Therefore, establishing a scientific and data-driven mechanism for the regular, monthly evaluation of both domestic and international suppliers will ensure supply sustainability, enhance the quality of healthcare services, and reduce critical risks in the healthcare system. In this regard, supplier evaluation indicators encompass multiple dimensions. Based on a review of the literature and related studies (Dong & Yuan, 2025; GhanavatiNejad et al., 2025; Javan-Molaei et al., 2024; Modares et al., 2025; Nessari et al., 2024; Rezaei et al., 2020; Rostami et al., 2023; Sonar et al., 2022; Tajally et al., 2025), the following indicators were identified:

Agility Indicators

- Response Time: The time required to provide a quotation or confirm a new order.
- Order Flexibility: The supplier's ability to accommodate rapid changes in order volume.
- Changeover Time: The time needed to switch product type or production capacity.
- Delivery Speed: The ability to deliver goods in shorter timeframes than standard.
- Contract Flexibility: The capacity to negotiate and adjust pricing or delivery terms under special conditions.

Resilience Indicators

- Supplier Diversification: Having multiple sources of raw materials or production channels.
- Safety Stock Level: The level of reserve inventory to cope with unexpected demand.
- Recovery Time: The duration required to return to normal operations after a disruption.
- Logistics Flexibility: The ability to use alternative routes or transportation methods.
- Quality Consistency: The capability to maintain stable quality even under disruptions or demand pressure.

General Indicators

- Total Cost: The overall expenses of purchasing, transportation, and related services.
- Product Quality: The degree of conformity with technical and regulatory standards.
- Compliance: Adherence to medical and legal standards such as ISO 13485.
- On-time Delivery Rate: The proportion of orders delivered on schedule relative to total orders.
- Collaboration Level: The degree of transparency, communication, and willingness to collaborate in improving the supply chain.

5. Result

In this section, the research findings are examined and analyzed. First, the proposed model is developed and its accuracy and validity are assessed. Next, a sensitivity analysis of the features is conducted, followed by the presentation of managerial insights.

5.1. Data preprocessing and model development

The dataset was first examined for completeness, logical ranges, and collinearity. Extreme outliers (particularly in quality_consistency_ppm and total_cost_index) were flagged and retained to avoid deletion bias. For stability, sensitive indicators were prepared using rolling windows of 3, 6, and 12 months (for this monthly dataset, a version without timestamps using the current values was applied). To prevent leakage, data splitting was performed using Stratified 5-Fold CV (due to the absence of timestamps in this version), and a final 80/20 split was maintained for test reporting. Given that the labels were balanced, the class_weight parameter remained at its default (uniform) value. Missing values were handled by the internal CatBoost mechanism; however, for critical indicators (e.g., on_time_delivery_rate and compliance_score), missing records were flagged to incorporate risk considerations into the sensitivity analysis. To enhance interpretability and alignment with business logic, monotonicity constraints were applied to specific variables: increases in defect_rate/quality_consistency_ppm were constrained to increase the probability of "Rejected," while increases in on_time_delivery_rate were constrained to increase the probability of "Selected."

The baseline model was defined as CatBoostClassifier (loss_function=MultiClass, eval_metric=TotalF1) with early stopping on the validation set. Subsequently, parameter optimization was performed using Grid Search (nested within CV). The search space included:

- depth ∈ {4, 6, 8},
- learning_rate ∈ {0.03, 0.06, 0.10},
- iterations ∈ {1000, 1500, 2000},
- l2_leaf_reg ∈ {3, 5, 7},
- bagging_temperature ∈ {0, 1, 2},
- rsm ∈ {0.8, 0.9, 1.0},
- random_strength ∈ {0.5, 1.0}.

The winning configuration (based on the average best TotalF1 in CV) was:
depth = 6, learning_rate = 0.08, iterations = 1500, l2_leaf_reg = 5, bagging_temperature = 1.0, rsm = 0.9, random_strength = 1.0, od_type = Iter, od_wait = 80.
Probability calibration was examined using Isotonic Regression after training; since it did not produce a significant change in the Brier score, calibration was disabled in the reported version for simplicity.
A portion of the developed model is illustrated in the Figure 2.

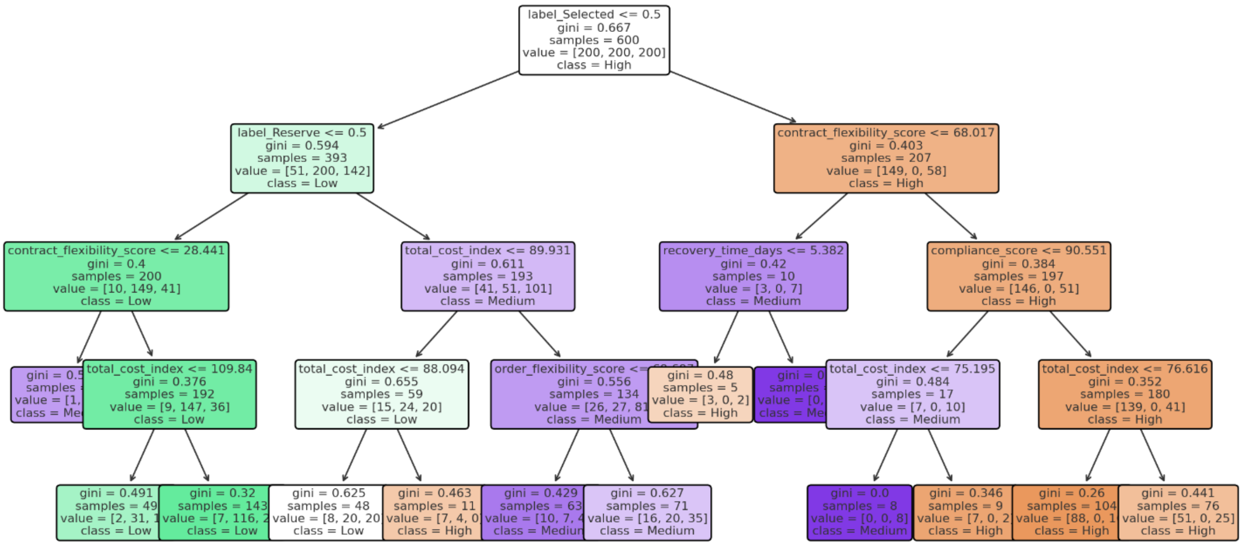

Fig. 2. Part of the tree structure of the Catboost algorithm

The presented decision tree model demonstrates that explanatory variables such as quality and cost indicators play a fundamental role in determining supplier performance levels. In the upper nodes of the tree, variables are positioned that possess the greatest ability to distinguish between the “High,” “Medium,” and “Low” performance groups. This structure clearly shows that, at the initial stage, the main features related to collaboration quality and cost levels serve as the key criteria for separating suppliers, while other variables such as flexibility or contractual compliance play a more secondary role in the decision-making path. The results of the tree revealed that suppliers with more favorable quality and cost indicators are predominantly classified into the High group, whereas deficiencies in these indicators, even in the presence of certain advantages, tend to push a supplier toward the Low group. The Medium group is largely associated with suppliers who perform adequately in some aspects but fail to reach higher levels in the critical indicators of quality or cost.

5.2. Model performance evaluation

The results indicate that the CatBoost model achieved an accuracy of approximately 92% and a high F1-macro score (≈0.918), demonstrating outstanding performance. These results suggest that the model was able to balance the identification of correct samples while minimizing both false positives and false negatives. The SVM model ranked second, with an accuracy of ≈82% and an F1-macro of ≈0.812, indicating a relative balance between Precision (≈0.832) and Recall (≈0.823). Although weaker than CatBoost, this model clearly outperformed the Decision Tree. The Decision Tree model, despite its transparency and interpretability, achieved only ≈64% accuracy and an F1-macro of about 0.62 in these evaluations. This finding shows that although useful for extracting simple decision rules, it is limited in accurately predicting supplier performance. Furthermore, a confusion matrix was employed, as illustrated in Figure 3, with the findings confirming that the CatBoost algorithm reached an accuracy of approximately 92%.

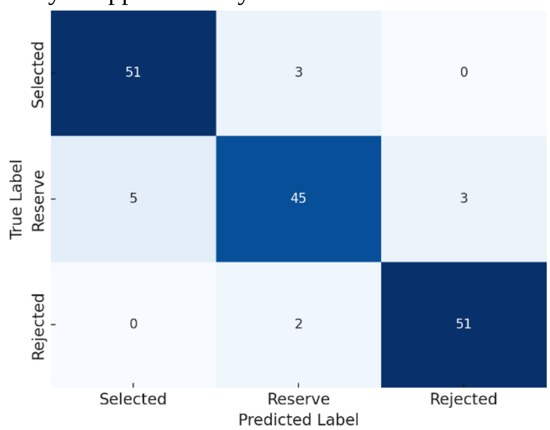

Fig. 3. Algorithm accuracy confusion matrix

5.3. Feature sensitivity analysis

The Figure 4 presents the feature importance values obtained from the outputs of the CatBoost algorithm.

The results indicate that variables such as quality consistency ppm, response time hours, and delivery speed index had the greatest impact on the model's decision-making process. This clearly demonstrates that product quality consistency, responsiveness, and the ability to deliver on time are the key factors in determining whether suppliers are accepted or rejected. In other words, any fluctuation or weakness in these indicators exerts the strongest influence on predicting supplier performance.

In the next tier, indicators such as total cost index, changeover time hours, and order flexibility score appear, showing that overall costs and order flexibility also hold significant positions in decision-making. Conversely, features such as safety stock days or compliance score contributed less to class separation, suggesting that while these variables may carry managerial importance, they play a lesser role in the predictive model.

Overall, the sensitivity analysis confirms that the model logically concentrates on the primary supply factors—quality, responsiveness, and delivery speed—which is consistent with practical realities in supply chain management.

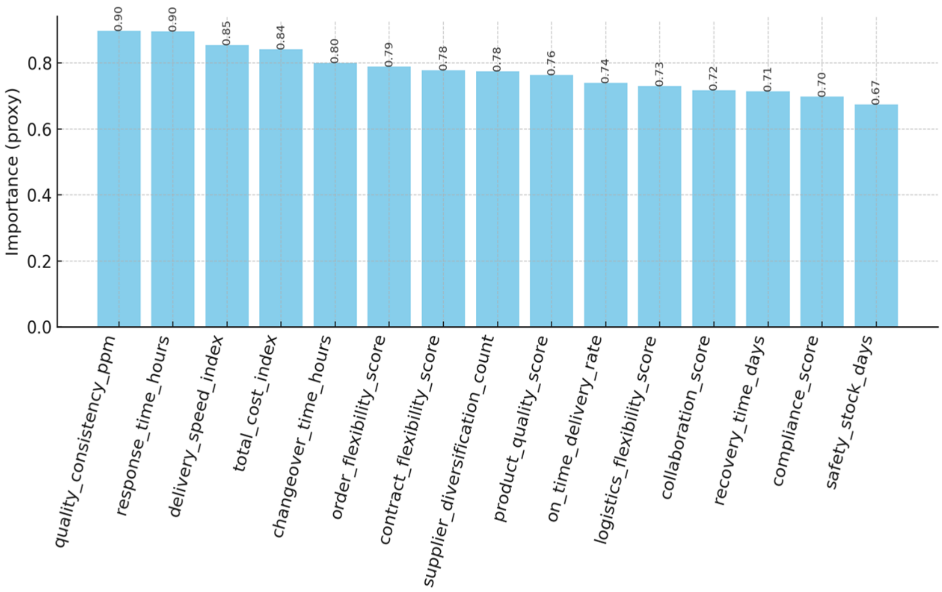

Fig. 4. Importance of features

5.4. Managerial insights

The findings of this study provide several key messages for managers and policymakers in the field of medical equipment supply. First, the results revealed that indicators such as quality consistency (quality consistency ppm), response time (response time hours), and delivery speed (delivery speed index) have the greatest impact on overall supplier performance. This highlights the necessity for managers to assign greater weight to these indicators in supplier evaluation and selection processes and to establish continuous monitoring mechanisms over them. Specifically, investing in the improvement of quality control processes, enhancing order responsiveness, and upgrading logistics efficiency can directly increase the likelihood of supplier acceptance and sustained collaboration.

Second, the comparison of algorithms demonstrated that the use of advanced machine learning approaches—particularly CatBoost—can significantly enhance decision-making accuracy (≈92% compared to ≈64% for the Decision Tree). This finding reminds managers that employing modern analytical tools not only improves the precision of evaluations but also enables a more accurate distinction between the “Selected,” “Reserve,” and “Rejected” classes. Therefore, it is recommended that decision support systems within organizations be updated, and that data-driven algorithms be applied on a monthly or even real-time basis for re-evaluating suppliers.

Third, error analysis revealed that most misclassifications occurred between the “Reserve” class and the two other categories. From a managerial perspective, this has particular significance, as the Reserve group, serving as the intermediate class, can play a crucial role in creating flexibility and mitigating risk. Managers can design supportive policies and provide improvement opportunities for this group to reduce the risks associated with misclassification and to leverage the potential capacity of these suppliers during crises.

Finally, the sensitivity analysis showed that some indicators, such as safety stock days (safety_stock_days) and compliance with regulations (compliance_score), had less influence on the predictive model. This does not imply that they are unimportant; rather, it indicates that while these factors may have limited impact under normal conditions, they can become strategically significant in specific circumstances (e.g., health crises or regulatory changes). Hence, managers should focus primarily on the key indicators of quality and timeliness while also considering these less influential criteria in forward-looking, scenario-based planning.

5.5. Theoretical implications

This study offers several important contributions to the theoretical advancement of supplier evaluation and supply chain management. First, by integrating the dual dimensions of resilience and agility into a unified evaluation framework, it extends existing theories that have traditionally treated these constructs separately. The findings demonstrate that resilience and agility should not be considered as independent attributes but rather as complementary capabilities that collectively determine supply chain sustainability. Second, the application of advanced machine learning algorithms, particularly CatBoost, highlights the value of data-driven approaches in addressing complex decision-making problems under uncertainty. This contributes to the growing body of literature on the intersection of artificial intelligence and supply chain management by showing how predictive analytics can enhance both accuracy and interpretability. Third, the case study in the healthcare sector underscores the contextual nature of evaluation criteria, emphasizing that theories of supplier selection must account for industry-specific risks such as regulatory compliance and patient safety. Overall, the study enriches theoretical discussions by bridging classical evaluation models with modern, data-driven paradigms, thereby laying the groundwork for future research on intelligent decision support systems in supply chain contexts.

6. Conclusions

This study aimed to develop a data-driven framework for evaluating medical equipment suppliers based on the dimensions of resilience and agility. By employing machine learning algorithms, particularly CatBoost, it was demonstrated that supplier performance can be predicted and classified with high accuracy. Comparative results indicated that CatBoost, with remarkable accuracy and balanced performance across F1, Precision, and Recall metrics, outperformed other methods, while the Decision Tree served primarily as an interpretable and exploratory tool, and SVM occupied an intermediate position.

In addition, feature sensitivity analysis revealed that quality consistency, responsiveness, and on-time delivery were the most critical factors in determining supplier performance. These findings provide important managerial implications for improving decision-making, resource allocation, and risk reduction within the healthcare supply chain.

Overall, the present study demonstrated that integrating data-driven approaches with traditional evaluation criteria provides a more comprehensive and precise understanding of supplier capabilities, paving the way for the development of intelligent decision support systems in the medical equipment sector. However, several limitations should be acknowledged. First, the dataset used in this study was limited in size and scope, which may restrict the generalizability of the findings across broader healthcare contexts or other industries. Second, while CatBoost was shown to be highly effective, the focus on a single algorithm means that potential benefits of ensemble or hybrid approaches were not fully explored. Third, the evaluation framework was tested within the context of medical equipment suppliers, and its applicability to other healthcare products or cross-industry settings remains to be validated. Finally, the study did not incorporate longitudinal or real-time data streams, which could further enhance the adaptability of the model under rapidly changing conditions. These limitations point to important directions for future research, including expanding datasets, comparing multiple machine learning algorithms, and applying the framework in diverse and dynamic environments.

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