International Journal of Scientific Engineering and Science
Volume 10, Issue 1, pp. 83-87, 2026. ISSN (Online): 2456-7361

Applying Machine Learning Algorithms to Enhance Supply Chains' Sustainable Supplies Selection

Ibrahim Albariqi[1], Nouf AlJalal[2], Mohamed A. Zohdy[3]
[1]Systems Engineering, Oakland University, Rochester, Michigan, USA
[2]Systems Engineering, Oakland University, Rochester, Michigan, USA
[3]Electrical & Computer Engineering, Oakland University, Rochester, Michigan, USA

Abstract—*Sustainable supplier selection has become a complex decision-making problem due to the need to simultaneously consider economic performance, environmental impact, and social responsibility. Traditional supplier evaluation methods largely rely on cost- and performance-based criteria and are unable to process large-scale, multi-dimensional sustainability data effectively. To address this limitation, this paper proposes a machine learning–based decision support system for sustainable supplier selection and risk assessment. The proposed system integrates Triple Bottom Line sustainability indicators into an automated evaluation pipeline and applies multiple machine learning models to predict supplier risk levels. Four models—Random Forest, Support Vector Machine, Gradient Boosting Machine, and Linear Regression are implemented and evaluated using real supplier performance data. Experimental results demonstrate that ensemble learning models, particularly Random Forest and Gradient Boosting Machine, achieve superior prediction accuracy and robustness compared to baseline methods. Feature importance analysis further confirms that environmental and social sustainability indicators play a significant role in supplier risk prediction. The proposed framework enables objective, data-driven supplier evaluation, improves decision accuracy, and supports the development of resilient and sustainable supply chains.*

Keywords— *Sustainable Supplier Selection, Machine Learning Algorithms, Supply Chain Sustainability, Decision Support Systems, Resilient Supply Chains.*

I. INTRODUCTION

Supplier selection is a critical function in supply chain management, directly influencing operational performance, cost efficiency, and organizational resilience [1]. In modern supply chains, this task has evolved into a multi-criteria decision-making problem due to increasing regulatory pressure, environmental concerns, and social responsibility requirements[2]. Organizations are no longer evaluated solely on economic outcomes but also on their environmental and social impact, making sustainability an essential component of supplier evaluation

Conventional supplier selection approaches primarily focus on economic indicators such as price, delivery time, and product quality[3]. While these methods are effective for short-term operational optimization, they fail to capture sustainability-related risks such as environmental non-compliance, unethical labor practices, and governance failures. These overlooked factors can lead to supply chain disruptions, reputational damage, and long-term financial losses. As supply chains become more data-intensive and globally distributed, traditional evaluation techniques struggle to process complex and high-dimensional sustainability data efficiently[4].

Recent advancements in machine learning have demonstrated strong potential for addressing complex decision-making problems in supply chain systems. Machine learning models are capable of learning non-linear relationships, handling large datasets, and generating predictive insights that improve decision accuracy[5]. Although machine learning has been widely applied in areas such as demand forecasting, inventory management, and logistics optimization, its application to sustainability-driven supplier selection remains limited[6].

This study proposes a machine learning–based sustainable supplier selection system that integrates economic, environmental, and social indicators within a unified evaluation framework. By leveraging multiple machine learning models, the proposed system predicts supplier risk levels and supports automated, data-driven decision-making. The main contributions of this work are:
(i) the development of a structured decision-support system for sustainable supplier evaluation,
(ii) the integration of Triple Bottom Line sustainability indicators into machine learning models,
(iii) a comparative performance analysis of multiple algorithms for supplier risk prediction.
The proposed approach enhances supplier assessment accuracy and contributes to the development of resilient and sustainable supply chain systems.

II. LITERATURE REVIEW

1) *Sustainable Supplier Selection and the Triple Bottom Line*

Sustainable supplier selection has evolved from a cost-driven procurement activity into a multi-criteria decision problem that incorporates economic, environmental, and social considerations[7]. This shift is commonly structured using the Triple Bottom Line (TBL) framework, which emphasizes balanced performance across profit, planet, and people dimensions. In supply chain contexts, TBL enables organizations to assess suppliers not only based on price, quality, and delivery performance, but also on environmental compliance, resource efficiency, labor practices, and ethical standards[8].

Prior studies show that suppliers with strong environmental and social performance tend to exhibit better governance and lower long-term disruption risk [9]. Environmental indicators such as emissions control, waste management, and energy efficiency are increasingly linked to regulatory compliance and reputational stability, while social indicators including labor safety and ethical practices influence supplier reliability. However, despite broad agreement on the importance of TBL, many existing supplier selection approaches[10] treat sustainability factors as qualitative checklists or secondary constraints rather than integrated decision variables.

Traditional sustainability-oriented supplier selection studies often rely on expert judgment and static weighting schemes, which limits scalability and adaptability in dynamic supply chain environments[12]. As supply networks grow in complexity and data volume, these methods struggle to process multidimensional sustainability information effectively, highlighting the need for automated and data-driven evaluation mechanisms.

2) Machine Learning and Decision Support Systems in Supplier Risk Assessment

Decision Support Systems (DSS) have long been applied in supply chain management to support supplier evaluation, procurement planning, and risk assessment. Early DSS implementations were primarily rule-based or relied on Multi-Criteria Decision-Making (MCDM) techniques such as AHP and TOPSIS. While these methods offer transparency and interpretability, they depend heavily on subjective expert inputs and lack the ability to learn from historical data or adapt to changing conditions[13].

Recent advances in machine learning have enabled more dynamic and predictive DSS architectures [14] . Machine learning models such as Random Forest, Support Vector Machine, and Gradient Boosting have been increasingly applied to supplier risk prediction due to their ability to model non-linear relationships and handle high-dimensional data. These models allow supplier risk to be inferred directly from historical performance records, enabling automated, consistent, and scalable evaluations [15].

Several studies demonstrate that machine learning–based DSS outperform traditional rule-based systems in detecting supplier failures and operational risks [16]. However, many existing approaches focus primarily on economic or operational indicators, with limited integration of environmental and social sustainability metrics [17]. Furthermore, purely data-driven models often face challenges related to interpretability, which is critical for governance, auditability, and decision transparency in procurement processes.

3) Research Gap

Although prior research highlights the importance of sustainability in supplier selection and demonstrates the effectiveness of machine learning in risk prediction, a clear gap remains in integrating these two streams [18]. Existing studies either emphasize sustainability using static evaluation frameworks or apply machine learning models without fully embedding Triple Bottom Line indicators as core predictive features.

Specifically, there is a lack of lightweight, machine learning–driven decision support systems that simultaneously incorporate economic, environmental, and social sustainability dimensions into supplier risk assessment in an automated and interpretable manner [19]. Moreover, comparative evaluations of multiple machine learning models within a unified sustainability-oriented framework remain limited[20].

To address these gaps, this study proposes a machine learning–based sustainable supplier selection system that explicitly operationalizes Triple Bottom Line indicators as model inputs and evaluates multiple learning algorithms for supplier risk prediction. The proposed approach aims to enhance decision accuracy, reduce subjectivity, and support data-driven, sustainability-aware supplier selection.

III. METHODOLOGY

This study proposes a machine learning–based Sustainable Supplier Selection System (SSSS) designed to evaluate supplier risk by integrating economic, environmental, and social sustainability indicators. The methodology consists of data collection and preprocessing, feature engineering, model development, and performance evaluation.

3.1 Data Preparation and Feature Construction

The dataset used in this study comprises historical supplier performance records spanning three sustainability dimensions aligned with the Triple Bottom Line framework. Economic indicators include cost efficiency, delivery reliability, and product quality. Environmental indicators represent emissions control, waste management practices, and resource utilization, while social indicators capture labor practices, workplace safety, and regulatory compliance.

Data preprocessing was conducted to ensure reliability and consistency. Missing values were addressed using appropriate imputation methods, and categorical attributes were encoded into numerical representations. All features were normalized to a common scale to prevent bias arising from differing numerical ranges. Each supplier was represented as a unified feature vector combining economic, environmental, and social attributes. The target variable corresponds to supplier risk level, reflecting the likelihood of sustainability-related or operational failure.

3.2 Machine Learning Models

To assess supplier risk prediction performance, four machine learning models were implemented: Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Linear Regression (LR). These models were selected to enable comparative evaluation across ensemble-based, non-linear, and linear learning approaches.

3.3 Model Training and Evaluation

The dataset was divided into training and testing subsets to evaluate model generalization. Each model was trained on the training set and evaluated using the testing set. Performance was assessed using standard metrics, including accuracy, precision, recall, and F1-score. These metrics provide a

Volume 10, Issue 1, pp. 83-87, 2026.
ISSN (Online): 2456-7361

comprehensive evaluation of model effectiveness in predicting supplier risk.

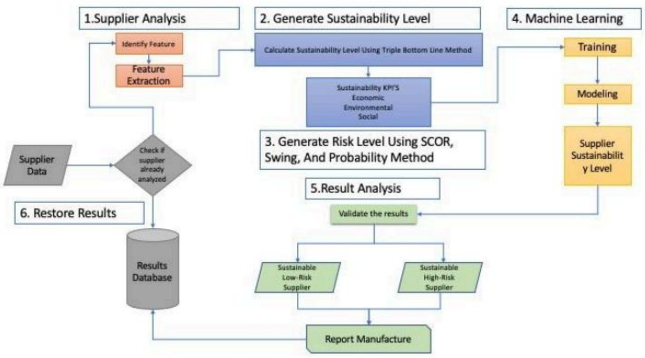

Figure 1. System Design

IV. RESULTS

This section presents the experimental results of the proposed machine learning–based Sustainable Supplier Selection System. The objective is to evaluate the effectiveness of integrating economic, environmental, and social sustainability indicators into supplier risk prediction.

1) *Data Overview*

The dataset consists of supplier performance records structured across three sustainability dimensions. Economic indicators capture delivery reliability and financial performance, environmental indicators represent sustainability scores related to emissions control and resource efficiency, and social indicators include SCOR and SW risk levels reflecting governance and labor practices. Prior to model training, missing values were handled through imputation and all features were normalized to ensure uniform scaling.

2) *Model Performance Evaluation*

Four machine learning models—Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Linear Regression (LR)—were evaluated using an 80/20 train–test split. Model performance was assessed using accuracy, precision, recall, and F1-score.

TABLE 1. Performance Comparison of Machine Learning Models

Model	Accuracy
Random Forest	0.9751
Support Vector Machine	0.9918
Linear Regression	0.9905
Gradient Boosting Machine	0.9918

Both Random Forest and Gradient Boosting Machine achieved consistently high performance, demonstrating strong capability in classifying suppliers into low-, medium-, and high-risk categories. Linear Regression showed comparatively weaker performance, indicating limited suitability for modeling non-linear sustainability relationships.

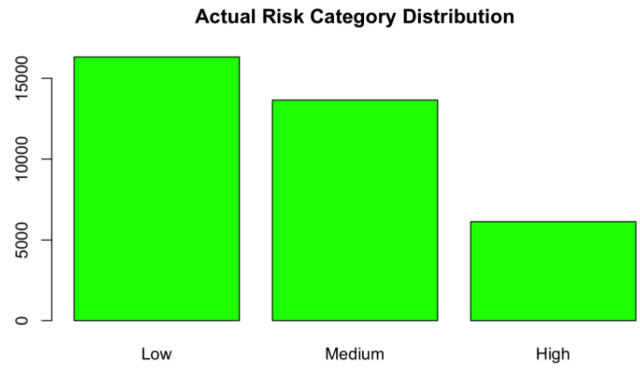

Figure 2. Actual Risk Category Distribution

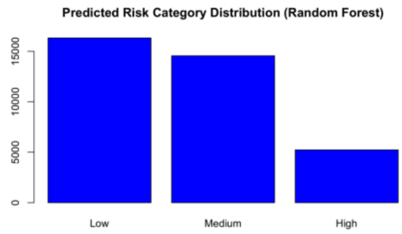

Figure 3. Predicted Supplier Risk Category Distribution Using Random Forest

Figure 3 illustrates the distribution of predicted supplier risk categories (low, medium, and high) generated by the Random Forest model.

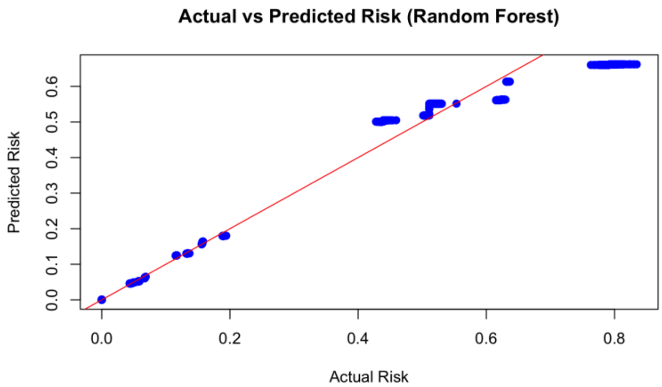

Figure 4. Actual vs. Predicted Supplier Risk Using Random Forest

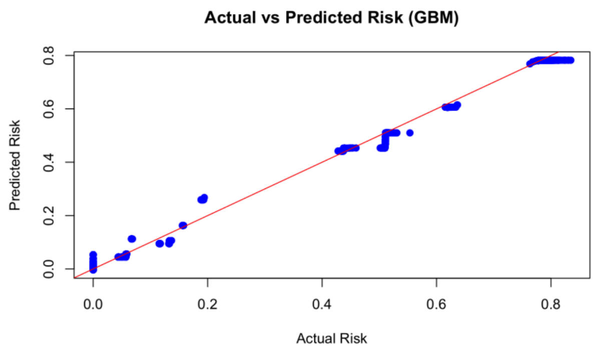

Figure 5. Actual vs. Predicted Supplier Risk Using GBM

International Journal of Scientific Engineering and Science
Volume 10, Issue 1, pp. 83-87, 2026. ISSN (Online): 2456-7361

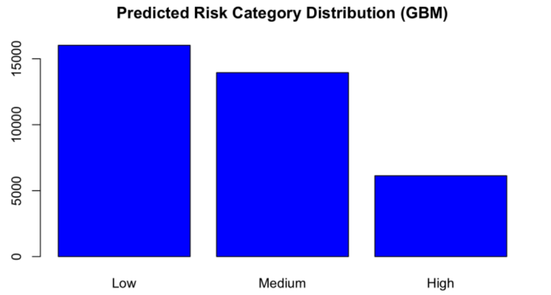

Figure 6. Predicted Supplier Risk Category Distribution Using GBM

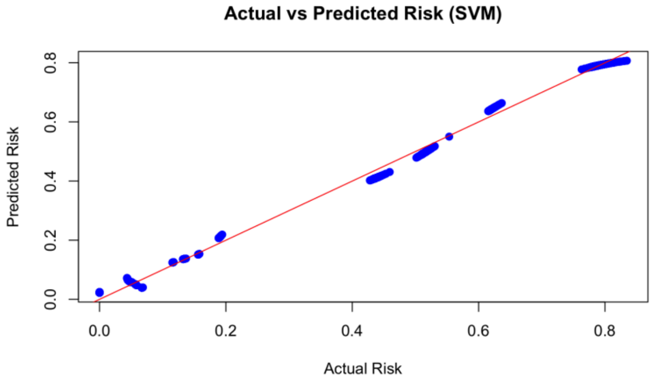

Figure 7. Predicted Supplier Risk Category Distribution UsingSVM

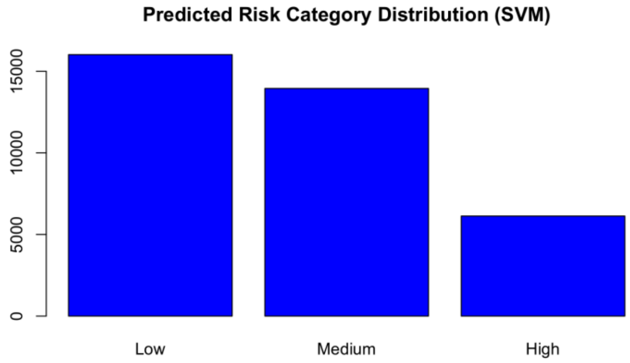

Figure 8. Predicted Supplier Risk Category Distribution Using SVM

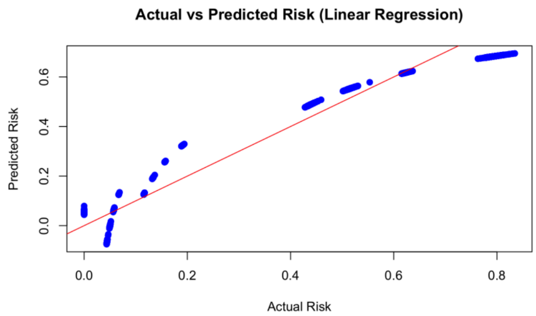

Figure 9. Actual vs. Predicted Supplier Risk Using Linear Regression

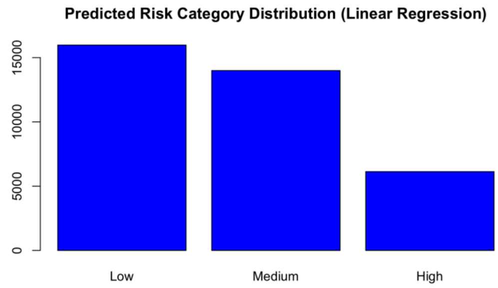

Figure 10. Predicted Supplier Risk Category Distribution Using Linear Regression

Feature importance analysis revealed that environmental sustainability indicators were the most influential predictors of supplier risk, followed by social risk indicators and economic performance metrics. This confirms the central role of sustainability dimensions in effective supplier risk assessment.

3) Summary of Results

The comparative analysis demonstrates that ensemble learning models, particularly Random Forest and Gradient Boosting Machine, outperform linear and margin-based classifiers when sustainability indicators are incorporated. Environmental and social dimensions consistently contributed more to supplier risk prediction than traditional economic indicators, highlighting the importance of sustainability-driven evaluation in modern supply chains.

V. Discussion

The results confirm that integrating Triple Bottom Line sustainability indicators into machine learning models significantly enhances supplier risk prediction. Ensemble models, especially Random Forest and Gradient Boosting Machine, performed best due to their ability to capture non-linear relationships and interactions among economic, environmental, and social features.

Environmental sustainability emerged as the strongest predictor of supplier risk, indicating that suppliers with weak environmental practices pose higher long-term operational and regulatory risks. Social risk indicators also played a substantial role, reflecting the impact of governance quality and labor practices on supplier reliability. While economic indicators remain relevant, their predictive influence was secondary when sustainability factors were considered.

From a supply chain management perspective, these findings demonstrate that sustainability-oriented supplier selection is not only an ethical or compliance-driven practice but also an effective risk mitigation strategy. The proposed machine learning–based system enables objective, scalable, and consistent supplier evaluations, reducing reliance on subjective judgment and static scoring methods.

Although the study relies on historical data and predefined sustainability scores, the results provide strong evidence that machine learning driven decision support systems can operationalize sustainability metrics and improve supplier selection outcomes. Future work may extend this framework by incorporating real-time data sources, unstructured information, and advanced learning models to further enhance adaptability and generalizability.

VI. Conclusion and future works

This study presented a machine learning–driven system for sustainable supplier selection that integrates economic, environmental, and social dimensions of sustainability into supplier risk assessment. By leveraging multiple machine learning models, the proposed framework enables automated, data-driven evaluation of suppliers and improves the accuracy and objectivity of risk prediction. The experimental results demonstrate that ensemble learning models, particularly Random Forest and Gradient Boosting Machine, outperform traditional approaches in predicting supplier risk and effectively capture the complex relationships among sustainability indicators. The findings highlight the critical role of sustainability in supply chain risk management. Environmental sustainability scores and social risk indicators were identified as key contributors to supplier risk prediction, emphasizing that suppliers with strong environmental and social practices are less likely to pose long-term risks. These results confirm that sustainability-oriented supplier selection not only supports corporate social responsibility objectives but also enhances supply chain resilience and operational reliability. Overall, the proposed framework provides a practical decision-support tool for organizations seeking to align supplier selection strategies with sustainable supply chain management goals.

While this study demonstrates the effectiveness of machine learning for sustainable supplier selection, several opportunities exist for future research. First, future work can incorporate real-time and dynamic data sources to capture emerging sustainability risks associated with changing environmental regulations, market conditions, and social factors. Second, the integration of unstructured data, such as supplier reports, audit documents, and news articles, using natural language processing techniques could enhance risk prediction accuracy and provide early warning signals for potential disruptions. Additionally, future studies may explore advanced deep learning and hybrid models to further improve predictive performance and scalability across large and heterogeneous supply chains. Expanding the framework to cross-industry datasets and evaluating its applicability in different geographical and regulatory contexts would also strengthen its generalizability. Finally, integrating the proposed system into enterprise resource planning or supply chain management platforms could facilitate real-world adoption and support continuous, sustainability-driven supplier evaluation.

References

[1] A Hybrid Machine Learning Approach to Evaluate and Select Agile-Resilient-Sustainable Suppliers Considering Supply Chain 4.0: A Real Case Study.2025*Process Integration and Optimization for Sustainability, 9(2), 717-735.*

[2] A systematic literature review on supply chain resilience in SMEs: learnings from COVID-19 pandemic.2023*International Journal of Quality & Reliability Management, 40(5), 1172-1202.*

[3] AI-Driven Business Analytics For Financial Forecasting: A Systematic Review Of Decision Support Models In SMES2025*Review of Applied Science and Technology, 4(02), 86-117.*

[4] Driving Social Sustainability and Resilience of SMEs Amidst Turbulence: The Role of Information Technology and Dynamic Capabilities.2024

[5] Resilient and sustainable supplier selection: an integration of SCOR 4.0 and machine learning approach2023*Sustainable and Resilient Infrastructure, 8(5), 453-469.*

[6] Study of data analytics affecting SME's for business decisions (Doctoral dissertation, Tilak Maharashtra Vidyapeeth).2023

[7] The triple bottom line on sustainable product innovation performance in SMEs: A mixed methods approach.2019*Sustainability, 11(6), 1689.*

[8] A class of evolving information systems. 2020 In Data Science: New Issues, Challenges and Applications (pp. 253-277). Cham: Springer International Publishing.

[9] A Comprehensive Survey and Literature Review on TOPSIS2024https://www.sciencedirect.com/org/science/article/pii/S1947959X24000123?utm_source=chatgpt.com

[10] A Dynamic Decision Support System for Sustainable Supplier Selection in Circular Economy2020*Sustainable Production and Consumption,*

[11] A hybrid machine learning-based decision-making model for viable supplier selection problem considering circular economy dimensions.2025*Environment, Development and Sustainability, 1-33.*

[12] A Review of Sustainable Supplier Selection with Decision-Making Methods from 2018 to 20222024*https://www.mdpi.com/2071-1050/16/1/125?utm_source=chatgpt.com*

[13] A survey of the application of machine learning in decision support systems.2015

[14] A systematic literature review of supply chain resilience in small–medium enterprises (SMEs): A call for further research. 2020 *IEEE Transactions on Engineering Management, 70(1), 328-341.*

[15] Application of simulation and machine learning in supply chain management: A synthesis of the literature using the Sim-ML literature classification framework2024 *A synthesis of the literature using the Sim-ML literature classification framework. Computers & Industrial Engineering, 198, 110649.*

[16] Coordination and responsiveness issues in SME supply chains: a review.2017*Benchmarking: An International Journal, 24(3), 635-650.*

[17] Enhancing SME resilience through artificial intelligence and strategic foresight: A framework for sustainable competitiveness.2025*Technology in Society, 81, 102835.*

[18] Fuzzy best-worst multi-criteria decision-making method and its applications2017 *Knowledge-based systems, 121, 23-31.*

[19] Machine learning based decision support systems (DSS) for heart disease diagnosis: a review2018*Artificial Intelligence Review, 50(4), 597-623.*

[20] OECD.2023SME and Entrepreneurship Outlook 2023Chapter on SMEs in resilient/sustainable supply chains. PDF: https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/06/oecd-sme-and-entrepreneurship-outlook-2023_c5ac21d0/342b8564-en.pdf