A Comparative Analysis of Machine Learning Model Utilization for the Optimization of Supplier Reliability Towards Sustainable Construction

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Received: 13 June 2025 | Revised: 30 July 2025 | Accepted: 11 August 2025

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ABSTRACT

The success of a construction project is significantly influenced by the reliability of its material suppliers, particularly when operational efficiency and sustainability factors are considered. Traditionally, project managers have relied on conventional scorecards and heuristic decision-making methods, which are often subjective and limited in scope. To provide a more objective and data-driven approach, this study introduces a Machine Learning (ML)-based pipeline for evaluating supplier reliability. Four ML algorithms, Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), were assessed, while Shapley Additive Explanations (SHAP) were employed to interpret model outputs and identify the supplier characteristics most influential to each algorithm. Additionally, a proprietary Sustainability Score (SS) was integrated to account for the sustainability aspect provided by each supplier. The dataset used consisted of 105 records from five major suppliers involved in two large-scale residential construction projects in Sri Lanka, incorporating key features such as waste generation, lead time, material cost, and delivery accuracy. Among the evaluated models, XGBoost demonstrated the best performance, achieving an F1-score of 0.89 and an Area Under the Curve (AUC) of 0.97, followed by RF. Notably, the SS analysis revealed that some medium-reliability suppliers achieved higher sustainability scores than high-reliability ones, highlighting the importance of multi-criteria evaluation frameworks that balance operational reliability with environmental responsibility in supplier selection. By facilitating precise, open, and ecologically responsible supplier evaluations, this integrated ML framework aids in sustainable procurement decisions for construction projects.

Keywords-artificial intelligence; machine learning; supply chain management; sustainable construction

I. INTRODUCTION

The construction sector remains one of the most resource-intensive industries, responsible for substantial material use, high energy consumption, and significant waste generation [1, 2]. In recent years, sustainable construction practices have gained momentum, aiming to minimize environmental impact while maintaining economic viability and operational efficiency. Within this context, supplier reliability has emerged as a significant determinant of project success and sustainability [3], as reliable suppliers guarantee prompt delivery of high-quality products, reduce logistical inefficiencies, and play a crucial role in maintaining project stability [4, 5]. However, the decision-making procedures related to supplier assessment by project managers mostly remain subjective and often depend on conventional scorecard methods or management heuristics [6]. Such methods lack the analytical precision and flexibility needed to fully evaluate the supplier characteristics, failing to capitalize on the increasing accessibility of project data, which supports more predictive and data-driven decision-making.

While previous research has explored supplier evaluation using methods such as Multi-Criteria Decision-Making (MCDM), fuzzy logic, and basic regression techniques [7-9], few studies have investigated the comparative performance of sophisticated Machine Learning (ML) models in predicting and enhancing supplier reliability [10]. Even fewer studies have explicitly linked these models to sustainability goals, such as waste reduction or enhanced material handling, highlighting a clear gap at the intersection of Artificial Intelligence (AI), supplier assessment, and sustainable construction management [11]. In previous studies, Support Vector Machine (SVM) and Random Forest (RF) have been employed to uncover complex, non-linear patterns within supplier datasets, surpassing human judgement and supporting objective decision-making in supplier selection [12]. Similarly, authors in [13] employed both Artificial Neural Network (ANN) and SVM models to predict supplier performance using 12 project- and supplier-related parameters, where the ANN slightly outperformed SVM in accuracy [13]. A follow-up Decision Tree (DT) analysis revealed that financial stability, the cost of order modifications, and supplier experience were the most influential factors, emphasizing ML's ability to identify reliability determinants often overlooked by human evaluation [14].

Ensemble methods have also been investigated, such as Gradient Boosting (GB) and RF, which often outperform traditional models in handling high-dimensional datasets [15]. For instance, authors in [16] utilized an Extreme Gradient Boosting (XGBoost) classifier, integrated with the Best-Worst Method (BWM) and the Supply Chain Operations Reference (SCOR) model, to rank pharmaceutical suppliers according to sustainability and resilience criteria. Likewise, authors in [17] compared five algorithms (SVM, DT, RF, Naïve Bayes, logistic regression) to predict supplier performance in a manufacturing setting. Interestingly, a simple logistic regression model achieved an Area Under the Curve (AUC) of 0.993, slightly outperforming more complex models. This demonstrates that even reasonably interpretable models may be highly helpful when sufficient clean data is available. Some studies have combined ML, optimization, and simulation to enhance supplier selection decisions. For example, authors in [18] proposed a hybrid three-step process incorporating a Long Short-Term Memory (LSTM) neural network for demand forecasting, followed by an ML-based supplier evaluation and a multi-objective optimization for order allocation. Additionally, for public infrastructure projects, authors in [19] developed an AI-based contractor selection model integrating sustainability and safety metrics, successfully minimizing project delays and cost overruns. Key predictors included annual turnover, experience, staff credentials, technology adoption, customer satisfaction scores, accident histories, and the socioeconomic impact on the community.

The incorporation of sustainability criteria into supplier performance models has emerged as a prominent theme in more recent literature. Sustainability in construction supply chains frequently means simultaneously assessing suppliers' economic value, social responsibility, and environmental impact [20-22]. Authors in [23] applied an RF model with recursive feature elimination to identify the most influential sustainability criteria for different product categories, reducing subjectivity and aligning evaluation metrics with actual procurement outcomes. Moreover, identifying niche criteria specific to particular product categories represents another key advantage of ML-based supplier evaluation. For instance, the percentage of recycled content may be a critical factor for concrete suppliers, whereas energy efficiency ratings are more relevant for equipment providers. By tailoring the supplier scorecard to emphasize the factors most influential to long-term performance in each context, this approach enhances both sustainability and decision precision [24]. Because ML algorithms can model complex trade-offs more effectively than heuristic methods, organizations adopting ML-driven supplier selection have reported improved overall performance and stronger alignment with sustainability objectives [25]. For instance, in [26, 27], the ML models employed revealed that a slightly higher-cost supplier with superior environmental compliance exhibits fewer delivery disruptions, making it the more advantageous long-term choice. In the construction industry, where environmental regulations are strict and project schedules are tightly constrained, such data-driven insights are important for developing resilient and sustainable supply chain management strategies [28]. In summary, as the construction industry transitions toward sustainability and resilience, AI-driven approaches have demonstrated substantial potential to enhance supplier evaluation accuracy and objectivity [29, 30].

This research aims to contribute to AI-driven approaches to evaluate supplier reliability in construction projects by overcoming previous methodological and practical shortcomings. By combining project, logistic, and environmental data, this study constructs and evaluates four predictive models, RF, XGBoost, SVM, and K-Nearest Neighbors (KNN), to determine the most efficient method in this task. Additionally, a novel Sustainability Score (SS) is introduced to quantify suppliers' environmental and logistical efficiency, offering a structured basis for sustainable procurement decisions. This framework provides actionable insights for scholars, project managers, and procurement professionals.

II. METHODOLOGY

The ML framework employed in this study consisted of four main phases, as illustrated in Figure 1, including i) data collection, ii) feature selection and preprocessing, iii) ML model development, and iv) model evaluation based on the metrics employed.

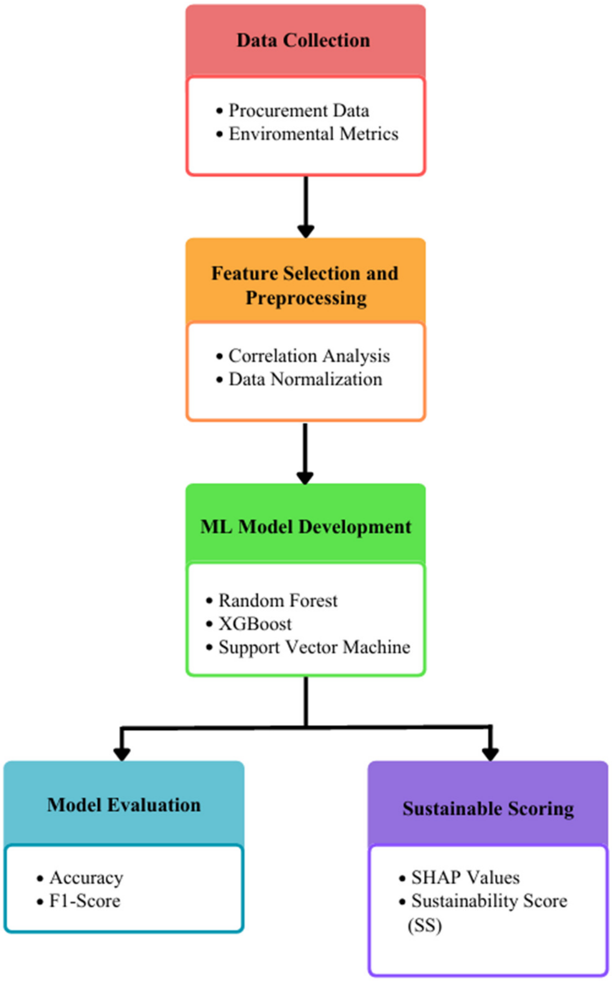

Fig. 1. The ML framework used.

A. Data Preprocessing

The dataset used comprised 105 records collected from five suppliers involved with two major residential construction projects in Colombo and Kandy, Sri Lanka, during the fiscal year 2023. Data sources included procurement records, on-site purchase logs, delivery reports, supplier performance reviews, and environmental compliance audits. Each observation corresponded to a distinct material delivery or acquisition event. Operational measurements, financial indicators, and environmental factors are among the three main categories in which the data collects multifaceted supplier characteristics. To ensure accuracy and consistency, all data was cross-validated by project managers and sustainability officers. Missing or inconsistent entries were excluded. Table I lists the feature variables used and their definitions.

To retain the statistical validity and unique distribution of the dataset, median imputation was applied to handle missing numerical values. Given the varying scales of features, Min-Max normalization was applied to all continuous variables using:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

where x is the original feature value, and x' is the normalized value. Feature selection was performed using RF Gini importance, identifying variables that reduced node impurity. Additionally, multicollinearity was tested using the Variance Inflation Factor (VIF), ensuring that no feature had a VIF above 5, which would suggest high linear coupling with other characteristics.

TABLE I. FEATURE DESCRIPTION OF THE VARIABLES USED

Feature variable	Unit	Description
Reliability	–	Supplier reliability score derived from performance records.
Size	m^2	Project size based on built-up area.
Duration	Days	Total project duration.
Lead_Time	Days	Average time required to deliver materials to the site.
Cost	LKR	Average material cost handled by the supplier.
Accuracy	%	Delivery accuracy rate of the supplier.
Waste_Ton	Ton	Total waste generated during material handling and delivery.
Distance	Km	Distance between the project site and the supplier's yard.
Handling_Cost	LKR	Cost of material handling and logistics.
Qty_Pref	unit	Quantity of materials managed or preferred by the supplier.
Waste_%	%	Percentage of material waste generated.

LKR: Sri Lankan Rupee

B. Model Selection and Formulation

For this study, four ML algorithms were selected based on their robustness to small, imbalanced, and structured datasets: RF, XGBoost, SVM, and KNN.

RF is an ensemble approach that creates a variety of DTs during training and reports the mode of their forecasts. It is resilient to overfitting and outliers. The model prediction is specified by:

$$\acute{y} = mode\{h_1(x), h_2(x) \dots . h_i(x)\} \quad (2)$$

where $h_i(x)$ indicates the i^{th} DT in the ensemble.

XGBoost implements GB over DTs with L2 regularization, providing great performance on structured datasets. Its loss function contains a regularization component as:

$$L = \sum_{i=1}^{n} l(y_i, \acute{y}_i) + \sum_{k=1}^{K} \Omega(f_k), \text{ where}$$

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \|\omega\|^2 \quad (3)$$

where T is the number of leaf nodes, ω is the vector of leaf weights, γ is the complexity penalty, and λ is the regularization parameter.

SVM tries to optimize the margin between classes and employs the Radial Basis Function (RBF) kernel to capture non-linear correlations. The basic formulation is:

$$f(x) = sign(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b)$$

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|)^2 \quad (4)$$

where α_i are Lagrange multipliers, y_i are class labels, K is the RBF kernel, and γ controls kernel width.

KNN is a non-parametric model that provides class labels based on the most common class among the k closest samples in feature space, as provided by the formula:

$$\acute{y} = mode\{y_j | x_j \in N_k(x)\} \quad (5)$$

where $N_k(x)$ signifies the neighborhood of x. Table II summarizes the role of each model in the sustainability-oriented evaluation.

TABLE II. SUSTAINABILITY APPLICATION OF EACH ML MODEL

Model	Sustainability application
RF	Assess how supplier reliability impacts the waste generation.
XGBoost	Optimize the material lead time.
SVM	Models the cost-waste tradeoffs.
KNN	Capture the spatial effects.

C. *Model Training and Validation*

Each algorithm was implemented with the xgboost and scikit-learn libraries in Python. Table III summarizes the hyperparameters and their corresponding tuning ranges for each model.

For the RF model, Bayesian optimization was employed to tune two primary hyperparameters: the number of estimators (trees) and the maximum tree depth. The number of estimators ranged from 100 to 300, while the maximum depth varied between 5 and 20. The XGBoost model was also optimized using regularized Bayesian optimization. The learning rate was tuned within the range 0.01-0.3, and the subsample ratio between 0.6 and 1.0, allowing control over the model's learning speed and the randomness of training samples to improve generalization. For the SVM model, hyperparameters were optimized using Grid Search, with C (regularization parameter) explored in the range 0.1-10 and γ (kernel width) in the range 0.001-0.1. For the KNN model, the optimal number of neighbors was determined through cross-validation, yielding k = 7 based on the highest F1-score. Uniform weighting and Euclidean distance were used for neighborhood computation.

TABLE III. ML MODELS' HYPERPARAMETERS AND RANGE

Feature variable	Parameter	Range
RF	n_estimators, depth	[100-300], [5-20]
XGBoost	learning_rate, subsample	[0.01-0.3], [0.6, 1.0]
SVM	C, γ	[0.1-10], [0.001-0.1]
KNN	k	[3-15]

To preserve the ordinal nature and class distribution of the target variable, stratified 5-fold cross-validation was applied. Several metrics were employed to evaluate the performance of each model. Firstly, the F1-score was used, which is the harmonic mean of precision and recall.

$$F_1 = 2\frac{Precision \cdot Recall}{Precision + Recall} \quad (6)$$

Additionally, accuracy, macro-averaged recall, and the AUC of the precision-recall curve were also computed. To interpret the trained models and understand the contribution of each feature, Shapley Additive Explanations (SHAP) values were calculated. Grounded on cooperative game theory, SHAP values quantify the marginal effect of each feature on the prediction output, expressed as:

$$\varphi_i = \sum_{S \subseteq F\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} \{f(S \cup \{i\}) - f(S)\} \quad (7)$$

where $f(S)$ denotes the model prediction based on the subset S of features, and φ_i represents the SHAP value for the feature i.

D. *Sustainability Impact Quantification*

To integrate the predictive outputs with sustainability objectives, the SS was calculated. This composite index aggregates the SHAP-weighted contributions of sustainability-related features for the five key suppliers, as expressed in (8):

$$SS = \sum_{i=1}^{m} w_i . f_i, \text{ where}$$

$$w_i = SHAP\ value\ of\ feature\ i \quad (8)$$

The SS score helps project managers prioritize low-waste, cost-effective suppliers so that predictive outputs for sustainable procurement can be turned into actionable insights.

III. RESULTS AND DISCUSSION

A. *Model Performance Comparison*

The four ML models were employed to execute a multiclass classification assignment, dividing providers into three dependability classes: high, medium, and low. The dependent variable, Supplier Reliability Class, was encoded with ordinal labels (2 = High, 1 = Medium, 0 = Low) based on previous procurement performance ratings.

The evaluation metrics achieved by the four ML models are depicted in Figure 2. XGBoost outperformed the other models by achieving the highest F1-score of 0.89 and accuracy of 0.89. RF was the second-best-performing model. To further examine the statistical validity of the observed variations in F1-scores, paired t-tests between the four ML models were used (Table IV), proving that the F1-score variations were statistically significant (p-value < 0.05).

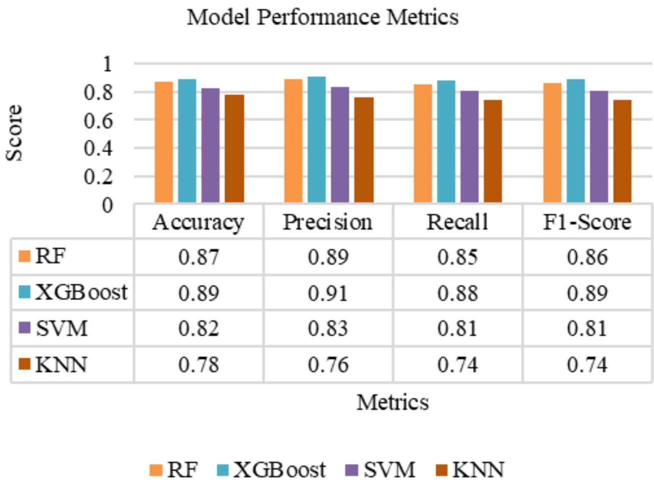

Fig. 2. Performance metrics for all four ML models.

Furthermore, all ML models exhibited high discriminative ability in their classification task, according to the Receiver Operating Characteristic Area Under the Curve (ROC-AUC) curve analysis depicted in Figure 3. XGBoost achieved the highest AUC of 0.97, followed by RF (0.95), SVM (0.93), and KNN (0.91).

TABLE IV. PAIRED T-TEST COMPARISON OF F1-SCORES BETWEEN ML MODELS

Model	p-value	Significant ($p < 0.05$)
RF vs XGBoost	0.027	Yes
RF vs SVM	0.014	Yes
RF vs KNN	0.021	Yes
XGBoost vs KNN	0.003	Yes
XGBoost vs SVM	0.011	Yes
SVM vs KNN	0.035	Yes

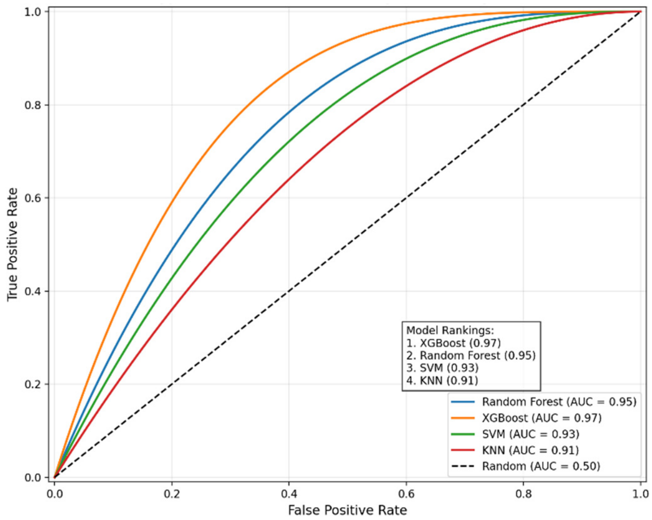

Fig. 3. ROC-AUC curves for each ML model.

To further validate the classification accuracy, Figure 4 presents the confusion matrix of the best-performing XGBoost model. The classifier achieved 92% accuracy for "High Reliability" suppliers, 85% for "Medium Reliability" suppliers, and 81% for "Low Reliability" suppliers, indicating effective discrimination across reliability categories. Most misclassifications occurred between adjacent reliability classes, as expected given the ordinal nature of the data.

B. Correlation Analysis

The correlation analysis, depicted in Figure 5, revealed several important relationships between supplier characteristics and project management dynamics. Supplier Reliability exhibited a strong positive correlation with Delivery Accuracy (%), suggesting that dependable suppliers enhance both timely delivery and reduce material waste. A modest negative correlation was observed between Supplier Reliability and Material Waste_%. Interestingly, Material Cost showed minimal correlation with Supplier Distance, indicating that project duration rather than transportation distance is a more important cost driver. Material Lead_Time was positively correlated with Project Size, reflecting the higher complexity of larger projects, while a pronounced negative correlation between Waste_Ton generation and Delivery Accuracy highlights how effective delivery practices reduce waste. Material Qty_Pref displayed a modest correlation with Project Size, whereas Supplier Distance was negatively correlated with Delivery Accuracy, demonstrating the advantage of geographical proximity on delivery performance.

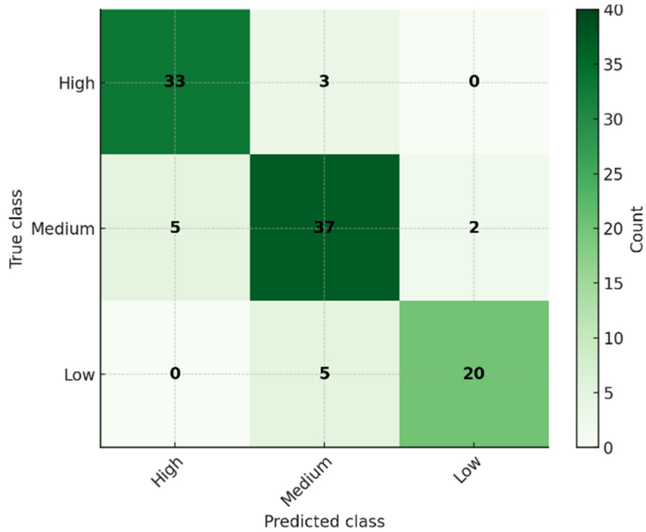

Fig. 4. Confusion matrix for the XGBoost model.

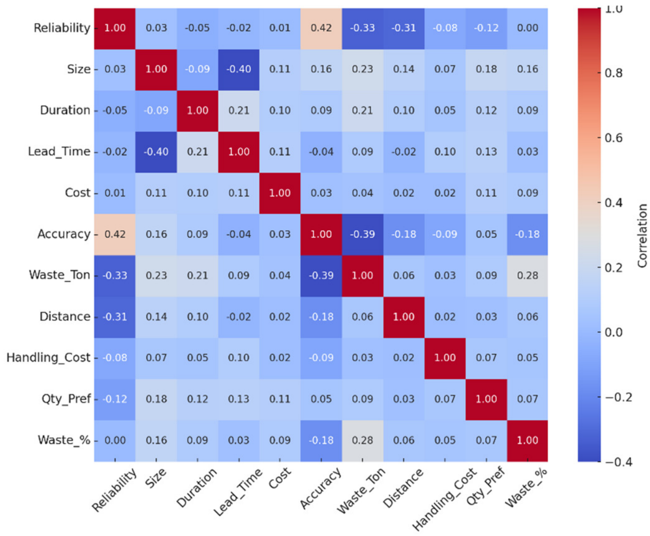

Fig. 5. Correlation heatmap.

C. SHAP-Weighted Sustainability Score Analysis

The assessment of the top five suppliers according to their SHAP-weighted SS exposes significant variation in their operational and environmental characteristics, as shown in Table V. Driven mostly by a high material handling cost and modest waste values, SUP5 achieved the best SS among the suppliers of 446.95. Although high handling costs may normally be considered as a downside, in this model, they are favorably weighted because of their significant link with logistical preparation and supplier reliability. Interestingly, SUP2, the sole supplier designated as "High Reliability", came second in SS (278.97), exhibiting an excellent balance between moderate prices and low waste. In comparison, suppliers such as SUP1 and SUP3, although still designated as "Medium Reliability", had much lower SS owing to their decreased material handling costs and increased waste, respectively.

TABLE V. SHAP-WEIGHTED SS FOR THE KEY SUPPLIERS

Supplier ID	Predicted reliability class	SC	Key Supplier Characteristics
SUP1	Medium Reliability	168.02	Moderate delivery accuracy, low handling cost, and high waste.
SUP2	High Reliability	278.97	High delivery accuracy, balanced cost, and low waste.
SUP3	Medium Reliability	225.25	Long lead time, medium cost, and moderate waste.
SUP4	Medium Reliability	389.91	High material cost and strong logistics control.
SUP5	Medium Reliability	446.95	High handling cost, low waste, and strong delivery record.

IV. CONCLUSION

Integrating interpretable Machine Learning (ML) models with sustainability assessment provides an innovative, transparent, and repeatable decision support tool for procurement in the construction industry. Through a comparison of four ML models, namely, Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), this research developed a thorough and data-driven framework to optimize supplier reliability in the construction sector. Addressing a critical gap in construction supply chain management, where traditional supplier selection methods frequently fail to capture complex interdependence and forecast long-term performance, this research integrates operational, logistical, and sustainability-related variables into a unified analytical framework.

The results demonstrate that all four ML models effectively assessed supplier reliability, with XGBoost achieving the highest accuracy. The incorporation of Shapley Additive Explanations (SHAP) values further improved interpretability, revealing the influence of key factors such as delivery accuracy, material lead time, and waste generation on supplier performance. Additionally, the introduction of a SHAP-weighted Sustainability Score (SS), a metric enabling a joint assessment of logistical and environmental performance, is crucial for evaluating the balance between ecological responsibility and operational excellence. Notably, certain medium-reliability suppliers exhibited higher SSs compared to high-reliability ones.

Overall, this study illustrates the potential of ML in advancing sustainable construction practices and helping construction managers to make more performance-aligned and objective procurement choices. Future work could expand this framework by incorporating additional contextual factors, deep learning architectures, and integrated decision-support systems.

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