# Assessing Material and Labor Cost Indices Impacts on Construction Firms' Financial Performance: A Machine Learning Comparison with Feature Engineering

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**Abstract**

**Financial performance serves as the primary metric in project management to make strategic decisions based on internal and external data. While traditional manufacturing sectors utilize these indicators to examine stability, the construction industry possesses distinct characteristics defined by high material reliance and labor-intensive operations. This study employs an interpretable machine learning framework to assess the impact of 11 material and labor indices on the return on assets of 20 major Korean construction firms from 2015 to 2023. The results show that engineered cost features contribute 56.97% to the predictive power, with the interaction between the asset turnover and cement producer price index emerging as the most influential predictor (15.00%). Material-related features (42.01%) substantially exceeded labor-related features (13.07%), reflecting the higher volatility of commodities. Time-lagged analysis confirms a two-quarter delay in the translation of cost changes to financial performance. These findings provide actionable insights into adaptive cost risk management and firm-specific hedging strategies.**

**Keywords –**

**Construction Management; Prediction; Financial Performance; Interpretable Machine Learning; Feature Engineering**

## 1 Introduction

The prediction of financial performance remains a key research focus in construction management and financial analysis [1]. Predicting financial performance is essential for analyzing a firm's stability and profitability, particularly in the early stages of operation, providing critical insights for managerial decision-making. Understanding the factors that influence the financial health of construction firms is particularly important because of the industry's unique characteristics, including labor-intensive operations and high reliance on material costs [2]. Because material and labor costs directly impact project profitability, research has increasingly focused on developing more accurate predictive models.

However, traditional models often overlook the complex, nonlinear synergies between a firm's operational efficiency and external market shocks [3,4]. A prior study by the authors demonstrated that augmenting financial ratio datasets with construction-specific cost indices (PPI and labor wages) improved ROA prediction accuracy by up to 56% using an XAI framework [5]. However, that study applied cost indices as raw variables without systematic feature engineering, leaving interaction effects, temporal delays, and cost aggregations unexplored. Feature engineering has proven effective in enhancing model performance across various fields [6,7], yet remains underexplored in construction financial forecasting [8].

While the construction industry's reliance on volatile material and labor costs is well established (see Section 2.1), existing predictive models have not systematically quantified how cost indices interact with firm-level operational efficiency indicators to drive profitability. This gap motivates the present study. The following three research questions guide this study:

- RQ1: Which material and labor cost indices most significantly influence the ROA?
- RQ2: Does domain-specific feature engineering improve ML-based financial performance prediction?
- RQ3: What is the temporal lag between construction cost index fluctuations and their impact on firm profitability?

# 2 Background

## 2.1 Financial Performance Prediction and Construction Industry

Financial performance prediction has been a sustained research focus in construction management, driven by the industry's project-based revenue structure and exposure to volatile input costs [1]. Early studies relied on multiple regression and structural equation modelling to identify relationships between financial ratios—profitability, liquidity, leverage—and firm outcomes, valued primarily for their interpretability [9,10]. However, these parametric approaches assume linear, stationary relationships, an assumption that is systematically violated in construction markets characterized by nonlinear cost–profit dynamics and supply-side shocks.

The adoption of machine learning (ML) introduced non-parametric alternatives capable of capturing complex patterns without prior distributional assumptions. Random forest, XGBoost, artificial neural networks (ANN), and long short-term memory (LSTM) networks have each been applied to construction firm financial prediction, consistently outperforming statistical baselines on prediction accuracy [3,8,10,11]. Despite these advances, three critical gaps remain. First, variable sets across virtually all studies are confined to raw financial ratios, systematically excluding the material and labour cost indices that directly shape construction profitability [2,12]. Second, feature engineering, the construction of interaction terms, time-lagged variables, and composite indices from domain knowledge, has not been applied to construction firm-level financial forecasting. Third, interpretability tools beyond basic variable importance rankings, which cannot reveal the direction or magnitude of individual feature contributions, have not been adopted.

## 2.2 Feature Engineering in Financial Performance Forecasting

Feature engineering has demonstrated consistent predictive improvements in adjacent financial forecasting domains. In real-estate price prediction, time-lagged price ratio features and composite location indices improved model accuracy beyond what model tuning alone could achieve [13]. In credit risk modelling, interaction terms between repayment behavior and borrower characteristics have become standard inputs for ensemble models [14]. Across these domains, a recurring finding is that domain-informed feature construction contributes more to predictive accuracy than model architecture selection, particularly under moderate sample sizes [6]. Construction financial forecasting, with its distinctive cost-to-revenue dynamics, procurement lag structure, and material price sensitivity, presents precisely the type of domain where engineered features would be expected to yield significant gains.

Model interpretability has emerged as a parallel priority. SHapley Additive exPlanations (SHAP) provides a theoretically grounded framework for decomposing model predictions into individual feature contributions, enabling both global importance rankings and local, instance-level attribution [15]. Unlike variable importance scores, SHAP reveals the directionality and conditionality of each predictor's effect, supporting actionable managerial inference. While SHAP has been adopted in infrastructure cost estimation and supply chain risk modelling, its combination with domain-specific feature engineering in construction financial forecasting has not been reported.

Table 1 maps these gaps across representative prior studies. As shown, no existing study simultaneously incorporates industry-specific cost index variables, systematic feature engineering, and SHAP-based interpretability. This tripartite gap directly motivates the variable selection procedure in Section 3.1.2 and the domain-driven feature engineering protocol in Section 3.2.

# 3 Methodology

## 3.1 Data Collection

### 3.1.1 Dependent Variable

A research model to forecast financial performance is developed based on the quarterly financial statements of construction companies. Three criteria were applied to select the analytical sample: (i) classified under Korean

Table 1. Comparison of representative studies on ML-based financial performance predictions

| Reference | Method | Variables | Interpretability |
|---|---|---|---|
| [1] | Regression | Financial | Coefficients |
| [3] | LSTM | Financial | - |
| [4] | Ensemble | Financial | - |
| [10] | RF, ANN | Financial | Var. importance |
| [12] | SVM, LR | Financial | - |
| [16] | RF | Financial | - |
| This study | RF, XGB, ANN, LSTM | Financial + construction indices + feature engineering | SHAP |

Standard Industry Classification codes 41–42 (general construction) as of Q1 2015; (ii) continuously listed on KOSPI or KOSDAQ without delisting, restatement, or merger events throughout 2015–2023; and (iii) complete quarterly financial records with no missing values for all target variables. Twenty construction companies satisfied all three criteria, yielding 720 firm-quarter observations (20 firms × 36 quarters). All consolidated financial statements were sourced from the Data Analysis, Retrieval and Transfer System (DART) operated by the Financial Supervisory Service of Korea, reported under K-IFRS, with all monetary values in KRW millions.

Return on assets (ROA) was selected as the dependent variable on two evidence-based grounds. First, De Wet and Du Toit [17] demonstrated that ROE is systematically distorted by financial leverage, rendering cross-firm comparisons unreliable in capital-intensive industries. Second, Seo et al. [10] confirmed ROA as the preferred profitability proxy for Korean construction firms given the industry's characteristically low fixed-asset ratios. No alternative indicator, ROE, net profit margin, or Tobin's Q, satisfied both validity and data-availability criteria simultaneously.

### 3.1.2 Independent Variable Selection

Independent variables were selected based on prior studies on construction firm financial performance reviewed in Section 2.1. Profitability ratios including ROA and ROE [10, 17], liquidity measures such as the current ratio (CR) and working capital ratio (WCR) [9], leverage indicators including the debt ratio [9], and the asset turnover ratio (ATR) as an operational efficiency proxy [10] were selected as key financial indicators. Cash flow from operations (CFO) and sales-related variables reflecting external spending patterns on construction firms [18] complete the nine-variable D1 baseline.

Cash flow variables, such as cash flow from operations, highlight operational health, while owner’s capital and total sales serve as indicators of financial stability and revenue generation. Sales and government expenses reflect the influence of external spending patterns on construction companies [18].

In addition, material costs represented by producer price index variables for cement (PPI_CM), ready-mixed concrete, concrete, rebar, metal, concrete piles, and plastic are vital, given their direct impact on project cost [2]. Labor costs, including rebar, concrete, form work, and plasterer workers cost, are critical in this labor-intensive industry [12].

## 3.2 Feature Engineering

Feature engineering was conducted according to a three-step domain-driven procedure following the approach reviewed in Section 2.2. Step 1 (Hypothesis Formulation): based on theoretical relationships in Section 2, five feature categories were hypothesized, (i) interaction effects between operational efficiency and cost shocks; (ii) temporal propagation through the procurement pipeline; (iii) aggregate cost exposure; (iv) cost-to-revenue ratios; and (v) cross-category cost interactions. Step 2 (Feature Generation): 27 candidate features were generated mathematically from the D1 variables and 11 cost indices. Step 3 (Retention Screening): features were retained if Pearson $|r| > 0.1$ with ROA and VIF < 10 to prevent multicollinearity. All 27 candidates passed, yielding the 36-feature D2 dataset.

### 3.2.1 Interaction Terms

We introduced interaction terms to capture the relationship between the operational efficiency and external cost shocks. The most critical feature is the ATR × PPI_CM, which reflects the hypothesis that firms with higher asset turnover are more sensitive to fluctuations in essential material prices [19].

### 3.2.2 Time-Lagged Variables

Construction projects typically span several years, which means that cost changes during the procurement phase are reflected in financial statements with a delay. We applied one- to four-quarter lags to all material and labor indices. The correlation analysis revealed that a two-quarter lag (six months) had the highest statistical significance with ROA, indicating the time required for material price volatility to affect corporate profitability [20].

### 3.2.3 Composite Cost Indices

Instead of using individual indices in isolation, we developed composite indices for the “material” and “labor” categories. These variables aggregate 11 different indices to provide a holistic view of the cost environment, allowing the model to distinguish between broad market trends and specific commodity shocks [21].

Table 1 summarizes the dataset composition. Dataset 1 (D1) comprises nine financial and macroeconomic variables as the baseline model. Dataset 2 (D2) augments D1 with 11 construction-specific cost indices (eight material, four labor) and 27 engineered features (five interactions, 16 time-lags, three composites, three ratios).

## 3.3 Model Selection Rationale

Model selection was governed by a three-tier comparative framework designed to systematically isolate the contribution of model complexity from feature engineering. Tier 1 (Baseline): moving average (MA) and linear regression (LR) establishes the minimum performance threshold and tests whether feature-engineered inputs can make simple parametric models competitive. Tier 2 (Tree-based ensembles): RF and

XGBoost were prioritized for (a) validated superiority on tabular financial data with moderate sample sizes [6]; (b) native compatibility with SHAP global and local interpretability [14,15]; and (c) robustness to correlated features. RF provides robust predictions through bagging, while XGBoost employs sequential gradient boosting. Tier 3 (Deep learning): ANN and LSTM were included to test whether nonlinear approximation or temporal sequence memory captures additional variance beyond tree-based models. Transformer-based architectures were excluded owing to insufficient sample size (n = 720) and inferior performance on tabular data [6].

The target variable ROA exhibits positive skewness (1.43) and excess kurtosis (7.81). Shapiro–Wilk tests confirmed non-normality (p < 0.01) for 28 of 36 D2 features, corroborating the use of non-parametric tree-based models. To preserve temporal ordering and avoid look-ahead bias, the 720 observations were split chronologically: 70% training (2015 Q1–2021 Q4, n = 504) and 30% test (2022, n = 108, 2023, n = 108). All reported performance metrics are computed on the held-out test set.

### 3.4 Model Evaluation Methods

To evaluate performance scale of ML regression models, differences between predicted and observed values are widely used.

The coefficient of determination $R^2$ measures the proportion of the variance in ROA explained by the model, with values closer to 1 indicating better fit.

$$R^2 = 1 - (\frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(y_i - \bar{y_i})^2} \quad (1)$$

Stacking these differences in absolute values quantifies the degree of model performance, which is expressed as the mean absolute error (MAE).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}| \quad (2)$$

The symmetric mean absolute percentage error (sMAPE) serves as the primary metric, providing balanced accuracy by averaging the actual and predicted values in the denominator, mitigating the traditional MAPE bias.

$$sMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y_i}|}{(|y_i| + |\hat{y_i}|)/2} \times 100 \quad (3)$$

error is squared and the square root is taken, it is restored to the same units, allowing for intuitive interpretation [22]. It is sensitive to outliers, and conducting an evaluation with MAE can enhance accuracy of model performance.

Table 2. Dataset description

| Dataset | Category | Variable | Abbreviation |
|---|---|---|---|
| D1 | Financial | Return to Asset | ROA |
| | | Current Ratio | CR |
| | | Working Capital Ratio | WCR |
| | | Debt Ratio | DR |
| | | Assets Turnover Ratio | ATR |
| | | Cash Flow from Operation | CFO |
| | | Total Sales | TS |
| | | Sales and government expenses | SGE |
| D2 | (Includes all D1 variables above) | | |
| | Material | PPI of Cement | PPI_CM |
| | | PPI of Ready-mixed Concrete | PPI_RE |
| | | PPI of Concrete | PPI_CO |
| | | PPI of Rebar | PPI_RB |
| | | PPI of Metal | PPI_M |
| | | PPI of Concrete Pile | PPI_CP |
| | | PPI of Plastic | PPI_P |
| | Labor | Rebar Labor Cost | Labor_RB |
| | | Concrete Labor Cost | Labor_CO |
| | | Form Work Labor Cost | Labor_FW |
| | | Plasterer Labor Cost | Labor_PL |
| | Engineered Features | (Note Below) | |

*Note: Engineered Features are including ‘Interaction Terms (ATR×PPI_CM, WCR×Material_Comp, DR×Labor_Comp, CFO×PPI_RB, TS×GDP),’ ‘Composite Indices (Material_Comp, Labor_Comp, Total_Cost_Comp),’ ‘Ratio Terms (Material/Sales, Labor/Sales, Material/Labor ratios).’

The root mean squared error (RMSE) represents the standard deviation of the prediction error. Because the

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \qquad (4)$$

### 3.5 Model Interpretation

Interpretability is increasingly becoming a key solution for understanding complex models or datasets [15]. Since understanding the black box is difficult owing to in depth complexity, IML is introduced as a solution. In particular, SHAP examines the importance of individual independent variables by interpreting the results [14]. It provides intuitive results of the relationship between dependent and independent variables to enable researchers to easily find the size of the impact and positive/negative impact scales.

$$f(x) = g(x') = \varphi_0 + \sum_{k=1}^{M} \varphi_k\, x'_k \qquad (5)$$

where $f(x)$ represents the ML, $x$ is the input variable for the model, $M$ is the size of samples, $\varphi_0$ is initial value of SHAP, and $\varphi_k$ is $k^{\text{th}}$ input variable's SHAP result.

### 3.6 Research Framework

To identify the impact of material and labor costs on the financial performance of construction companies and to examine the most suitable regression model, the research procedure is designed as follows:

1. The collected data are classified by financial and construction characteristics: D1, which consists of only financial variables normally used in previous research, and D2, which consists of construction variables (material and labor indices), are added to analyze the performance.
2. The datasets were divided into training (70%) and test (30%) sets. The training set utilized each ML regression method (RF, XGBoost, ANN, and LSTM) to calculate predicted values.
3. The predicted values and test set of each dataset were compared to examine the impact of construction variables on the predicted financial performance. Model evaluation methods were also used to determine the best performance model.
4. SHAP was used to assess the impact of construction variables on the financial performance of construction companies.

## 4 Result

### 4.1 Baseline Comparison

Table 1 presents the comprehensive performance evaluation across six models on both datasets. XGBoost on D2 achieved the best performance with an sMAPE of 130.99%, representing a 3.45% improvement over D1 and outperforming the baseline MA by 11.14%. Tree-based ML models consistently outperformed deep learning approaches, with XGBoost and RF achieving substantially lower error rates than the ANN and LSTM on D2. This pattern confirms recent findings that ensemble methods excel on tabular financial data with moderate sample sizes, where the structural advantages of tree-based algorithms outweigh the pattern-learning capabilities of neural networks [6]. Notably, the simpler ANN architecture outperformed the temporal LSTM model, suggesting that cross-sectional feature interactions may be more important than temporal dependencies in quarterly financial data.

The inclusion of engineered cost features in D2 improved performance across most models. LR showed the largest improvement at 11.52%, followed by LSTM at 6.21% and RF at 5.18%, indicating that feature

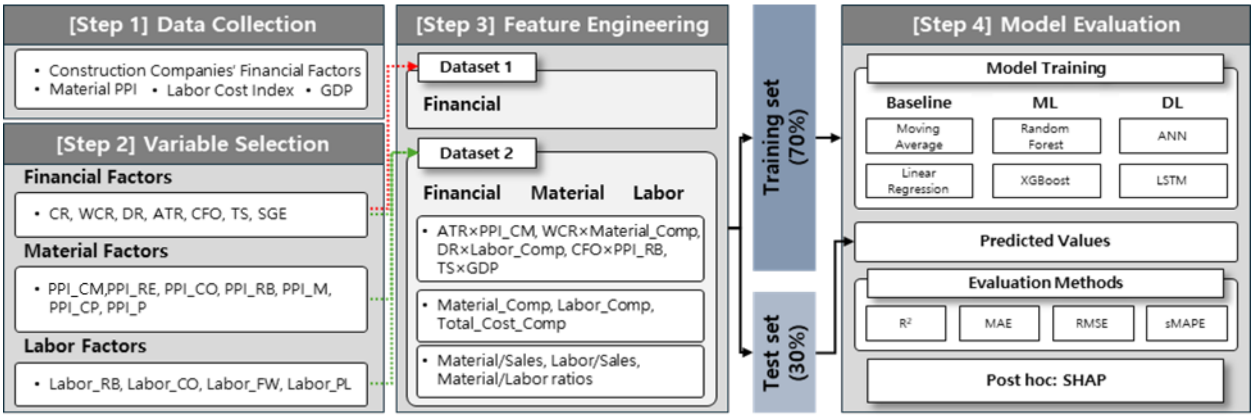


Figure 1. Research framework

Table 3. Results of ROA forecasting performance evaluation

| Dataset | Type | Model | $R^2$ | MAE | RMSE | sMAPE |
|---|---|---|---|---|---|---|
| D1 | Baseline | MA | -0.684 | 1.003 | 1.269 | 142.13 |
| | | LR | -9.203 | 0.878 | 2.074 | 143.64 |
| | ML | RF | -0.072 | 0.737 | 1.022 | 139.89 |
| | | XGB | -0.397 | 0.842 | 1.161 | 134.44 |
| | DL | ANN | 0.037 | 0.693 | 0.968 | 136.70 |
| | | LSTM | -0.278 | 0.818 | 1.102 | 145.50 |
| D2 | Baseline | MA | -0.684 | 1.003 | 1.269 | 142.13 |
| | | LR | -4.184 | 0.873 | 1.714 | 132.12 |
| | ML | RF | -0.071 | 0.732 | 1.02 | 134.71 |
| | | **XGB** | **-0.369** | **0.848** | **1.146** | **130.99** |
| | DL | ANN | -0.084 | 0.746 | 1.026 | 137.73 |
| | | LSTM | -0.341 | 0.84 | 1.128 | 139.29 |

engineering particularly benefits simpler models and those that capture nonlinear interactions. Only the ANN showed marginal degradation of 1.03%, likely due to overfitting on the expanded 36-feature space.

The negative $R^2$ values observed across most models in Table 2 warrant explicit interpretation. All $R^2$ values reported in this study are out-of-sample metrics computed on the held-out test set (2023 Q1–Q4). A negative out-of-sample $R^2$ indicates that the model performs worse than a horizontal mean baseline on unseen data—a documented outcome in highly volatile financial time series where the distributional characteristics of the test period diverge from training [23]. In the present study, this distributional shift is attributable to the post-pandemic material price spikes of 2022–2023, which generated ROA volatility substantially beyond the training-period range. Accordingly, sMAPE is adopted as the primary evaluation criterion, as it is bounded, scale-invariant, and robust to this type of volatility.

### 4.2 Feature Importance Analysis

To ensure the interpretability of results, SHAP analysis was conducted on the D2 dataset. Cost-related features are the primary drivers of the model's predictions.

The engineered cost variables accounted for 56.97% of the total predictive power, significantly outweighing the influence of internal financial ratios. Among these, the interaction term ATR × PPI_CM emerged as the most influential feature, contributing 15.00% of the model's output. This underscores the importance of the synergy between a firm's operational efficiency and external material price shocks.

The analysis further revealed a disparity between the impacts of different cost categories. Material-related features (42.01%) had a 3.2 times greater impact on ROA than labor-related features (13.07%). This quantifiable difference suggests that the financial performance of Korean construction firms is far more sensitive to commodity price volatility than to changes in labor costs.

The model also captured the temporal dynamics of cost reflection. Features with a two-quarter lag (six months) showed higher SHAP values than current-quarter indices. This result indicates a structural delay in the construction industry, where procurement-stage cost fluctuations require approximately six months to be fully reflected in the firm's quarterly financial statements.

## 5 Discussion

Material cost exposure emerged as the dominant profitability driver, with material-related features accounting for 42.01% of SHAP contribution—3.2 times the 13.07% of labour-related features. Critically, the leading predictor was not a raw index but the ATR × PPI_CM interaction (15.00%), revealing that the financial impact of cement price shocks is conditional on a firm's operational efficiency. This extends Seo et al. [10] by demonstrating that efficiency indicators must be interpreted alongside external cost conditions, not in isolation.

Systematic feature engineering consistently improved prediction accuracy across model types. The most telling result is that LR on D2 (sMAPE: 132.12%) outperformed several ML models on D1, confirming that domain-informed feature construction partially substitutes for model complexity—a practically significant finding where data availability is limited [6].

The two-quarter lag reflects the structural mechanics of the construction procurement cycle: cost commitments are locked in at contract signing but recognized in earnings reports 1–2 periods later. This six-month window is strategically actionable, managers can initiate hedging and bidding adjustments in response to observable cost index movements before profitability impact is realized.

The dataset covers 20 major Korean firms, limiting

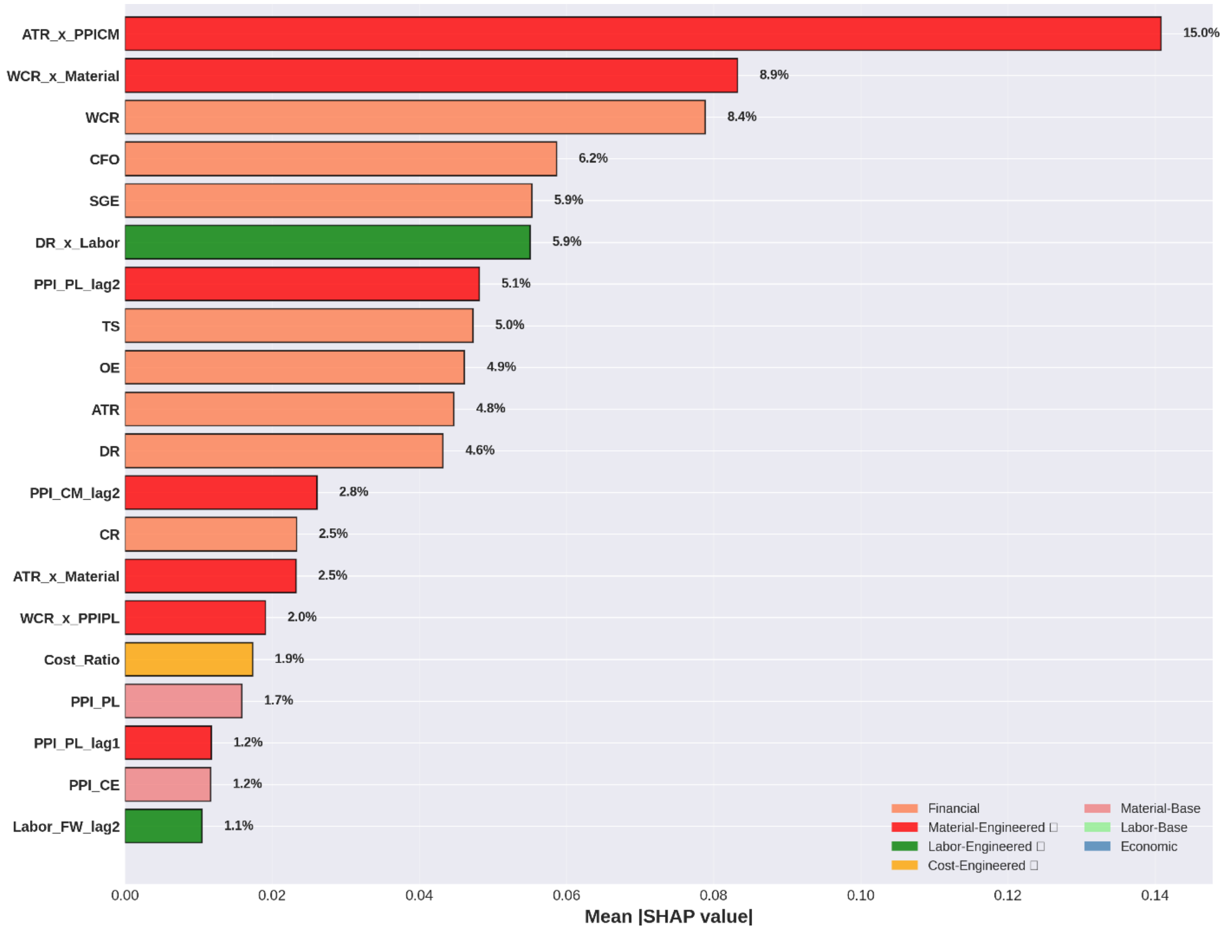


Figure 2. SHAP feature importance analysis using XGBoost and Dataset 2

generalizability to SMEs or international markets. The negative out-of-sample $R^2$ values reflect distributional shift in the 2022–2023 test period due to post-pandemic price spikes [23]. Future work should incorporate global commodity indices, firm-specific procurement data, and ESG-related cost factors.

## 6 Conclusion

This study proposed an IML framework to quantify the impact of material and labor costs on the financial performance of construction firms. By engineering 36 features, including interaction terms and time-lagged variables, and applying SHAP analysis, the study achieved substantial improvement in predictive accuracy compared to baseline approaches. XGBoost on the enhanced dataset achieved the optimal performance with an sMAPE of 130.99%, outperforming the MA baseline by 11.14 percentage points.

The analysis revealed that the engineered cost features accounted for 56.97% of the predictive power of the model, with material prices serving as the primary driver. The interaction between the ATR and PPI_CM emerged as the most significant individual predictor at 15.00%, highlighting the synergistic relationship between operational efficiency and material cost exposure. Material-related features demonstrated a 3.2 times greater impact than labor-related features, reflecting the commodity-intensive nature of construction operations. In addition, the two-quarter time lag between cost volatility and its impact on return on assets provides a proactive management window for strategic adjustments. Tree-based ML models demonstrated clear superiority over deep learning approaches, validating their suitability for tabular financial data with moderate sample sizes.

This study moves beyond black-box predictions to provide transparent, actionable insights for construction financial management. These findings enable firms to prioritize risk management resources for material cost hedging, particularly for high-efficiency operations with elevated commodity exposure. The identified temporal lag allows the proactive adjustment of bidding strategies and contract negotiations, rather than reactive responses to realized losses. The proposed interpretable framework serves as a data-driven tool for construction firms to navigate the increasing volatility of global materials markets and stabilize their long-term financial health in an era of supply chain uncertainty.


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