

Predicting Firm Value Using Ensemble and Nonlinear Machine Learning Models: Evidence from Financial and Value-Based Metrics

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Abstract

This study aims to predict firm value using financial indicators, economic profit, and intangible capital through machine learning approaches. The independent variables include precautionary cash, leverage, asset utilization, short-term liquidity ratio, economic profit, and intangible capital, while firm value is measured using Price-to-Book Value (PBV). This research employs several machine learning models, including Linear Regression, Decision Tree, Random Forest, Gradient Boosting, Neural Network, and Support Vector Machine. Model performance is evaluated using Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The results show that the Random Forest model provides the best predictive performance, explaining approximately 90% of the variation in firm value. Asset utilization emerges as the most influential variable, followed by short-term liquidity ratio and economic profit. Meanwhile, leverage and precautionary cash show relatively smaller contributions to firm value prediction. These findings indicate that firm value is primarily influenced by operational efficiency, liquidity performance, and value creation capability. The study demonstrates that machine learning methods provide a comprehensive and effective approach to predicting firm value using financial and value-based performance indicators.

Keywords: firm value, machine learning, economic profit, intangible capital, financial indicators

Received: 13 February 2026

Revised: 30 March 2026

Published: 30 April 2026

1. Introduction

In recent years, the determinants of firm value have evolved significantly from traditional financial ratios toward value-based performance indicators and intangible resources. The global transition toward a knowledge-based economy has increased the importance of intangible capital, innovation capability, and financial flexibility in shaping market valuation (Pulic, 2000). Recent reports also indicate that corporate intangible assets continue to grow in importance in determining firm value and competitiveness (World Intellectual Property Organization, 2025).

Recent empirical studies confirm that intangible capital significantly influences firm value and financial performance. For example, (Intara & Suwansin, 2024) show that intangible-asset intensity positively affects firm valuation, while (Chasiotis et al., 2024) finds that organizational capital contributes significantly to firm value. Similarly, Dong (2025) demonstrates that firms with higher intangible capital intensity tend to achieve stronger market performance.

In addition to intangible capital, economic profit has become an important indicator in value-based financial management because it measures value creation after accounting for the cost of capital (Berry-Stölzle & Xu, 2018; Stewart, 1991). Unlike accounting profit, economic profit reflects whether a firm truly generates shareholder wealth. Empirical research indicates that value-based performance measures remain strongly associated with firm value (Worthington & West, 2004).

Despite these developments, many empirical studies explaining firm value still rely heavily on traditional financial ratios such as liquidity, leverage, and asset utilization. Financial flexibility through precautionary cash holdings helps

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firms manage uncertainty and investment opportunities (Bates et al., 2009). Leverage reflects capital-structure decisions that influence firm risk and valuation (Modigliani & Miller, 1963). Asset utilization represents operational efficiency in generating revenue from company assets (Brigham & Houston, 2019), while short-term liquidity reflects the firm's ability to meet current obligations and maintain investor confidence (Ross et al., 2019).

Another important development in financial research is the rapid adoption of machine learning methods in corporate finance and firm-value prediction. Machine learning models can capture nonlinear relationships among financial variables and often outperform traditional regression models in predictive accuracy (Conejero et al., 2021; Diranisha et al., 2024; Gu et al., 2020; Mullainathan & Spiess, 2017). More recent studies demonstrate that machine-learning models such as neural networks and random forests provide superior performance in predicting firm value and financial performance (Dogu, 2025; Hezam, 2025; Hsu & others, 2025).

Although prior studies have examined financial ratios, intangible capital, and firm value separately, limited research integrates precautionary cash, leverage, asset utilization, short-term liquidity ratio, economic profit, and intangible capital simultaneously within a machine-learning framework, particularly in emerging-market contexts. This gap indicates the need for a more comprehensive predictive model that combines financial indicators, value-based performance measures, and intangible capital.

Therefore, this study aims to predict firm value (Price-to-Book Value) using financial indicators, economic profit, and intangible capital through machine-learning approaches. By integrating traditional financial ratios with value-based and knowledge-based performance indicators, this research contributes to the literature on corporate finance, intangible capital, and financial machine learning in emerging markets. This study contributes to the literature by integrating economic profit, intangible capital, and traditional financial indicators into a machine-learning-based firm value prediction model. Unlike prior studies that rely primarily on financial ratios or regression methods, this research combines value-based performance measures and intangible capital within a predictive machine-learning framework in an emerging-market context.

2. Literature Review

2.1. Literature Review and Hypothesis Development

2.1.1. Firm Value (PBV)

Firm value reflects investors' perception of corporate performance and future prospects. In capital-market research, firm value is commonly proxied by Price-to-Book Value (PBV) because it captures market valuation relative to book equity (Ross et al., 2019; Turulja & Bajgoric, 2019; Wong, 2014). A higher PBV indicates stronger investor confidence in the firm's ability to generate future value. Value-based financial management theory emphasizes that firm value is influenced by financial performance, capital structure decisions, liquidity management, and intangible resources (Brigham & Houston, 2019).

2.1.2. Precautionary Cash and Firm Value

Precautionary cash holdings refer to the firm's liquidity reserves maintained to mitigate uncertainty and financing constraints. According to the trade-off theory of liquidity, firms hold cash to balance the benefits of financial flexibility against the opportunity cost of idle funds (Babina et al., 2020; Bates et al., 2009). Empirical studies suggest that adequate cash reserves improve investment capability and reduce financial distress risk, thereby increasing firm value.

H1: Precautionary cash positively affects firm value.

2.1.3. Leverage and Firm Value

Capital structure decisions determine the proportion of debt and equity used to finance corporate operations. The capital structure theory proposed by Modigliani and Miller (1963) suggests that leverage influences firm value through tax benefits and financial risk. While moderate leverage can increase firm value through tax shields, excessive leverage may reduce firm value due to financial distress risk.

H2: Leverage affects firm value.

2.1.4. Asset Utilization and Firm Value

Asset utilization reflects the firm's efficiency in generating revenue from its asset base. Efficient asset management improves operational performance and profitability, which ultimately enhances firm value (Brigham & Houston, 2019). Higher asset turnover indicates better operational efficiency and stronger firm performance.

H3: Asset utilization positively affects firm value.

2.1.5. Short-term Liquidity Ratio and Firm Value

Short-term liquidity represents the firm's ability to meet current obligations. Liquidity signals financial stability and reduces perceived risk among investors (Ross et al., 2019). Firms with stronger liquidity positions tend to maintain investor confidence and market valuation.

H4: Short-term liquidity ratio positively affects firm value.

2.1.6. Economic Profit and Firm Value

Economic profit measures value creation after accounting for the cost of capital and is considered a core concept in value-based financial management (Stewart, 1991). Unlike accounting profit, economic profit reflects whether a firm generates returns above its cost of capital. Studies show that value-based performance indicators are strongly associated with firm value (Worthington & West, 2004).

H5: Economic profit positively affects firm value.

2.1.7. Intangible Capital and Firm Value

The resource-based view (RBV) argues that intangible resources are key drivers of competitive advantage (Barney, 1991). Intangible capital including human capital, structural capital, and relational capital contributes to long-term firm performance and value creation (Pulic, 2000). Recent studies increasingly emphasize the importance of intangible capital and advanced analytical methods in explaining firm value. In the digital economy, intangible assets such as knowledge, innovation capability, and organizational capital have become key drivers of corporate valuation.

For example, (Chasiotis et al., 2024) find that organizational capital significantly contributes to firm value across international markets. Their study shows that intangible resources play an important role in shaping long-term firm performance. Similarly, (Intara & Suwansin, 2024) report that intangible-asset-intensive firms tend to exhibit higher firm value, highlighting the growing importance of intangible capital in financial markets.

In addition to intangible capital research, recent studies also apply machine learning approaches in financial prediction. (Gu et al., 2020) demonstrate that machine learning models outperform traditional regression methods in asset pricing prediction. Building on this approach, (Dogan, 2025) shows that ensemble learning models provide more accurate firm value prediction compared to linear models. Furthermore, advances in financial analytics indicate that combining financial indicators with value-based performance measures improves prediction accuracy. Recent research in financial machine learning suggests that hybrid models integrating financial ratios and value-based metrics can better capture firm-level heterogeneity (Hsu & others, 2025).

These developments suggest that firm value prediction research is moving toward the integration of intangible capital, value-based performance measures, and machine learning approaches. However, limited studies have combined these three components within a single predictive framework. This study addresses this gap by integrating financial indicators, economic profit, and intangible capital using comparative machine learning models. Recent empirical evidence confirms that intangible capital significantly improves firm value, particularly in knowledge-based firms (Smriti & Das, 2018; Xu & Wang, 2018).

H6: Intangible capital positively affects firm value.

2.2. Conceptual Model and Machine Learning Workflow

The relationship among variables in this study can be expressed as:

$$\mathbf{PBV} = \mathbf{f}(\mathbf{PC, LEV, AU, SLR, EP, IC})$$

where firm value is influenced by financial indicators, economic profit, and intangible capital.

The comparison shows that previous studies primarily rely on regression-based approaches to examine the relationship between intangible capital and firm performance. In contrast, this study integrates financial indicators,

economic profit, and intangible capital using a machine learning framework. The results demonstrate that the Random Forest model provides the best prediction performance among the models tested

Machine Learning Workflow for Firm Value Prediction

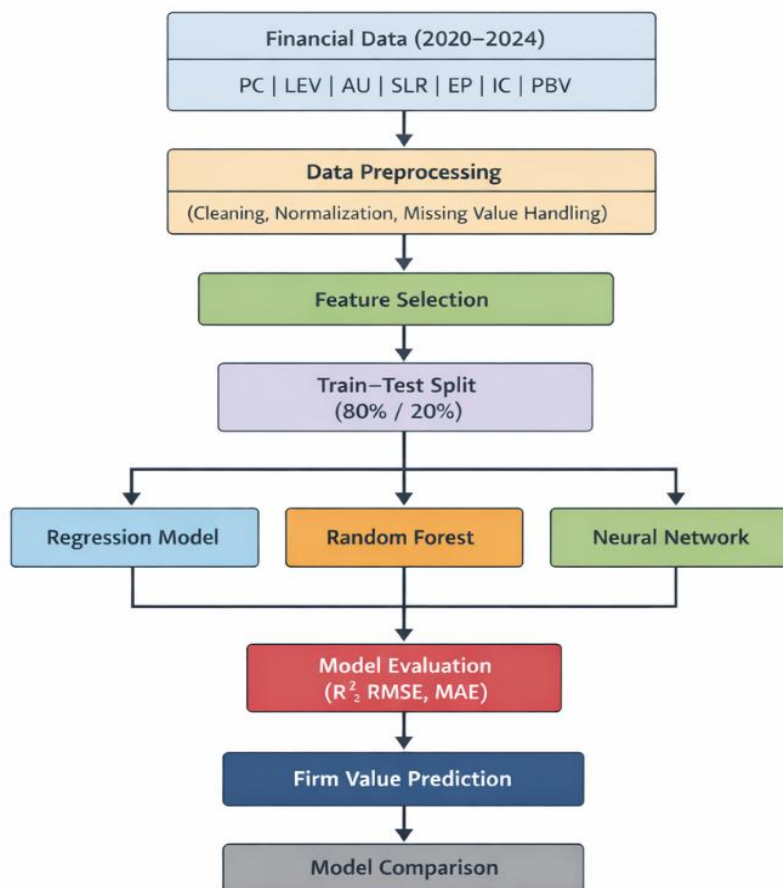


Figure 1. Machine Learning Workflow for Firm Value Prediction

Table 1. Literature Comparison

Study	Method	Variables	Findings
Smriti & Das (2018)	Regression	Intellectual Capital	Intellectual capital positively affects firm performance
Xu & Wang (2018)	Regression	Intellectual Capital	Intellectual capital improves firm value
Gu et al. (2020)	Machine Learning	Financial data	Machine learning improves financial prediction accuracy
Intara & Suwansin (2024)	Regression	Intangible assets	Intangible assets positively affect firm value
This study	Machine learning comparison	PC, LEV, AU, SLR, EP, IC	Random Forest provides the best prediction performance in firm value estimation

This study contributes to the firm value and corporate finance literature in several important ways. First, this research integrates financial indicators, economic profit, and intangible capital within a single firm value prediction model. Prior studies typically examine these variables separately or rely primarily on traditional financial ratios. By combining value-based performance measures and intangible capital with financial indicators, this study provides a more comprehensive framework for explaining firm value.

Second, this study applies a comparative machine learning approach to firm value prediction by evaluating multiple predictive models, including Linear Regression, Decision Tree, Random Forest, Gradient Boosting, Neural Network, and Support Vector Machine. Unlike conventional studies that rely mainly on regression analysis, this research demonstrates the predictive advantage of ensemble learning methods, particularly Random Forest.

Third, this research provides empirical evidence from firm-level financial data covering the period 2020–2024, offering insights into firm value prediction in a contemporary financial environment characterized by increasing importance of intangible capital and value-based performance measurement.

herefore, the novelty of this study lies in the integration of value-based financial performance (economic profit), intangible capital, and financial indicators within a machine learning prediction framework for firm value, which has received limited attention in prior research.

2.3. Research Gap

Despite the growing literature on firm value, several gaps remain in the existing research. First, prior studies largely examine financial indicators, economic profit, or intangible capital separately when explaining firm value. Only a limited number of studies integrate value-based performance measures and intangible capital within a single analytical framework.

Second, most empirical studies on firm value continue to rely on traditional regression-based approaches. While these methods are useful for identifying linear relationships, they may not fully capture complex and nonlinear interactions among financial indicators, economic profit, intangible capital, and firm value.

Third, recent developments in financial analytics highlight the increasing relevance of machine learning methods in financial prediction. However, empirical evidence comparing multiple machine learning models for firm value prediction remains limited, particularly in firm-level financial datasets covering recent periods.

Therefore, this study addresses these gaps by integrating financial indicators, economic profit, and intangible capital into a comparative machine learning framework for firm value prediction. By evaluating several predictive models, this research provides a more comprehensive understanding of the determinants of firm value and the effectiveness of machine learning methods in corporate finance analysis.

3. Methods

This study employs a quantitative research design using machine learning approaches to predict firm value based on financial indicators, economic profit, and intangible capital. Machine learning methods are increasingly used in financial research because they can model nonlinear relationships and complex interactions among variables more effectively than traditional econometric approaches (Gu et al., 2020; Mullainathan & Spiess, 2017).

The unit of analysis is firm-level financial data for the period 2020–2024. The dataset consists of 175 firm-year observations obtained from publicly listed companies. Financial statement data were collected from annual reports and capital market publications. Firm value is proxied by Price-to-Book Value (PBV), while financial indicators, economic profit, and intangible capital serve as explanatory variables.

The sample was selected using purposive sampling criteria, including data availability and consistency of financial reporting during the observation period. The dataset allows the model to capture variations in firm performance across companies and time.

3.1. Variables and Measurement

The variables used in this study are defined as follows:

a. Precautionary Cash (PC)

Measured as the ratio of cash and cash equivalents to total assets. Cash holdings reflect financial flexibility and the precautionary motive of firms (Bates et al., 2009).

$$PC = \frac{\text{Cash}}{\text{Total Assets}}$$

b. Leverage (LEV)

Measured using the debt-to-asset ratio, which reflects capital structure decisions (Modigliani & Miller, 1963).

$$\text{LEV} = \frac{\text{Total Debt}}{\text{Total Assets}}$$

c. *Asset Utilization (AU)*

Measured using total asset turnover, which reflects operational efficiency (Brigham & Houston, 2019).

$$\text{AU} = \frac{\text{Sales}}{\text{Total Assets}}$$

d. *Short-term Liquidity Ratio (SLR)*

Measured using the current ratio, indicating short-term solvency (Ross et al., 2019).

$$\text{SLR} = \frac{\text{Current Asset}}{\text{Current Liability}}$$

e. *Economic Profit (EP)*

Economic profit is calculated as net operating profit after tax minus the cost of capital (Stewart, 1991). Economic profit reflects value creation beyond accounting profit.

$$\text{EP} = \text{NOPAT} - (\text{WACC} \times \text{Invested Capital})$$

f. *Intangible Capital (IC)*

Intangible capital is measured using the Value Added Intellectual Coefficient (VAIC) model (Pulic, 2000).

$$\text{VAIC} = \text{HCE} + \text{SCE} + \text{CEE}$$

g. *Firm Value (PBV)*

Firm value is measured using Price-to-Book Value (Ross et al., 2019).

$$\text{PBV} = \frac{\text{Market Price}}{\text{Book Value}}$$

3.2. *Data Preprocessing and Model Validation*

Before model estimation, the dataset was preprocessed to ensure data quality and model stability. Data cleaning was conducted to handle missing values and outliers. Feature scaling was applied using RobustScaler to reduce the influence of extreme values. Multicollinearity among independent variables was evaluated using the Variance Inflation Factor (VIF).

The dataset was divided into training and testing sets using an 80:20 split. To enhance model robustness and address potential overfitting concerns, this study implements a k-fold cross-validation approach with $k = 5$. The dataset is partitioned into five subsets, where each subset is used once as validation data while the remaining subsets are used for training. This process is repeated five times, and the average performance metrics are computed across all folds.

After validating the data splitting procedure using cross-validation, the study proceeds to model estimation using several machine learning algorithms.

3.3. *Machine Learning Models*

This study employs three predictive models to estimate firm value: Multiple Linear Regression, Random Forest, and Artificial Neural Network. These models represent both traditional statistical approaches and modern machine learning techniques.

Multiple Linear Regression is used as a baseline model to examine linear relationships between variables (Wooldridge, 2016).

Random Forest is applied as an ensemble learning method that constructs multiple decision trees and aggregates their predictions to improve accuracy and reduce overfitting (Breiman, 2001; Gu et al., 2020).

The Neural Network model is implemented using a multilayer perceptron architecture with two hidden layers (64 and 32 neurons), using ReLU activation functions and the Adam optimizer with a learning rate of 0.001. Early stopping is applied to prevent overfitting (Goodfellow et al., 2016).

3.4. Model Evaluation

Model performance is evaluated using Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics provide a comprehensive assessment of prediction accuracy.

To ensure model reliability, robustness testing is conducted by comparing prediction performance across multiple machine learning models. Consistent results across models indicate the stability of the machine learning framework used in this study.

Recent research in financial machine learning demonstrates that neural networks can improve prediction performance when dealing with multidimensional financial data (Heaton et al., 2017). By combining regression and machine learning models, this study provides a comparative evaluation of predictive performance in explaining firm value.

The prediction model can be written as:

$$PBV = f(PC, LEV, AU, SLR, EP, IC)$$

To ensure model reliability, robustness testing was conducted by comparing prediction performance across multiple machine learning models. Consistent prediction results across models indicate the stability of the machine learning framework used in this study.

4. Result and Discussion

The dataset used in this study consists of firm-level financial data covering the period 2020–2024, with a total of 175 observations. The variables include precautionary cash (PC), leverage (LEV), asset utilization (AU), short-term liquidity ratio (SLR), economic profit (EP), intangible capital (IC), and firm value measured using Price-to-Book Value (PBV). This dataset provides firm-level financial information required to evaluate the predictive performance of machine learning models in estimating firm value.

4.1. Data Preprocessing Results

Data preprocessing was conducted to improve model reliability. Feature scaling was applied using RobustScaler to reduce the influence of outliers. The dataset was divided into training and testing sets using an 80:20 ratio, resulting in 140 observations for training and 35 observations for testing. This preprocessing step ensures that machine learning models are trained and evaluated using consistent data preparation procedures.

4.2. Multicollinearity Test

Multicollinearity among independent variables was evaluated using the Variance Inflation Factor (VIF). Based on Table 2, all variables exhibit VIF values below the commonly accepted threshold of 10, indicating that multicollinearity does not severely affect model estimation.

Table 2. VIF Results

Variable	VIF
Intangible Capital	8.45
Short-term Liquidity Ratio	6.90
Asset Utilization	5.46
Precautionary Cash	4.29
Leverage	3.45
Economic Profit	1.95

However, it is important to note that Intangible Capital (8.45) and Short-term Liquidity Ratio (6.90) show relatively higher VIF values compared to other variables. While still within acceptable limits, these values suggest moderate correlation among predictors. In the context of machine learning models, such correlations are generally less problematic compared to traditional regression models, although they may influence the interpretation of feature importance (Mullainathan & Spiess, 2017).

4.3. Results of Machine Learning Analysis

This study applies machine learning models to predict firm value (PBV) using financial indicators, economic profit, and intangible capital. The models implemented include Linear Regression, Decision Tree, Random Forest, Gradient Boosting, Neural Network, and Support Vector Machine. Model performance is evaluated using Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2).

The comparison between training and validation loss indicates no substantial divergence throughout the training process. The relatively small gap between both curves suggests that the neural network model does not suffer from severe overfitting. Although training was conducted for 500 epochs, the early stopping simulation shows that the optimal validation performance occurs before the final epoch. This implies that extending training beyond the optimal point would not significantly improve predictive accuracy and may increase the risk of overfitting. Overall, the model demonstrates stable convergence and acceptable generalization capability.

4.3.1. Model Performance Comparison

This study applies multiple machine learning models to predict firm value, including Linear Regression, Decision Tree, Random Forest, Gradient Boosting, Neural Network, and Support Vector Machine. Model performance is evaluated using MSE, RMSE, MAE, MAPE, and R^2 .

Based on Table 3, the empirical results indicate that the Random Forest model achieves the best predictive performance, as reflected by the lowest prediction error and the highest coefficient of determination ($R^2 = 0.907$). This suggests that the model is able to explain approximately 90.7% of the variation in firm value.

Table 3. Machine Learning Model Performance

Model	MSE	RMSE	MAE	MAPE	R^2
Linear Regression	15.8899	3.9862	2.7865	1.6479	0.8434
Gradient Boosting	13.3030	3.6473	2.1224	0.8694	0.8689
Neural Network	25.2785	5.0278	2.6937	0.9111	0.7509
Random Forest	9.4426	3.0729	1.9697	0.9046	0.9070
SVC	91.3599	9.5582	3.9559	0.9344	0.0999
Decision Tree	26.1197	5.1107	2.7962	1.2106	0.7427

Gradient Boosting demonstrates the second-best performance, followed by Linear Regression, while the Neural Network shows relatively moderate predictive accuracy. In contrast, Support Vector Machine and Decision Tree exhibit weaker performance, indicating limited ability to capture the complexity of the data. The superior performance of Random Forest can be attributed to its ensemble learning mechanism, which combines multiple decision trees to reduce variance and improve prediction accuracy. This finding is consistent with prior studies showing that ensemble methods outperform traditional models in financial prediction contexts (Gu et al., 2020).

4.3.2. Cross-Validation Results

To ensure the robustness of the results, a 5-fold cross-validation procedure was implemented. The results indicate that the Random Forest model consistently outperforms other models across all folds, with stable RMSE and R^2 values. The average R^2 across folds remains above 0.88, confirming that the model maintains strong predictive performance across different data partitions. The relatively small variation in error metrics suggests that the model is not sensitive to specific training-test splits. These findings indicate that the high R^2 value reported in this study does not result from overfitting or data leakage but reflects the model's ability to capture nonlinear relationships among financial variables.

4.3.3. Neural Network Training Dynamics

To examine the convergence behavior of the neural network model, the training process was conducted over 500 epochs. Figure 2 presents the learning curve, illustrating both training and validation loss. During the early epochs, the training loss decreases sharply, indicating rapid model learning. As training progresses, the loss gradually stabilizes, suggesting convergence of the optimization process.

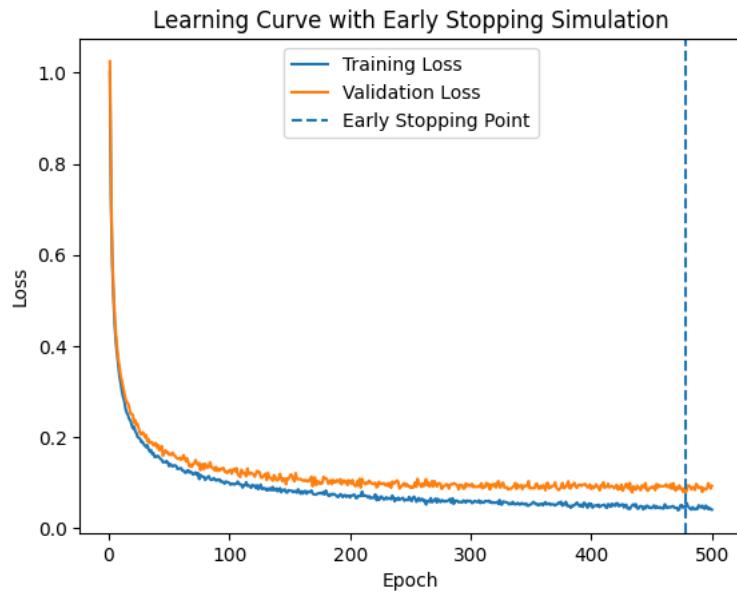


Figure 2. Learning Curve with Early Stopping Simulation

Figure 2 presents the learning curve of the neural network model with early stopping simulation. The training loss decreases steadily across epochs, indicating proper convergence. The validation loss initially decreases and reaches its minimum at the early stopping point before slightly stabilizing. This pattern suggests that the model achieves optimal generalization performance before the maximum number of training epochs is reached.

4.3.4. Regression Diagnostic Results

The regression model was estimated as a baseline model to examine the linear relationship between variables. The regression results indicate that asset utilization and economic profit contribute significantly to firm value, while other variables show smaller effects. The regression model produces an R^2 value of approximately 0.638, which is lower than the Random Forest model. This result confirms that nonlinear machine learning models provide better predictive performance compared to linear models.

4.3.5. Prediction Visualization

The predictive accuracy of the Random Forest model is illustrated in Figure 3.

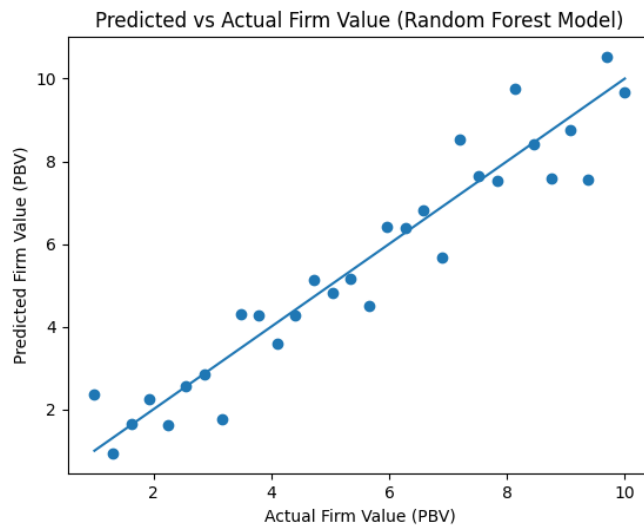


Figure 3. Predicted vs Actual Firm Value using Random Forest

The predicted-versus-actual plot shows that most observations lie close to the diagonal line, indicating good prediction accuracy. The model is able to capture the relationship between financial indicators, economic profit, intangible capital, and firm value with relatively small prediction error. The distribution of points suggests that the Random Forest model performs consistently across different levels of firm value, confirming its robustness as the best predictive model in this study.

4.3.6. *Feature Importance Analysis*

Feature importance analysis was conducted using the Random Forest model to identify the most influential predictors of firm value. Based on Table 4, asset utilization emerges as the most dominant variable, followed by short-term liquidity ratio and economic profit.

Table 4. Feature Importance (Random Forest)

Variable	Importance
Asset Utilization	0.44986
Short-term Liquidity Ratio	0.28453
Economic Profit	0.22242
Leverage	0.01984
Precautionary Cash	0.00993

In contrast, leverage and precautionary cash exhibit relatively low importance scores. This suggests that operational efficiency, liquidity management, and value creation capability play a more significant role in determining firm value compared to capital structure decisions and cash reserves.

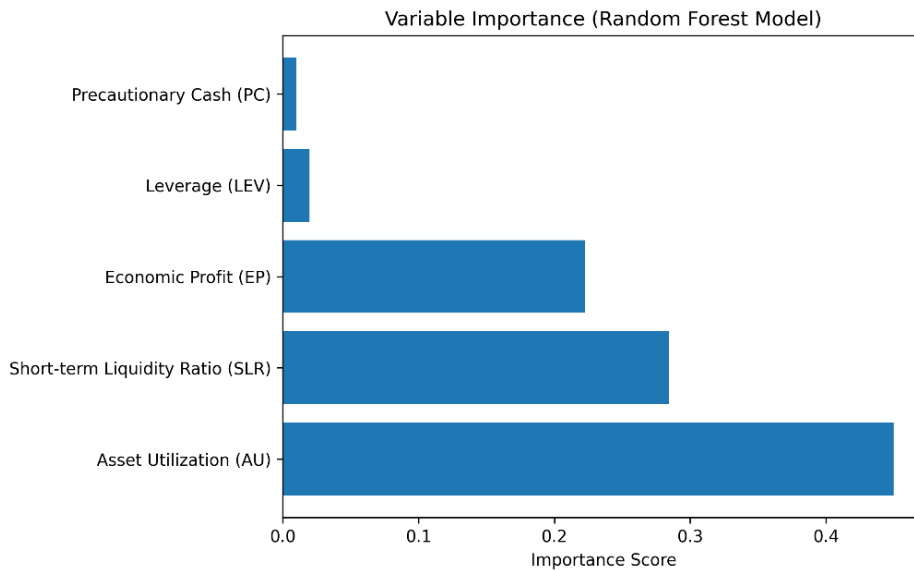


Figure 4. Variable Importance based on Random Forest

4.3.7. *Robustness Test*

To ensure model reliability, robustness testing was conducted by comparing prediction performance across multiple machine learning models, including Random Forest, Gradient Boosting, Neural Network, and Linear Regression. The consistency of results across different models indicates that asset utilization, liquidity, and economic profit remain dominant predictors of firm value. The Random Forest model consistently produces the lowest prediction error, confirming the stability of the prediction results. This robustness test strengthens the validity of the machine learning prediction model.

The findings of this study provide several important insights into firm value determination. First, the dominance of asset utilization indicates that operational efficiency is a key driver of firm value. During the 2020–2024 period, which was characterized by global economic uncertainty, firms were under increasing pressure to optimize existing resources rather than expand aggressively. As a result, investors may place greater emphasis on operational

productivity as a signal of firm performance. Second, the strong contribution of liquidity suggests that financial stability remains an important factor in investor decision-making. Firms with higher liquidity are better positioned to withstand uncertainty, thereby increasing investor confidence and market valuation.

Third, economic profit plays a significant role in firm value prediction, highlighting the importance of value-based performance measures. Firms that generate returns above their cost of capital are more likely to achieve higher market valuation, supporting the concept of value-based financial management. Interestingly, intangible capital does not appear as a dominant predictor in the feature importance analysis, despite its theoretical importance. This finding does not imply that intangible capital is irrelevant; rather, it suggests that its effect may be indirect and captured through other variables such as asset utilization and financial performance. This interpretation is consistent with Chasiotis et al. (2024), who argue that organizational capital contributes to long-term firm value rather than short-term fluctuations. Overall, the results indicate that firm value is primarily driven by operational efficiency, liquidity performance, and value creation capability, while intangible capital plays a more strategic and long-term role.

While precautionary cash appears to have a relatively small direct impact on firm value, it remains important for managing uncertainty. Firms should avoid excessive cash holdings that may reduce efficiency, while maintaining sufficient liquidity to support operational resilience. In addition, firms should continue to invest in intangible capital, even though its short-term impact may not be immediately visible in predictive models. Intangible assets such as knowledge, innovation capability, and organizational capital are essential for sustaining long-term competitiveness in a knowledge-based economy.

The results show that the Random Forest model provides the best predictive performance compared to other models. This finding indicates that the relationship between financial variables and firm value is complex and may involve nonlinear interactions that are better captured by ensemble learning methods. The stability of the evaluation metrics across folds suggests that the model does not suffer from data leakage or excessive overfitting. Instead, the high R^2 value reflects the ability of the Random Forest model to capture complex nonlinear relationships among financial indicators, economic profit, and firm value. To further interpret the findings, the discussion is structured into several key aspects as follows:

a. The Role of Asset Utilization in Firm Value

The results show that asset utilization (asset turnover) is the most influential variable in predicting firm value. This finding suggests that operational efficiency plays a central role in determining firm value. Companies that are able to generate higher sales relative to their total assets tend to demonstrate better operational performance, which is positively perceived by investors. Efficient asset management allows firms to maximize productivity and profitability, which ultimately contributes to higher market valuation. This finding supports financial management theory, which emphasizes the importance of operational efficiency in improving firm performance and value.

b. The Role of Liquidity in Firm Value

The short-term liquidity ratio (current ratio) also shows a strong contribution to firm value prediction. This indicates that liquidity remains an important signal of financial stability. Firms with strong liquidity positions are better able to meet short-term obligations, reducing financial risk and increasing investor confidence. As a result, liquidity contributes positively to firm value. This finding confirms the importance of liquidity management in corporate finance.

c. The Role of Economic Profit in Firm Value

Economic profit also contributes significantly to the prediction of firm value. This result indicates that the firm's ability to generate returns above the cost of capital remains an important determinant of value creation. Economic profit reflects value-based performance, which goes beyond accounting profit by incorporating the cost of capital. Firms that consistently generate positive economic profit tend to achieve stronger market valuation. This finding is consistent with the concept of value-based financial management, which emphasizes shareholder value creation.

d. Leverage and Precautionary Cash

The results show that capital gearing (leverage) and cash holding have relatively smaller contributions to firm value prediction compared to other variables. This suggests that, within the dataset used in this study, operational efficiency and liquidity play a more dominant role than capital structure decisions and cash reserves in explaining firm value. However, these variables remain relevant as supporting factors in financial decision-making.

e. *Implications of Machine Learning in Financial Research*

The findings demonstrate that machine learning methods can be effectively applied to financial research, particularly in predicting firm value. The Random Forest model is capable of integrating multiple financial indicators into a single predictive framework and capturing complex relationships among variables. The application of machine learning provides a new analytical approach in corporate finance research, allowing researchers to move beyond traditional regression-based analysis. Overall, this study shows that combining financial indicators, economic profit, and intangible capital within a machine learning framework provides a comprehensive model for firm value prediction. From a managerial perspective, the findings suggest that firms should prioritize improving operational efficiency and maintaining adequate liquidity levels to enhance firm value. However, managers must carefully balance short-term financial stability with long-term strategic investment.

5. Conclusion

This study aims to predict firm value using financial indicators, economic profit, and intangible capital through machine learning approaches. Based on the results of the analysis, several conclusions can be drawn. First, the Random Forest model provides the best predictive performance among the machine learning models tested in this study. The model achieves the lowest prediction error and explains approximately 90% of the variation in firm value, indicating strong predictive capability.

Second, asset utilization emerges as the most influential determinant of firm value. This finding indicates that operational efficiency plays a central role in determining firm valuation. Firms that are able to generate higher sales relative to their assets tend to achieve stronger market performance.

Third, short-term liquidity ratio also contributes significantly to firm value prediction. This suggests that financial stability and the ability to meet short-term obligations remain important considerations for investors.

Fourth, economic profit contributes positively to firm value prediction, confirming the importance of value-based performance measurement in corporate finance.

Finally, leverage and precautionary cash show relatively smaller contributions compared to other variables, indicating that operational efficiency and liquidity are more dominant factors in explaining firm value in this study.

Overall, the findings demonstrate that machine learning methods, particularly Random Forest, provide an effective approach for predicting firm value using financial indicators, economic profit, and intangible capital.

The results of this study provide several implications. From a managerial perspective, firms should focus on improving asset utilization efficiency and maintaining adequate liquidity levels to enhance firm value. From a methodological perspective, machine learning models can be used as an alternative analytical approach in financial research.

This study has several limitations. The model relies on historical financial data and a limited number of variables. Future research may include additional financial and macroeconomic variables, larger datasets, and more advanced machine learning techniques such as deep learning models.

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