

Enhancing the accuracy of stock return movement prediction in Indonesia through recent fundamental value incorporation in multilayer perceptron

Stiven Agusta, Fuad Rakhman, Jogiyanto Hartono Mustakini and Singgih Wijayana

*Department of Accounting, Faculty of Economics and Business,
Gadjah Mada University, Yogyakarta, Indonesia*

Abstract

Purpose – The study aims to explore how integrating recent fundamental values (RFVs) from conventional accounting studies enhances the accuracy of a machine learning (ML) model for predicting stock return movement in Indonesia.

Design/methodology/approach – The study uses multilayer perceptron (MLP) analysis, a deep learning model subset of the ML method. The model utilizes findings from conventional accounting studies from 2019 to 2021 and samples from 10 firms in the Indonesian stock market from September 2018 to August 2019.

Findings – Incorporating RFVs improves predictive accuracy in the MLP model, especially in long reporting data ranges. The accuracy of the RFVs is also higher than that of raw data and common accounting ratio inputs.

Research limitations/implications – The study uses Indonesian firms as its sample. We believe our findings apply to other emerging Asian markets and add to the existing ML literature on stock prediction. Nevertheless, expanding to different samples could strengthen the results of this study.

Practical implications – Governments can regulate RFV-based artificial intelligence (AI) applications for stock prediction to enhance decision-making about stock investment. Also, practitioners, analysts and investors can be inspired to develop RFV-based AI tools.

Originality/value – Studies in the literature on ML-based stock prediction find limited use for fundamental values and mainly apply technical indicators. However, this study demonstrates that including RFV in the ML model improves investors' decision-making and minimizes unethical data use and artificial intelligence-based fraud.

Keywords Fundamental value, Artificial intelligence, Multilayer perceptron, Stock prediction, Market efficiency, Machine learning

Paper type Research paper

JEL Classification — C12, C45, G14, G17, M41

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1. Introduction

The application of machine learning (ML) models as artificial intelligence (AI) techniques to predict stock price movement has been growing in popularity (Blasco *et al.*, 2024; Manogna and Anand, 2023; Ozbayoglu *et al.*, 2020). These models process fundamental and technical analysis inputs to increase accuracy (Nti *et al.*, 2020; Olorunnimbe and Viktor, 2023). However, existing research on ML-based stock prediction finds limited use for fundamental value (FV) and mainly applies technical indicators (TI) (Blasco *et al.*, 2024; Bustos and Quimbaya, 2020; Jiang, 2021; Nti *et al.*, 2020; Olorunnimbe and Viktor, 2023). Meanwhile, conventional financial accounting studies rigorously update fundamental determinants of stock return; we define these determinants as recent fundamental value (RFV). RFV, as the updated FV, can improve the accuracy of the ML models. Therefore, it is essential to explore the potential role of RFV in enhancing ML predictive accuracy.

We investigate whether the RFVs of Indonesian public companies improve the accuracy of the ML model for stock prediction. The investigation in Indonesia is interesting since the country could exemplify promising AI development among developing countries, particularly as it strives toward AI ethics development. Indonesia has defined its national AI strategy for 2020–2045 (BPPT, 2020). The strategy is crucial to regulating AI utilization and for coping with the risk of data manipulation and the issues of legal, ethical, privacy and quality regarding unstructured data (OECD, 2021). Since the issuance of the guidelines, Indonesia has performed better on AI implementation than other developing countries. Among the top three developing countries with the highest growth of AI readiness index from their AI strategy's issuance year to 2023, Indonesia ranked 3rd in the growth and 1st in the index value (or 42 out of 193 countries) (Insights, 2024). As developed countries emphasize ethics frameworks (Demaidi, 2023), countries with higher rankings in the AI readiness index should prioritize AI ethics development.

However, Indonesia faces several challenges in developing AI ethics, particularly in the financial sector. Ethical issues have been a major concern in East Asia (Insights, 2024). In Indonesia, the issues are more pressing, as evidenced by investment fraud phenomena involving AI applications that use unreliable data with losses of at least IDR 13.02 trillion (USD 867.8 million) during 2021–2023 (Santika, 2023). Financial literacy and digital financial literacy indicators can elucidate Indonesia's fraud phenomena through the level of financial decision-making capabilities using available information and technology (OECD, 2023). In 2022, based on the ratio of adults achieving the minimum threshold in (digital) financial literacy scores, Indonesia ranked (28th) 33rd out of (28) 39 countries (OECD, 2023). This result indicates the underutilization of FV. Structured FV from financial reports can mitigate ethical issues in using AI in the financial sector through the transparency, fairness and accountability of its sources (IASB, 2018). Also, the national seminar on AI implementation in financial services affirmed the essential role of FV in stock prediction (OJK, 2023). Therefore, validating RFV-driven stock prediction accuracy in Indonesia is crucial to affirming the pivotal role of FV and demonstrating its credibility in addressing AI ethical issues in the financial sector. The finding is expected to provide practical benefits through improved investment decisions, especially for investors in developing countries.

Empirically, conventional accounting and ML-based studies hold different views on predicting stock price direction. Conventional financial accounting studies make a distinguished contribution based on accounting and non-accounting data (Dunham and Grandstaff, 2022; Nicolò *et al.*, 2023). Investors benefit from timely and valuable information conveyed in accounting data. Subsequently, numerous conventional accounting studies examined the key values of fundamental analysis (see Appendix A). Therefore, critical FVs calculated from accounting and non-accounting data can forecast stock returns. By comparison, ML studies revealed the primary role of TI input (Olorunnimbe and Viktor, 2023; Picasso *et al.*, 2019). Various stock price calculations define TI ratios for the ML model's input

(see [Appendix B](#)). In conclusion, sophisticated TIs processed from stock prices can predict stock movements.

Drawing from contrasting perspectives in ML and conventional accounting studies, we hypothesize that RFV can improve the prediction accuracy of the ML model. Given that RFVs are mainly based on long data ranges (e.g. quarterly), we assume a long RFV data range increases predictive accuracy. ML analysis offers various methods for testing hypotheses, with the artificial neural network (ANN) being the most commonly utilized ([Kumbure et al., 2022](#)). Here, we select the multilayer perceptron (MLP) model, a subtype of ANN. This model offers broad applicability ([Nti et al., 2020](#)), high accuracy in forecasting index volatility ([Qian et al., 2020](#)) and deep learning capability ([Olorunnimbe and Viktor, 2023](#); [Ozbayoglu et al., 2020](#)). Furthermore, a deep learning model (e.g. MLP) is a subset of ML that requires extensive computational time. This model allows testing with only a few specific companies (e.g. [Hu and Yang, 2024](#); [Weng et al., 2017, 2018](#); [Xu et al., 2024](#)). In this part, we analyze 900 input data sets from 10 companies in the September 2018 to August 2019 day-trading range. The MLP model processes the input data of RFV and TI variables under various scenarios to analyze the prediction accuracy of stock return movement.

Our study is expected to make two contributions. Empirically, it shows that FVs defined from recent conventional accounting studies are essential for ML stock prediction models. Also, using the Indonesian stock market as our sample enriches the existing ML literature among emerging markets. The findings may prompt market regulators to regulate RFV-based AI applications for predicting stock movements. Also, it benefits practitioners, analysts and investors by providing them with another perspective when developing self-AI tools. Those activities can improve investor decision-making, reduce AI-based fraud and minimize unethical data use.

The following section discusses the literature review and the development of the hypotheses. [Section 3](#) explains the data and methods applied in this study. [Section 4](#) provides the results, discussion and implications. [Section 5](#) shows the robustness tests. Finally, the last section presents the conclusions.

2. Literature review and hypotheses development

2.1 Theoretical background

Theoretically, stock movement prediction analysis challenges the efficient market hypothesis (EMH) by assuming that the market is not fully efficient ([Blasco et al., 2024](#); [Hsu et al., 2016](#); [Kumbure et al., 2022](#); [Malkiel, 2003](#); [Nicolò et al., 2023](#); [Shynkevich et al., 2017](#)). [Fama \(1970\)](#) formulated the EMH theory and stated three market forms: strong, semi-strong and weak. Under this theory, the market fully absorbs and reflects the information into the stock price. However, certain released information shows a delayed reaction due to the anomaly issue ([Nicolò et al., 2023](#)), as supported by indications that future stock prices can be partially expected ([Malkiel, 2003](#)). As such, the capital market efficiency research requires further analysis ([Nicolò et al., 2023](#)).

In Indonesia, at least two evidence support the market inefficiency argument. First, high cross-ownership structures in numerous public companies in Indonesia lead to information asymmetry ([Li et al., 2023](#)). Second, while Asian countries like Indonesia have shown improved efficiency ([Kim et al., 2019](#)), the market in Indonesia remains inefficient ([Yaya et al., 2024](#)). Also, other studies suggested stock market predictability in the East Asian markets. For example, anomalies are found in the Vietnam stock market ([Huang et al., 2023](#); [Lokanan et al., 2019](#)). Therefore, stock prediction analysis and EMH testing should focus on emerging markets like Indonesia. This argument is supported by the finding that emerging markets still suffer from market inefficiencies and lax law enforcement ([Hsu et al., 2016](#); [Nicolò et al., 2023](#)).

2.2 FVs application in ML studies and RFVs' role in stock prediction

The analysis of potential FV for stock price prediction requires various methods. Conventional studies apply fundamental analysis to identify mispriced stocks for investment decisions (Nicolò *et al.*, 2023). These studies have also pioneered methods such as technical analysis (Brock *et al.*, 1992) for short-term gains and event studies (Ball and Brown, 1968) for detecting abnormal returns. Both methods emphasize stock price volatility driven by investor responses to FV (Zhao and Li, 2022). Conventional studies mainly rely on linear models to assess FV and stock price relationships (Dunham and Grandstaff, 2022). However, other models are required since linear models cannot examine nonlinear relationships (Ahmed *et al.*, 2022; Dunham and Grandstaff, 2022). Despite efforts to develop nonlinear models, further research is still needed (Barth *et al.*, 2023). ML methods provide an alternative option as they utilize nonlinear models. These models outperform linear models in predicting stock movements (Manogna and Anand, 2023) and broaden econometrics by combining computer science with stock market data (Olorunnimbe and Viktor, 2023).

Nevertheless, research in the literature on ML for stock prediction indicates a lower usage of FV than TI when testing the accuracy of the ML model. Nti *et al.* (2020) found that only 23% of ML studies from 2007 to 2018 used FV, while 66% employed TIs. FV from financial news and social media are the most commonly used inputs. Similarly, Jiang (2021) noted that around 70% of samples from 2017 to 2019 relied on TI, while fundamental and macroeconomic data accounted for less than 20%. Kumbure *et al.* (2022) indicated that 62% of articles sampled from 2000 to 2019 used TI, while the usage of fundamental and macroeconomic data stood at 20.07%. Lastly, Dakalbab *et al.* (2024) explained that from 2015 to 2023, only 12% of their samples used FV, while 71% applied TI.

Furthermore, FV calculated from unstructured data has gained more attention in ML research (e.g. Wang *et al.*, 2023; Weng *et al.*, 2017, 2018) than structured data. Structured data is organized in a defined format, typically in tables or columns, such as financial reports, financial status, political data and climate data (Cao *et al.*, 2024; Nti *et al.*, 2020). Meanwhile, unstructured data requires conversion or initial data processing into categorical or numerical data, like texts, news, satellite imagery, or tweets (Olorunnimbe and Viktor, 2023).

Structured data has not been widely used in ML studies due to its limitations, such as low data frequency (e.g. monthly, quarterly, or annual) (Bustos and Quimbaya, 2020; Henrique *et al.*, 2019; Olorunnimbe and Viktor, 2023) and inaccurate reporting dates (Jiang, 2021). As a result, FV calculations based on structured data are generally considered less effective in predicting daily stock movements. However, conventional accounting studies widely apply structured data in defining FV. Accounting information is still a significant consideration in stock investment decision-making (Agbodjo *et al.*, 2022; Cao *et al.*, 2024). Although historical, structured data can influence future stock movements due to market anomalies (Choy *et al.*, 2023). For example, the earning announcement strategy considers earning surprise in directing the stock price reaction (Prasad and Prabhu, 2020; Tsafack *et al.*, 2023). Therefore, FV derived from structured data is supposed to remain valuable for increasing the accuracy of the ML model of stock prediction. Also, the data is advantageous because it is primarily freely available from companies or governments and thus raises fewer ethical concerns regarding transparency, fairness and accountability.

RFVs are evidence of FVs' valuability since conventional accounting studies consistently (re)define FVs for stock return analysis. In this part, FV is stated as RFV when it is derived from recent conventional studies. We selected 17 recent studies published in leading accounting journals [1] in the last five years (see Table 1) and used their findings in our study.

No	Author	Summary
1	Akbas et al. (2020)	Information content and insider investment horizons relationship influence future returns
2	Alti and Titman (2019)	Systemic factors and the company's character-driven return predictability relationship explain fundamental value evolution
3	Andreou et al. (2020)	Valuation failure impacts the negative relationship between stock returns and risk distress
4	Armstrong et al. (2019)	Accounting quality impacts corporate financial policies
5	Atanasov et al. (2020)	Cyclical consumption and consumption-based variables predict stock returns
6	Balakrishnan et al. (2019)	Stock price competition level affects price asymmetry
7	Barberis et al. (2021)	The asset pricing model evaluates risk and stock market anomalies
8	Beaver et al. (2020)	Concurrent information increases investor response to earnings announcements
9	Bird et al. (2019)	Earnings management correlates with earning surprise facts: discontinuity distribution and abnormal earnings
10	Bonsall et al. (2020)	The high demand for financial reports in high market uncertainty during earnings announcements leads to higher media coverage
11	Gallo and Kothari (2019)	Accounting quality affects corporate returns' sensitivity to financial policy news
12	He and Narayanamoorthy (2020)	Earnings acceleration predicts future corporate return excess
13	Lewellen and Resutek (2019)	Accruals correlate with subsequent earnings
14	Nagar et al. (2019)	Government economic policy uncertainty has significant information
15	Nallareddy et al. (2020)	Temporary accrual component shifts and operating environment affect cash flow and earnings forecast predictive ability
16	Penman and Zhang (2020)	Accounting conservatism correlates with capital cost
17	Tsileponis et al. (2020)	Voluntary financial news of the company's performance support financial media coverage

Source(s): Authors' work

Table 1.
Summary of a sample
of recent conventional
accounting studies

Both accounting and non-accounting data sources form RFVs (see Table 1). Accounting-based RFVs utilize accounting data, e.g. accrual ([Barberis et al., 2021](#)). Economics-based RFVs rely on economic data, e.g. the economic uncertainty index ([Nagar et al., 2019](#)). Stock-based RFVs are derived from stock price and volume analysis, e.g. 1-day U-statistic ([Beaver et al., 2020](#)). Other-based RFVs encompass diverse fields, e.g. media coverage analysis ([Bonsall et al., 2020](#)). Lastly, combination-based RFVs use combined data, e.g. the cost of equity capital ([Balakrishnan et al., 2019](#)). The usage of various forms means that RFVs are suitable input data for ML models to predict stock price movement. Therefore, we hypothesize:

H1. RFVs improve the predictive accuracy of ML models for stock return direction.

Furthermore, to ensure robust stock movement prediction results, data reporting range differences should be examined ([Dunham and Grandstaff, 2022](#)). ML studies prefer shorter data ranges to enhance accuracy ([Hsu et al., 2016](#); [Olorunnimbe and Viktor, 2023](#)) and address infrequent reporting ([Bustos and Quimbaya, 2020](#); [Henrique et al., 2019](#); [Jiang, 2021](#)), thus limiting FV's effectiveness in predicting daily stock movements ([Bustos and Quimbaya, 2020](#)). However, while some FV calculations employ shorter reporting data ranges, such as daily or monthly intervals (e.g. [Barberis et al., 2021](#); [Bird et al., 2019](#)), FV calculations typically involve longer reporting data ranges due to the periodic nature of financial reporting (e.g. quarterly or yearly intervals). This indicates that the longer reporting data range has a more vital value of information than the shorter one. Therefore, the following hypothesis is:

3. Methodology

3.1 MLP illustration as the platform for analysis

To develop a method for analyzing the RFV's role, we selected MLP. MLP is a nonlinear prediction method involving bias (α) and weight terms (β) that can be compared to regression methods (see Figure 1) (Aryadoust and Baghaei, 2016). This model processes nonlinear weighted data input in the hidden layer's activation unit and minimizes errors through the backpropagation step before presenting the final output (Haykin, 1998). Hence, MLP offers greater flexibility and precision than linear models due to its freedom from linear function constraints (Aryadoust and Baghaei, 2016).

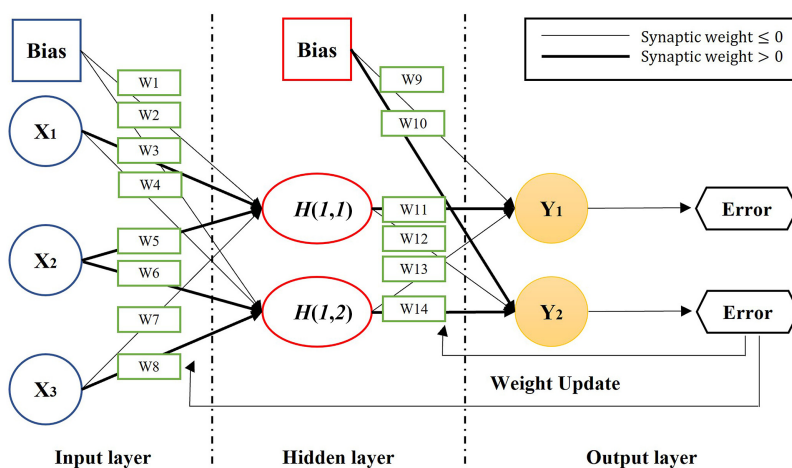
The neurons form the interconnection layer within the MLP method (Asadi et al., 2012). The nonlinear activation function σ is embedded in every layer's neuron containing input x , weight w and bias b terms (Ozbayoglu et al., 2020). The accumulation of weighted input in each neuron of the preceding layer produces the output y :

$$y_i = \sigma \sum_i w_i x_i + b_i \tag{1}$$

Thus, for example, if the method consists of one hidden layer, the value calculation in the output y_t is as below (Asadi et al., 2012):

$$y_t = f \left(\sum_{j=1}^n w_{1,j} f \left(\sum_{i=1}^m w_{0,ij} x_i + b_{0,j} \right) \right) + b_1 + \varepsilon_t \tag{2}$$

where m and n consecutively are the input node and hidden node numbers; f is the nonlinear activation such as sigmoid or hyperbolic tangent; and ε is the error term.



Source(s): Figure modified from Aryadoust and Baghaei (2016)

Figure 1. MLP model

3.2 Data selection

The study utilized various data sources. These included financial report data from Osiris; daily news data from Google News, stockbit.com and Wikipedia Hit; daily stock, market price data and other information from investing.com; and Google trends. A one-year trading-day period from September 2018 to August 2019 was employed to avoid unusual events that affect anomalies, such as commodity price declines, political events, or global pandemics. For example, the corporate announcement did not have a proper impact during the worst time of the COVID-19 pandemic (Pandey *et al.*, 2022). The short-sample period approach is also common in ML studies. For example, Li *et al.* (2014) and Picasso *et al.* (2019) applied a one-year data period.

Due to the high computational demands, deep learning models (e.g. MLP) often utilize small sample sizes, such as three samples (Li *et al.*, 2020) or even one sample (e.g. Weng *et al.*, 2017, 2018). Hence, a few samples are acceptable for our study. We ranked the 646 listed companies based on the average daily trading volume in 2019 and divided them into five quartiles. From each quartile, we excluded the banking and finance sectors. Then, we omitted stocks with fewer than 400-day trades or daily average prices below IDR 100 in 2019 to avoid data insufficiency and low anomalies. Lastly, we selected the top two companies from each quartile (see Table 2). These samples represent the level of investor interest in companies based on total trading volume.

3.3 Methods, scenario and model evaluation

This study used the modified method from Weng *et al.* (2017) to represent each category input, as shown in Figure 2.

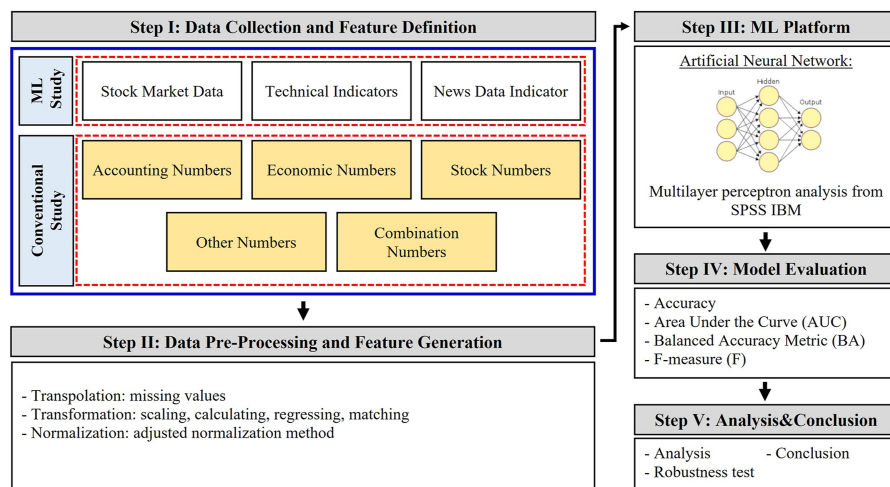
We automated the architecture to ensure MLP analysis consistency and reliability and epochs to avoid over(under)fitting (see Table 3) (Gunduz *et al.*, 2017). Over(under)fitting can lead to biased results because the model works with over(under) performance.

Next, the MLP model requires converting raw data into an acceptable form (Shynkevich *et al.*, 2017), which entails three steps. First, the interpolation process is a step in data cleaning to improve its quality (Cao *et al.*, 2024). Data cleaning for structured data was less sophisticated than the treatment for unstructured data. We filled the missing values in the raw data with the previous values if the current values were unavailable. Second, the transformation process involved calculating each RFV from the data sources and merging all RFVs into a dataset by company. Lastly, a normalization process is necessary to minimize the outlier's effect and ensure the comparison's fairness of each variable. We applied an adjusted normalization method to accommodate the hyperbolic tangent function in the hidden layer activation. The normalization formula for each x in group X where $x \in \mathbb{R} \rightarrow x' \in (-1, 0, 1)$ is:

No.	Ticker	Quartile	Average volume of daily transaction (IDR)
1.	TLKM,JK	1	338,966,961,353
2.	ASII,JK	1	234,966,713,838
3.	TOPS,JK	2	6,469,731,497
4.	PCAR,JK	2	6,319,589,433
5.	RAJA,JK	3	851,745,744
6.	MBSS,JK	3	769,758,620
7.	CLPI,JK	4	144,238,627
8.	BTON,JK	4	141,464,987
9.	BSSR,JK	5	18,605,427
10.	AMIN,JK	5	16,232,394

Table 2.
List of Indonesian firms in the sample based on their average daily transaction in 2019

Source(s): investing.com



Source(s): Figure modified from Weng *et al.* (2017)

Figure 2. Flowchart of the method

Input layer	Rescaling method for covariates	: Adjusted normalized
Hidden Layer(s)	Activation Function	: Hyperbolic tangent
Output Layer	Activation Function	: Softmax
	Error Function	: Cross-entropy
Batch Size		: Auto (1–50)
Training (Testing) data		: 70% (30%)
Holdout		: 0
Epochs		: Auto
Lambda		: 0.0000005
Sigma		: 0.00005

Source(s): SPSS configuration

Table 3. General MLP network information

$$x' = \frac{2 \times (x - \text{MIN}(\mathbf{X}))}{(\text{MAX}(\mathbf{X}) - \text{MIN}(\mathbf{X}))} - 1 \quad (3)$$

Then, following Shynkevich *et al.* (2017), the dependent variables were labeled as “Down,” “No Move,” and “Up” based on the forecasted values.

$$Label_{(d,h)} \left\{ \begin{array}{l} \text{“Up”}, \quad \text{if } \frac{\hat{p}_{d+h} - \hat{p}_d}{\hat{p}_d} > \theta \\ \text{“No Move”}, \quad \text{if } 0 \leq \frac{\hat{p}_{d+h} - \hat{p}_d}{\hat{p}_d} \leq \theta \\ \text{“Down”}, \quad \text{if } \frac{\hat{p}_{d+h} - \hat{p}_d}{\hat{p}_d} < 0 \end{array} \right. \quad (4)$$

where p is the stock price; d is the current day of the transaction; h is the future day-horizon, which is stated in $h_n = d + n$; $n = \{1, 5, 10, 20, 40, 60\}$; and ϑ is the stock transaction expense, such as brokerage commission, taxes and other fees (averagely 0.48% in Indonesia).

Furthermore, we formed feature datasets to test **H1** and **H2** (see notes in **Table 4**). We compared the MLP analysis results of TI&RFV, No_TI and No_RFV conditions to test **H1**. Similarly, we tested **H2** by comparing the results of the RFV_Long and RFV_Short conditions. The MLP results were derived from the model evaluation. The evaluation method for direction-of-movement prediction is accuracy-based (Henrique *et al.*, 2019). Therefore, following Kumbure *et al.* (2022), we applied accuracy, area under the curves (AUC) (SPSS output), balanced accuracy metric (BA) (Chatzis *et al.*, 2018) and F-measure (F) (Gunduz *et al.*, 2017) as evaluation parameters.

In more detail, we divided each condition into three categories of TI movement periods (see notes in **Table 4**) to deepen the analysis. Each category was based on combining conventional (see **Appendix A** and **Online Supplementary Table S1**) and ML study variables (see **Appendix B** and **Online Supplementary Table S2**), which formed many different feature data sets. In total, 15 feature data sets were generated and paired one by one with each target data, that is, six future day horizons of stock movement direction. We generated 900 input data sets from 10 samples ($10 \times 15 \times 6$) to test in the ML model.

4. Result, discussion and implication

4.1 Results of the MLP model and descriptive statistics

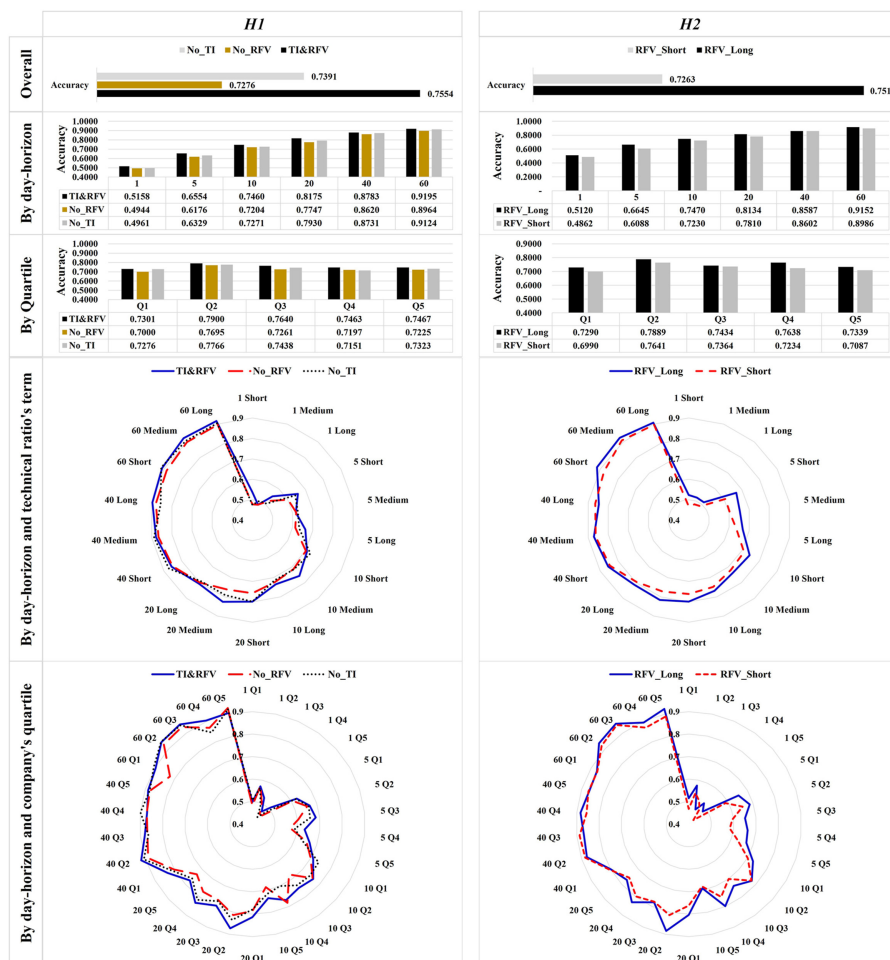
Figure 3 shows the accuracy ratios of the MLP model to test **H1** and **H2**. In this figure, the columns under **H1** demonstrate that RFV inclusion achieved higher accuracy than TI inclusion (73.91 vs 72.76%). Meanwhile, both combinations of RFV and TI performed the highest accuracy (75.54%). By including RFV only, the accuracy drastically increased from day 1–60 (49.61–91.24%) and was relatively similar among companies’ quartiles of Q1 to Q5 (72.76–73.23%). Furthermore, patterns in the radar chart show that by technical ratio term, day 1 had the highest accuracy disparity. Meanwhile, by the company’s quartile term, the RFV and TI combinations exhibited the least variability in accuracy. Next, Part **H2** exhibits that including RFV with a long-data reporting range generally yielded a higher accuracy

Hypothesis Condition TI period category Feature data set	H1									H2					
	TI&RFV			No_TI			No_RFV			RFV_Long			RFV_Short		
	S	M	L	S	M	L	S	M	L	S	M	L	S	M	L
ML_Stock	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
ML_News[5]	x			x			x			x			x		
ML_News[10]		x			x			x			x			x	
ML_News[15]			x			x			x			x			x
ML_TI_Short[5; 6; null]	x						x			x			x		
ML_TI_Medium[10; 9; null]		x						x			x			x	
ML_TI_Long[20; 14; null]			x						x			x			x
RFV_All_Range	x	x	x	x	x	x									
RFV_Short_Range													x	x	x
RFV_Long_Range										x	x	x			

Note(s): **Appendix A** and **B** variables form feature datasets based on data type (x). From **Appendix A**, by data ranges: RFV_Short (daily and monthly), RFV_Long (quarterly). From **Appendix B**, TI period categories by order in the bracket []: short, medium, long, or null if no bracket is found

Source(s): Authors’ work

Table 4.
Feature data set matrix
to test **H1** and **H2**



Source(s): Authors' work

Figure 3.
The breakdown of
predictive accuracy
results for H1 and H2

ratio than RFV with a short-data reporting range (75.18 vs 72.63%). The results were also relatively similar among companies' quartiles, both in the long-range (72.9–73.39%) and short-range (69.9–70.87%). Lastly, two types of radar charts for H2 show similar patterns to H1 in terms of future day-horizon, technical ratio term and company's quartile. The results confirm that RFV inclusion increases the MLP prediction accuracy for stock movement direction, proving the crucial role of structured data such as those presented in financial reports. Furthermore, the similar results among the company's quartiles show the sufficiency of the selected samples to represent the effect of RFV inclusion.

Next, we conducted statistical analysis to test the significance of the H1 and H2 results (Table 5). As expected, the statistical analysis results demonstrate strong consistency in both H1 and H2 conditions, with high paired *t*-test correlations (>0.8) for all technical ratio terms, quartiles and future day horizons. The evidence that the H1 pair had a positive significance across all criteria (at least 10%) confirmed that adding RFV input data statistically improved

	H1 (all Vs No_RFV)		H2 (RFV_Long Vs RFV_Short)	
	Correlation	Paired <i>t</i> -value	Correlation	Paired <i>t</i> -value
Short	0.993	3.399**	0.996	5.248***
Medium	0.990	2.262*	0.996	4.16***
Long	0.996	3.512**	0.996	2.058*
Q1	0.993	3.318**	0.990	2.65**
Q2	0.991	2.181*	0.981	2.142*
Q3	0.986	3.124**	0.977	0.476
Q4	0.982	2.022*	0.993	4.836***
Q5	0.993	2.025*	0.995	2.811**
1	0.825	3.474***	0.530	3.102**
5	0.397	4.113***	0.819	10.232***
10	0.602	2.641**	0.899	5.236***
20	0.741	6.456***	0.828	4.833***
40	0.896	3.952***	0.820	-0.192
60	0.743	2.815**	0.872	4.484***
Overall	0.998	6.653***	0.994	3.316**

Table 5.
Paired *t*-test results of
H1 and H2

Note(s): The significance is defined in * (p -value $\leq 10\%$); ** (p -value $\leq 5\%$); and *** (p -value $\leq 1\%$)
Source(s): Authors' work

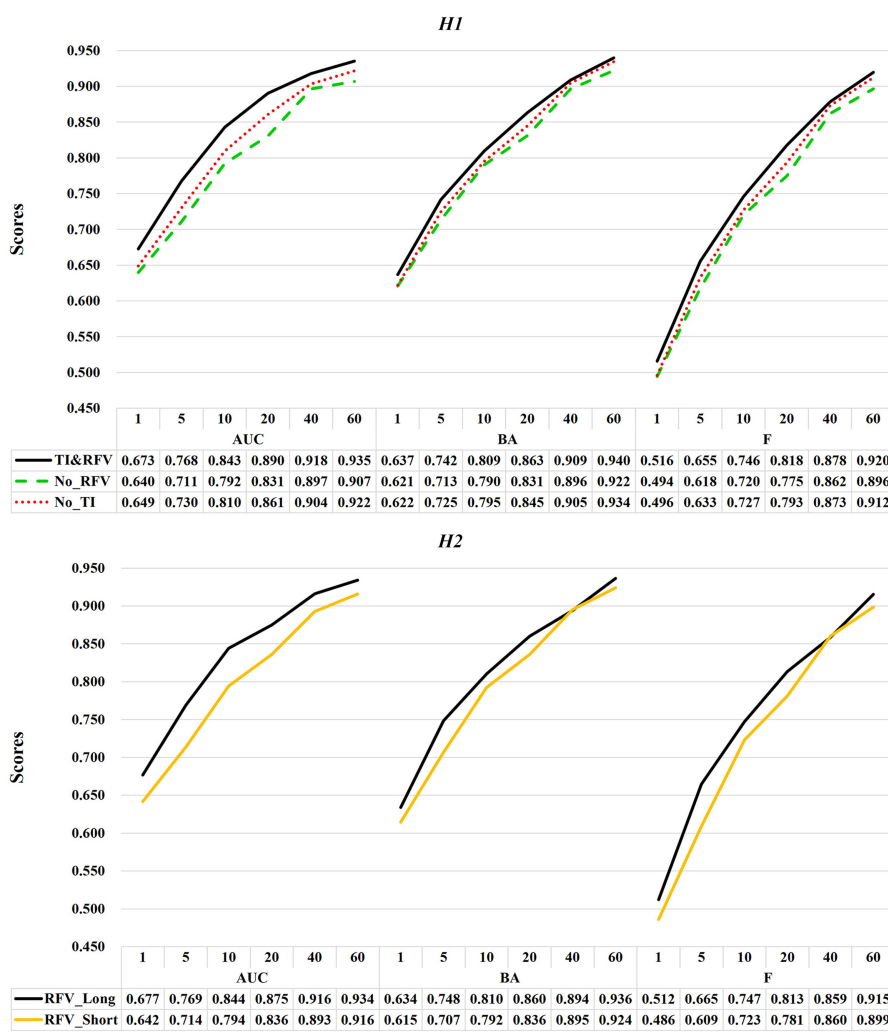
model accuracy. This result was consistent with the H2 pair, where RFV with an extended data range statistically outperformed RFV with a shorter data range.

Furthermore, Figure 4 presents the other evaluation scores. This figure supports H1 and H2 by showing that combined data (RFV and TI) outperformed RFV or TI alone and long-data reporting ranges surpass short-data reporting ranges. Additionally, all evaluation scores improved with longer day horizons, demonstrating better predictive performance. For instance, the AUC score transitions from fair (0.6–0.7) to excellent (0.9–1.0) (Bekkar *et al.*, 2013). Hence, the scores strengthen the accuracy result of the MLP model.

4.2 Discussion and implications of the results

The popularity of AI techniques for predicting stock price movement has been expanding (Blasco *et al.*, 2024; Ozbayoglu *et al.*, 2020). Following the trend, countries like Indonesia have formulated national AI strategies to enhance AI implementation, enforce AI ethics and reduce AI fraud (OECD, 2021). In Indonesia, the use of unreliable data has caused AI fraud in financial services with significant losses. Structured FV from financial reports, with its transparency, fairness and accountability, can mitigate AI ethical issues in the finance sector (IASB, 2018). However, ML-based stock prediction literature shows that FV is less used than other input data, such as TI (Bustos and Quimbaya, 2020; Dakalbab *et al.*, 2024; Henrique *et al.*, 2019; Jiang, 2021; Nti *et al.*, 2020). Confirming the result of conventional studies that structured FV can influence future stock movements (Cao *et al.*, 2024; Choy *et al.*, 2023; Prasad and Prabhu, 2020; Tsafack *et al.*, 2023), our findings in Indonesia reveal that RFVs improve ML model accuracy. This indicates RFVs' potential as ML predictors for stock return movements and their pivotal role in addressing AI ethical issues in the financial sector.

Our results also show that the long reporting data range in RFV outperforms the short. This result may be because FV calculations are mainly based on long data periods due to financial reporting periodicity (e.g. quarterly or yearly). It may imply to ML studies that the low data frequency caused by low reporting range should not be a concern (Bustos and Quimbaya, 2020; Henrique *et al.*, 2019; Jiang, 2021). Therefore, financial reports may remain the key to stock investment decision-making (Agbodjo *et al.*, 2022). Accordingly, ML studies may consider this structured data as the ML input for stock prediction analysis.



Source(s): Authors' work

Figure 4.
Evaluation scores of
MLP model results for
each condition in the
H1 and *H2*

The empirical findings have academic implications and offer practical solutions to financial business challenges, significantly leveraging AI for investment decision-making. The findings from Indonesia support previous results that the emerging markets in Asia are not fully efficient (Huang *et al.*, 2023; Lokanan *et al.*, 2019; Yaya *et al.*, 2024). Therefore, predicting stock return movements using conventional or modern analyses remains possible, where integrating conventional and contemporary methods leads to better results (Olorunnimbe and Viktor, 2023). Conventional studies analyzing relevant FVs remain crucial (Barth *et al.*, 2023; Dunham and Grandstaff, 2022) as these values provide valuable input for modern studies. Meanwhile, modern studies can develop ML models enhancing prediction accuracy with RFV input, given their superiority over linear models (Manogna and Anand, 2023). Both studies can improve human resource quality and accelerate AI applications, which aligns with Indonesia's national AI strategies (BPPT, 2020).

Next, the practical debate from accounting and AI perspectives leads to critical issues concerning input data and ethical concerns. Financial fraud cases in Indonesia (Santika, 2023) serve as evidence that these issues are particularly prevalent in emerging countries with higher market inefficiency and less effective law enforcement (Hsu et al., 2016; Nicolò et al., 2023). The empirical findings demonstrate RFV as a viable solution for ML input. RFV is more reliable as it utilizes structured official data from the government or companies, thereby ensuring safety and transparency regarding ethical concerns. Therefore, financial regulators can enhance investor decision-making, mitigate AI-based fraud and reduce unethical data usage by regulating AI inputs and providing AI-based financial information based on RFV. Also, the RFV-based AI tools can offer analysts, practitioners and investors additional perspectives, enabling more rational and prudent decision-making.

5. Robustness test

5.1 RFV numbers vs raw accounting data and common accounting ratios

The first robustness test assesses the predictive capabilities of two data sets. The first data set comprises three bases of RFV: accounting, combination and all. Alternatively, the comparison data include raw accounting data derived from the Osiris database (see Appendix C) and common accounting ratio calculations from previous ML studies (see Appendix D). Table 6 shows that RFV generally outperformed accounting raw data and common ratios in predictive accuracy. The results exhibit high consistency (correlation >0.97) but various significance based on comparison factors. Lastly, Figure 5 reveals a consistent pattern in the evaluation scores of RFV features and other accounting data. Therefore, predictive performance improves with longer day horizons in RFV features and other accounting data. This first robustness results validate the H1 and H2 results by showing that RFV inclusion outperformed the accuracy of raw accounting data and common accounting ratios.

5.2 The linear regression analysis of the ML study

The second robustness test formalizes the ML testing for hypotheses by modifying the Hsu et al. (2016) model with several parameters from earlier analyses. The measurement parameters are conditions COND (condition of H1 or H2), day-horizons HOR (day +1 to day

Features	Accuracy						Paired correlation		Paired t-value	
	1	5	10	20	40	60	Raw data	Common ratio	Raw data	Common ratio
RFV_accounting	0.511	0.612	0.669	0.782	0.838	0.871	0.992	0.994	10.753***	1.351
RFV_combination	0.521	0.614	0.701	0.772	0.849	0.899	0.998	0.989	14.068***	2.419*
RFV_all	0.455	0.633	0.718	0.801	0.864	0.918	0.979	0.977	5.216***	1.606
Accounting raw data	0.449	0.52	0.587	0.661	0.728	0.786				
Accounting common ratio	0.5	0.613	0.638	0.759	0.834	0.885				

Table 6. Average predictive accuracy of the RFV features and other accounting data through six-day horizons

Note(s): The paired t-test result significance is defined in * (*p*-value ≤ 10%); ** (*p*-value ≤ 5%); and *** (*p*-value ≤ 1%)

Source(s): Authors' work

+60), technical and media indicator periods *PERIOD* (short, medium and long) and sample quartiles *QUART* (Q1 to Q5). These parameters are stated as dummy variables of 1 (if applied) and 0 (if not applied). Meanwhile, the dependent variable applied the testing data accuracy. Therefore, the second robustness model is as follows:

$$Accuracy = \alpha + \beta_0COND + \beta_1HOR + \beta_2PERIOD + \beta_3QUART + \epsilon \quad (5)$$

Next, the descriptive statistics in [Table 7](#) show a wide accuracy range in [H1](#) and [H2](#) (0.3086–1) and (0.2687–0.987), with an average of 0.7348 and 0.739, respectively. The calculation results show no correlation among inter-dummy variables, minimizing the model’s multicollinearity risk.

The regression results in [Table 8](#) reveal positive and significant results across all conditions and day horizons at the 1% level. Additionally, the normality graphs of residuals

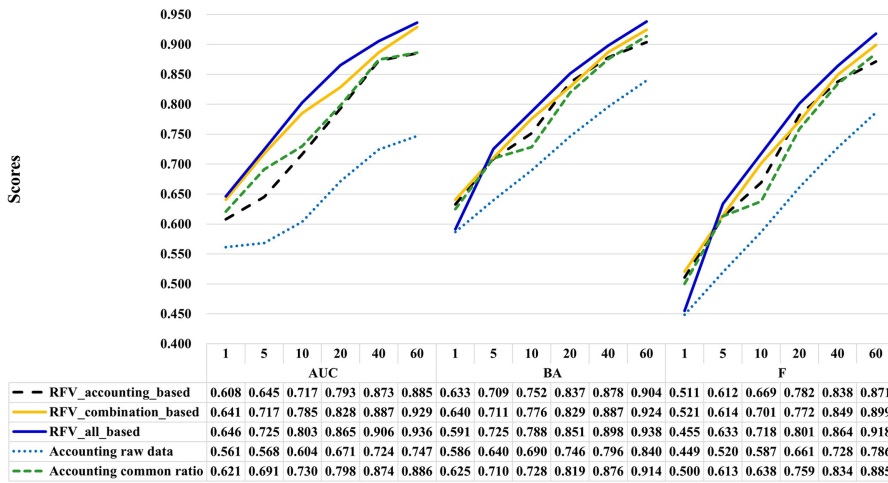


Figure 5. Evaluation scores of RFV features and other accounting data

Source(s): Authors’ work

	Variables	N	Min	Max	Mean	SD	Skewness	Kurtosis
H1	accuracy	1,260	0.3086	1.0000	0.7348	0.1550	-0.3924	-0.7216
	condition_ti&rfv	1,260	0	1	0.4286	0.4951	0.2890	-1.9195
	condition_no_ti	1,260	0	1	0.4286	0.4951	0.2890	-1.9195
	condition_no_rfv	1,260	0	1	0.1429	0.3501	2.0437	2.1801
	hor_day (1-60)	1,260	0	1	0.1667	0.3728	1.7910	1.2096
	term (short; medium; long)	1,260	0	1	0.3333	0.4716	0.7079	-1.5012
	q(1-5)	1,260	0	1	0.2000	0.4002	1.5018	0.2558
H2	accuracy	360	0.2687	0.9870	0.7390	0.1525	-0.4828	-0.5584
	condition_long	360	0	1	0.5000	0.5007	0.0000	-2.0112
	condition_short	360	0	1	0.5000	0.5007	0.0000	-2.0112
	hor_day (1-60)	360	0	1	0.1667	0.3732	1.7963	1.2337
	term (short; medium; long)	360	0	1	0.3333	0.4721	0.7101	-1.5042
	q(1-5)	360	0	1	0.2000	0.4006	1.5063	0.2704

Source(s): Authors’ work

Table 7. Descriptive statistics of the variables in the robustness model

Variables	H1	H2
condition_no_ti	-0.021*** (-5.494)	
condition_no_rfv	-0.022*** (-4.105)	
condition_long		0.027*** (4.211)
hor_day5	0.134*** (21.795)	0.141*** (12.444)
hor_day10	0.221*** (36.009)	0.239*** (21.158)
hor_day20	0.293*** (47.765)	0.294*** (26.003)
hor_day40	0.371*** (60.591)	0.359*** (31.766)
hor_day60	0.409*** (66.759)	0.407*** (36.045)
term_medium	0.003 (0.692)	0.008 (0.942)
term_long	0.011** (2.499)	0.014* (1.761)
q2	0.049*** (8.764)	0.065*** (6.259)
q3	0.029*** (5.131)	0.035*** (3.416)
q4	0.006 (1.15)	0.043*** (4.145)
q5	0.007 (1.165)	0.008 (0.82)
intercept	0.486*** (75.284)	0.448*** (38.103)
adjusted R^2	0.836	0.835

Note(s): The significance is defined in * (p -value $\leq 10\%$); ** (p -value $\leq 5\%$); and *** (p -value $\leq 1\%$)
Source(s): Authors' work

Table 8.
Robustness regression
results

in Figure 6 affirm the strength of the linear models. In summary, the second robustness test formalizes the findings and thus reinforces H1 and H2.

6. Conclusion

In sum, the study offers RFV to increase the accuracy of an ML prediction model for stock movement direction. We applied the MLP model to demonstrate that RFV inclusions improve ML model accuracy in Indonesia's public companies. Its accuracy is better in the longer future day horizon and higher for RFV with a long reporting data range. It suggests that structured data of financial reports may remain critical for ML data input. Two robustness tests validated the findings. Therefore, applying RFV as the input for an ML-based prediction model is possible. In broad thinking based on Indonesia's context, governments can regulate RFV-based AI applications for stock prediction. Also, practitioners, analysts and investors can be inspired to develop RFV-based AI tools. Those actions can enhance investor decision-making, minimize unethical data use and reduce AI-based fraud.

Lastly, our study used only samples from Indonesia's public companies, and the applicability of our findings could be limited. Indonesia is one of the emerging Asian markets that recently announced its national AI strategy. Therefore, our findings apply to other

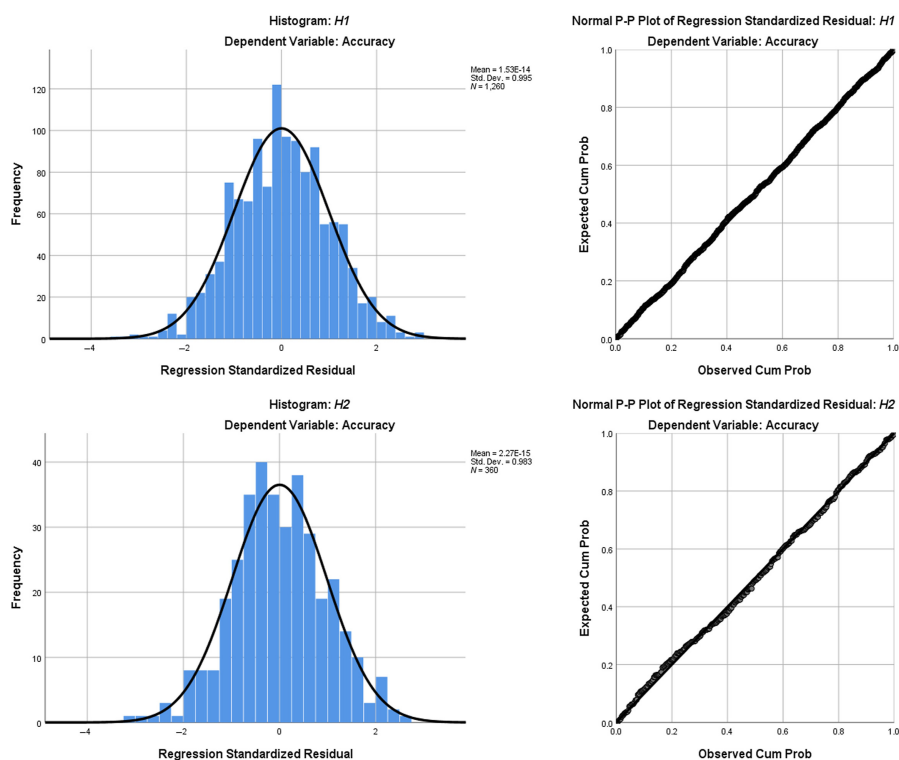


Figure 6.
Normal P-P plot of the
standardized residuals
from the
regression model

Source(s): SPSS output

emerging Asian markets and add to the existing ML literature on stock prediction. Nevertheless, expanding to different samples could strengthen the conclusions. Furthermore, there is room to improve the ML accuracy by incorporating additional RFVs from other studies in the literature. Also, exploring other ML models to derive better accuracy is possible. Lastly, our study needs to address several issues in financial accounting studies, e.g. the value relevance effect, thus leaving room for further research with sufficient data.

Note

1. The articles are published in the following three journals: *The Journal of Finance*, *Journal of Accounting and Economics* and *British Accounting Review*. These journals are rated A* in the ABDC Journal Lists and among the top fifteen journals (91% highest percentile) on Scopus in the accounting area.

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Appendix

The appendix for this article can be found online.

Supplementary material

The supplementary material for this article can be found online.

Corresponding author

Stiven Agusta can be contacted at: stiven.agusta@mail.ugm.ac.id

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