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Received 3 January 2024
Revised 22 March 2024
4 May 2024
6 June 2024
Accepted 19 June 2024

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

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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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The authors thank Prof. Iman Harymawan, the Editor-in-Chief, Dr. Shaista Wasiuzzaman, the Associate Editor, and the two anonymous reviewers for their insightful feedbacks that improved the quality of the manuscript.

Funding: This research was supported by the Lembaga Pengelola Dana Pendidikan/LPDP (LOG-7210/LPDP.3/2024).

Note: Supplementary materials that are included in the article are available online.

Asian Journal of Accounting Research
Vol. 9 No. 4, 2024
pp. 358-377
Emerald Publishing Limited
e-ISSN: 2443-4175
p-ISSN: 2459-9700
DOI 10.1108/AJAR-01-2024-0006

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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

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(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).

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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.

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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:

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H2. RFVs using a long reporting data range generate a higher increase in the predictive accuracy of ML studies than RFVs applying a short reporting data range.

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).

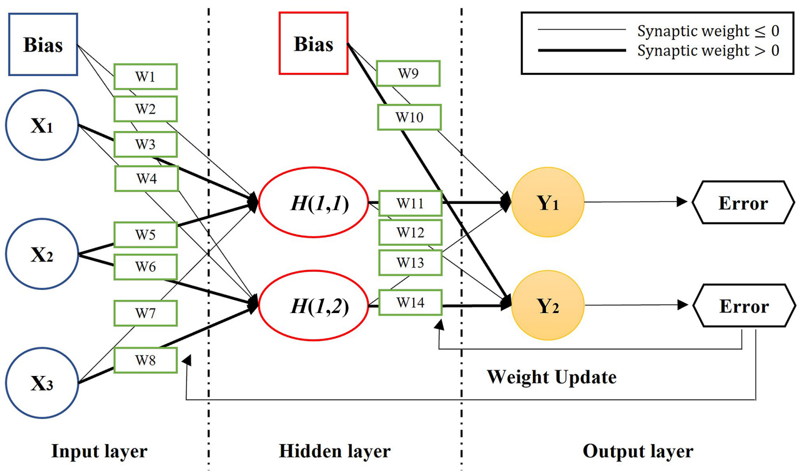
The neurons form the interconnection layer within the MLP method (Asadi *et al.*, 2012). The nonlinear activation function σ is embedded in every layer's neuron containing input x, weight w and bias b terms (Ozbayoglu *et al.*, 2020). The accumulation of weighted input in each neuron of the preceding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

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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 $\mathbf{X}$ where $x \in \mathbb{R} \rightarrow x' \in (-1, 0, 1)$ is:

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

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

Source(s): investing.com

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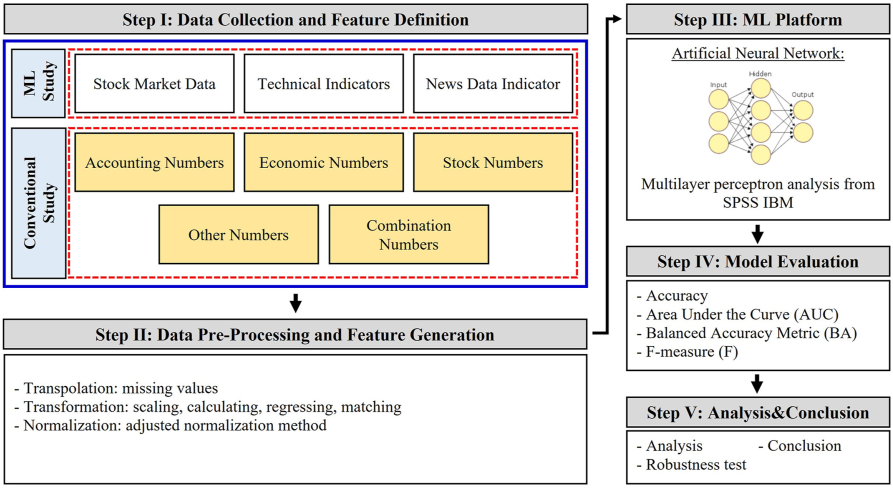

Source(s): Figure modified from Weng *et al.* (2017)

Figure 2.
Flowchart of the method

Input layer	Rescaling metdod 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

$$x' = \frac{2 \times (x - MIN(\boldsymbol{X}))}{(MAX(\boldsymbol{X}) - MIN(\boldsymbol{X}))} - 1 \tag{3}$$

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

$$Label_{(d,h)} \begin{cases} \text{“Up”}, & \text{if } \dfrac{p_{d+h} - p_d}{p_d} > \theta \\ \text{“No Move”}, & \text{if } 0 \leq \dfrac{p_{d+h} - p_d}{p_d} \leq \theta \\ \text{“Down”}, & \text{if } \dfrac{p_{d+h} - p_d}{p_d} < 0 \end{cases} \tag{4}$$

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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

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

Hypothesis	H1									H2					
Condition	TI&RFV			No_TI			No_RFV			RFV_Long			RFV_Short		
TI period category	S	M	L	S	M	L	S	M	L	S	M	L	S	M	L
Feature data set	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
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

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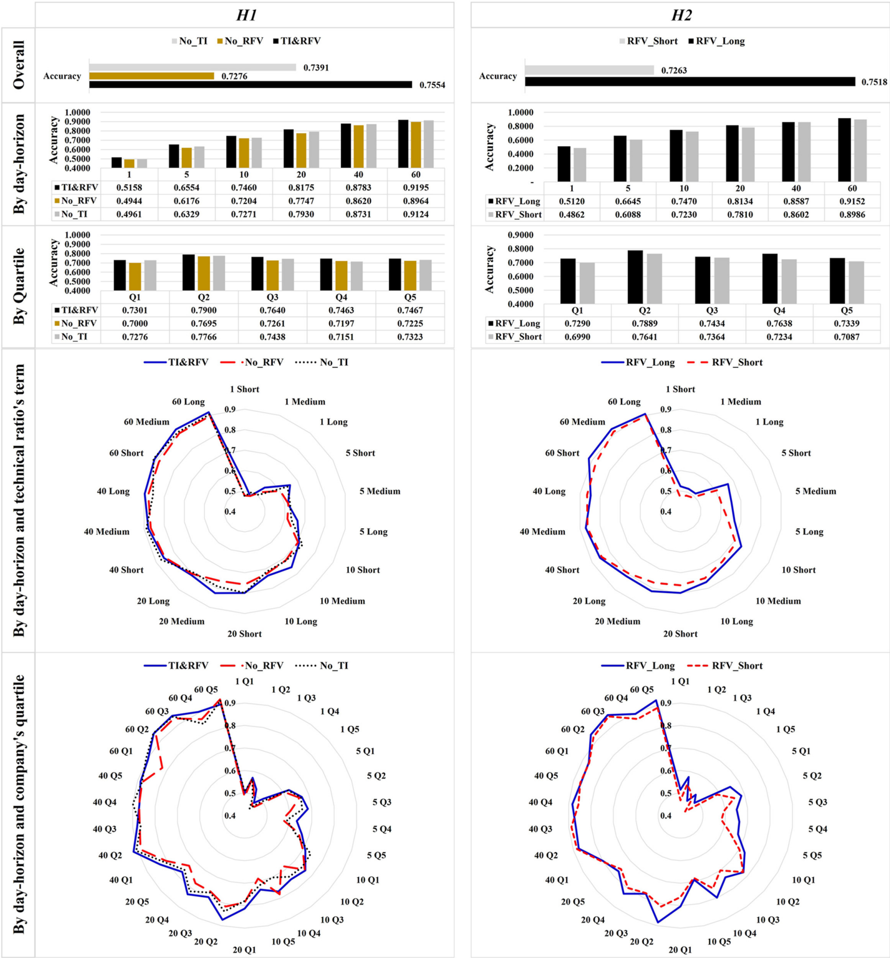

Source(s): Authors' work

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

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	H1 (all Vs No_RFV) Correlation	Paired t-value	H2 (RFV_Long Vs RFV_Short) Correlation	Paired t-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**

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

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

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.

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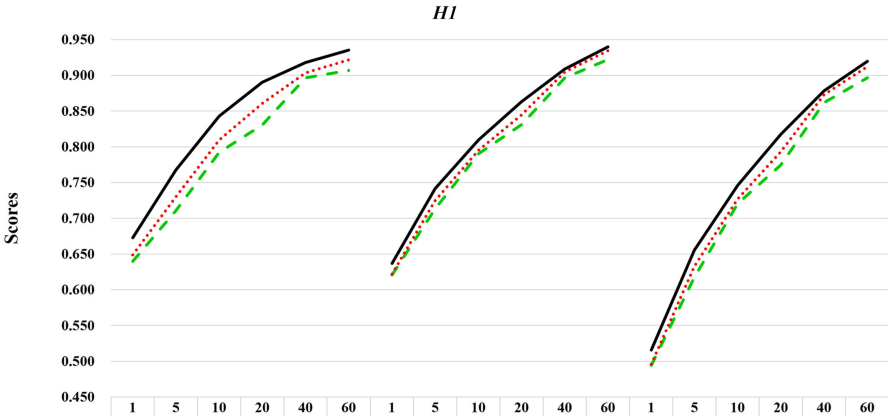
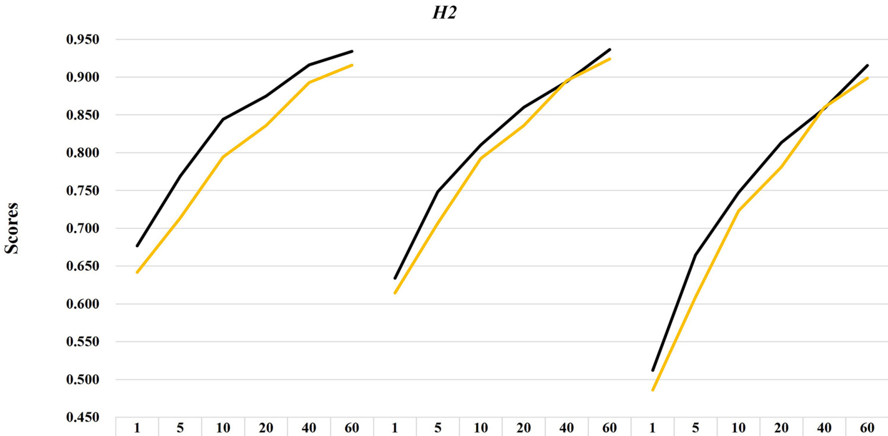


	AUC 1	AUC 5	AUC 10	AUC 20	AUC 40	AUC 60	BA 1	BA 5	BA 10	BA 20	BA 40	BA 60	F 1	F 5	F 10	F 20	F 40	F 60
TI&RFV	0.673	0.768	0.843	0.890	0.918	0.935	0.637	0.742	0.809	0.863	0.909	0.940	0.516	0.655	0.746	0.818	0.878	0.920
No_RFV	0.640	0.711	0.792	0.831	0.897	0.907	0.621	0.713	0.790	0.831	0.896	0.922	0.494	0.618	0.720	0.775	0.862	0.896
No_TI	0.649	0.730	0.810	0.861	0.904	0.922	0.622	0.725	0.795	0.845	0.905	0.934	0.496	0.633	0.727	0.793	0.873	0.912



	AUC 1	AUC 5	AUC 10	AUC 20	AUC 40	AUC 60	BA 1	BA 5	BA 10	BA 20	BA 40	BA 60	F 1	F 5	F 10	F 20	F 40	F 60
RFV_Long	0.677	0.769	0.844	0.875	0.916	0.934	0.634	0.748	0.810	0.860	0.894	0.936	0.512	0.665	0.747	0.813	0.859	0.915
RFV_Short	0.642	0.714	0.794	0.836	0.893	0.916	0.615	0.707	0.792	0.836	0.895	0.924	0.486	0.609	0.723	0.781	0.860	0.899

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).

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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

	Accuracy						Paired correlation		Paired t-value	
Features	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				

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

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

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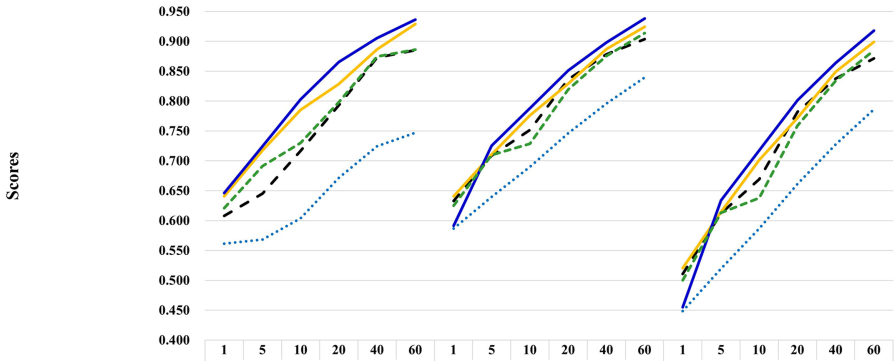
+60), technical and media indicator periods *PERIOD* (short, medium and long) and sample quartiles *QUART* (Q1 to Q5). These parameters are stated as dummy variables of 1 (if applied) and 0 (if not applied). Meanwhile, the dependent variable applied the testing data accuracy. Therefore, the second robustness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

$$Accuracy = \alpha + \beta_0 COND + \beta_1 HOR + \beta_2 PERIOD + \beta_3 QUART + \varepsilon \quad (5)$$

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



	AUC						BA						F					
	1	5	10	20	40	60	1	5	10	20	40	60	1	5	10	20	40	60
RFV_accounting_based	0.608	0.645	0.717	0.793	0.873	0.885	0.633	0.709	0.752	0.837	0.878	0.904	0.511	0.612	0.669	0.782	0.838	0.871
RFV_combination_based	0.641	0.717	0.785	0.828	0.887	0.929	0.640	0.711	0.776	0.829	0.887	0.924	0.521	0.614	0.701	0.772	0.849	0.899
RFV_all_based	0.646	0.725	0.803	0.865	0.906	0.936	0.591	0.725	0.788	0.851	0.898	0.938	0.455	0.633	0.718	0.801	0.864	0.918
Accounting raw data	0.561	0.568	0.604	0.671	0.724	0.747	0.586	0.640	0.690	0.746	0.796	0.840	0.449	0.520	0.587	0.661	0.728	0.786
Accounting common ratio	0.621	0.691	0.730	0.798	0.874	0.886	0.625	0.710	0.728	0.819	0.876	0.914	0.500	0.613	0.638	0.759	0.834	0.885

Source(s): Authors' work

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

	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

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

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

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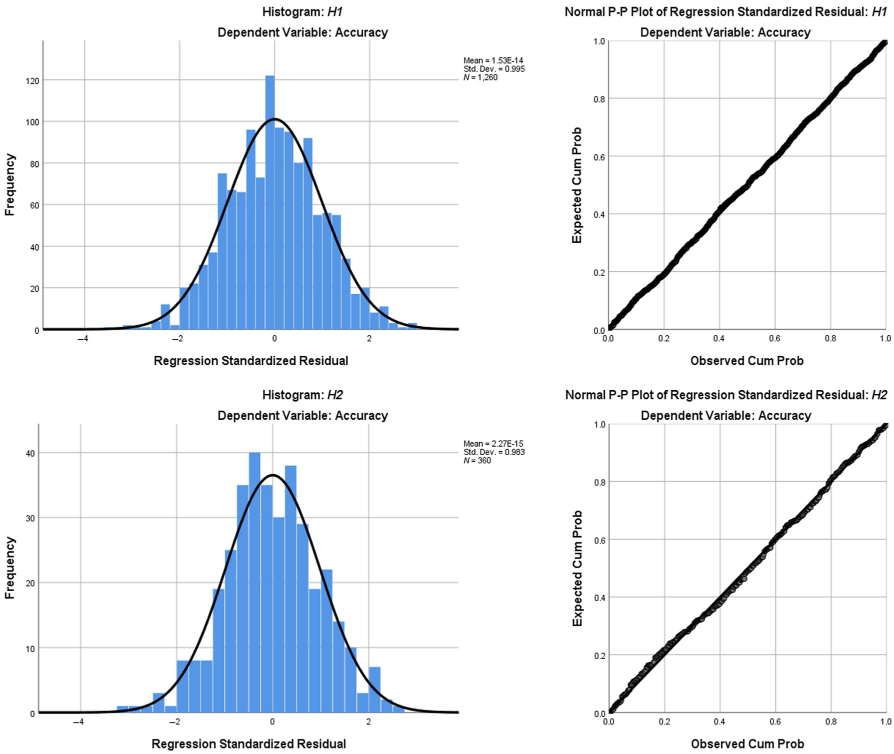

Source(s): SPSS output

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

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.

References

Agbodjo, S., Seny Kan, K.A., Zori, S.G. and Hussainey, K. (2022), "Unraveling the existence of the necessity and sufficiency of accounting information", *Journal of Applied Accounting Research*, Vol. 23 No. 5, pp. 1095-1113, doi: 10.1108/JAAR-03-2021-0077.

Ahmed, S., Alshater, M.M., Ammari, A.El and Hammami, H. (2022), "Artificial intelligence and machine learning in finance: a bibliometric review", *Research in International Business and Finance*, Vol. 61, 101646, doi: 10.1016/j.ribaf.2022.101646.

Downloaded from http://ftp.nowpublishers.com/ajar/article-pdf/9/4/358/9468951/ajar-01-2024-0006.pdf by guest on 15 May 2026

Akbas, F., Jiang, C. and Koch, P.D. (2020), "Insider investment horizon", *The Journal of Finance*, Vol. 75 No. 3, pp. 1579-1627, doi: 10.1111/jofi.12878.

Alti, G. and Titman, S. (2019), "A dynamic model of characteristic-based return predictability", *The Journal of Finance*, Vol. 74 No. 6, pp. 3187-3216, doi: 10.1111/jofi.12839.

Andreou, C.K., Lambertides, N. and Panayides, P.M. (2020), "Distress risk anomaly and misvaluation", *The British Accounting Review*, Vol. 53 No. 5, 100972, doi: 10.1016/J.BAR.2020.100972.

Armstrong, C.S., Glaeser, S. and Kepler, J.D. (2019), "Accounting quality and the transmission of monetary policy", *Journal of Accounting and Economics*, Vol. 68 Nos 2-3, pp. 1-30, doi: 10.1016/J.JACCECO.2019.101265.

Aryadoust, V. and Baghaei, P. (2016), "Does EFL readers' lexical and grammatical knowledge predict their reading ability ? Insights from a perceptron artificial neural network study", *Educational Assessment*, Vol. 21 No. 2, pp. 135-156, doi: 10.1080/10627197.2016.1166343.

Asadi, S., Hadavandi, E., Mehmanpazir, F. and Nakhostin, M.M. (2012), "Hybridization of evolutionary Levenberg–Marquardt neural networks and data pre-processing for stock market prediction", *Knowledge-Based Systems*, Vol. 35, pp. 245-258, doi: 10.1016/J.KNOSYS.2012.05.003.

Atanasov, V., Møller, S.V. and Priestley, R. (2020), "Consumption fluctuations and expected returns", *The Journal of Finance*, Vol. 75 No. 3, pp. 1677-1713, doi: 10.1111/jofi.12870.

Balakrishnan, K., Vashishtha, R. and Verrecchia, R.E. (2019), "Foreign competition for shares and the pricing of information asymmetry: evidence from equity market liberalization", *Journal of Accounting and Economics*, Vol. 67 No. 1, pp. 80-97, doi: 10.1016/J.JACCECO.2018.08.015.

Ball, R. and Brown, P. (1968), "An empirical evaluation of accounting income numbers", *Journal of Accounting Research*, Vol. 6 No. 2, pp. 159-178, doi: 10.2307/2490232.

Barberis, N., Jin, L.J. and Wang, B. (2021), "Prospect theory and stock market anomalies", *The Journal of Finance*, Vol. 76 No. 5, pp. 2639-2687, doi: 10.1111/jofi.13061.

Barth, M.E., Li, K. and McClure, C.G. (2023), "Evolution in value relevance of accounting information", *The Accounting Review*, Vol. 98 No. 1, pp. 1-28, doi: 10.2308/TAR-2019-0521.

Beaver, W.H., McNichols, M.F. and Wang, Z.Z. (2020), "Increased market response to earnings announcements in the 21st century: an empirical investigation", *Journal of Accounting and Economics*, Vol. 69 No. 1, 101244, doi: 10.1016/J.JACCECO.2019.101244.

Bekkar, M., Djemaa, H.K. and Alitouche, T.A. (2013), "Evaluation measures for models assessment over imbalanced data Sets", *Journal of Information Engineering and Applications*, Vol. 3, pp. 27-38.

Bird, A., Karolyi, S.A. and Ruchti, T.G. (2019), "Understanding the 'numbers game", *Journal of Accounting and Economics*, Vol. 68 Nos 2-3, 101242, doi: 10.1016/J.JACCECO.2019.101242.

Blasco, T., Sánchez, J.S. and García, V. (2024), "A survey on uncertainty quantification in deep learning for financial time series prediction", *Neurocomputing*, Vol. 576, 127339, doi: 10.1016/j.neucom.2024.127339.

Bonsall, S.B., Green, J. and Muller, K.A. (2020), "Market uncertainty and the importance of media coverage at earnings announcements", *Journal of Accounting and Economics*, Vol. 69 No. 1, p. 101264, doi: 10.1016/J.JACCECO.2019.101264.

BPPT (2020), *Strategi Nasional Kecerdasan Artifisial Indonesia 2020-2045*, BPPT Press, London.

Brock, W., Lakonishok, J. and LeBaron, B. (1992), "Simple technical trading rules and the stochastic properties of stock returns", *The Journal of Finance*, Vol. 47 No. 5, pp. 1731-1764, doi: 10.1111/j.1540-6261.1992.tb04681.x.

Bustos, O. and Quimbaya, A.P. (2020), "Stock market movement forecast: a systematic review", *Expert Systems with Applications*, Vol. 156, 113464, doi: 10.1016/J.ESWA.2020.113464.

Cao, S.S., Jiang, W., Lei, L.G. and Zhou, Q.C. (2024), "Applied AI for finance and accounting: alternative data and opportunities", *Pacific-Basin Finance Journal*, Vol. 84, 102307, doi: 10.1016/j.pacfin.2024.102307.

Downloaded from http://ftp.nowpublishers.com/ajar/article-pdf/9/4/358/9468951/ajar-01-2024-0006.pdf by guest on 15 May 2026

Chatzis, S.P., Siakoulis, V., Petropoulos, A., Stavroulakis, E. and Vlachogiannakis, N. (2018), "Forecasting stock market crisis events using deep and statistical machine learning techniques", *Expert Systems with Applications*, Vol. 112, pp. 353-371, doi: 10.1016/J.ESWA.2018.06.032.

Choy, S.K., Lewis, C. and Tan, Y. (2023), "Can the changes in fundamentals explain the attenuation of anomalies?", *Journal of Financial Economics*, Vol. 149 No. 2, pp. 142-160, doi: 10.1016/j.jfineco.2023.04.005.

Dakalbab, F., Talib, M.A., Nasir, Q. and Saroufil, T. (2024), "Artificial intelligence techniques in financial trading: a systematic literature review", *Journal of King Saud University – Computer and Information Sciences*, Vol. 36 No. 3, 102015, doi: 10.1016/j.jksuci.2024.102015.

Demaidi, M.N. (2023), "Artificial intelligence national strategy in a developing country", *AI and Society*, pp. 1-13, doi: 10.1007/s00146-023-01779-x.

Dunham, L.M. and Grandstaff, J.L. (2022), "The value relevance of earnings, book values, and other accounting information and the role of economic conditions in value relevance: a literature review", *Accounting Perspectives*, Vol. 21 No. 2, pp. 237-272, doi: 10.1111/1911-3838.12280.

Fama, E.F. (1970), "Efficient Capital Markets: a review of theory and empirical work", *The Journal of Finance*, Vol. 25 No. 2, pp. 383-417, doi: 10.2307/2325486.

Gallo, L.A. and Kothari, S.P. (2019), "Discussion of 'Accounting quality and the transmission of monetary policy'", *Journal of Accounting and Economics*, Vol. 68 Nos 2-3, 101262, doi: 10.1016/J.JACCECO.2019.101262.

Gunduz, H., Yaslan, Y. and Cataltepe, Z. (2017), "Intraday prediction of Borsa Istanbul using convolutional neural networks and feature correlations", *Knowledge-Based Systems*, Vol. 137, pp. 138-148, doi: 10.1016/J.KNOSYS.2017.09.023.

Haykin, S. (1998), *Neural Networks: A Comprehensive Foundation*, 2nd ed., Macmillan College, New York.

He, S. and Narayanamoorthy, G.(G.) (2020), "Earnings acceleration and stock returns", *Journal of Accounting and Economics*, Vol. 69 No. 1, 101238, doi: 10.1016/J.JACCECO.2019.101238.

Henrique, B.M., Sobreiro, V.A. and Kimura, H. (2019), "Literature review: machine learning techniques applied to financial market prediction", *Expert Systems with Applications*, Vol. 124, pp. 226-251, doi: 10.1016/J.ESWA.2019.01.012.

Hsu, M.W., Lessmann, S., Sung, M.C., Ma, T. and Johnson, J.E.V. (2016), "Bridging the divide in financial market forecasting: machine learners vs financial economists", *Expert Systems with Applications*, Vol. 61, pp. 215-234, doi: 10.1016/J.ESWA.2016.05.033.

Hu, X. and Yang, J. (2024), "G-LASSO/G-SCAD/G-MCP penalized trinomial logit dynamic models predict up trends, sideways trends and down trends for stock returns", *Expert Systems with Applications*, Vol. 249, 123476, doi: 10.1016/j.eswa.2024.123476.

Huang, X., Liu, C. and Shu, T. (2023), "Factors and anomalies in the Vietnamese stock market", *Pacific-Basin Finance Journal*, Vol. 82, 102176, doi: 10.1016/j.pacfin.2023.102176.

IASB (2018), *The Conceptual Framework for Financial Reporting*, International Accounting Standards Board, London.

Insights, O. (2024), "Government AI readiness index 2023", available at: https://oxfordinsights.com/ai-readiness/ai-readiness-index/ (accessed 20 April 2024).

Jiang, W. (2021), "Applications of deep learning in stock market prediction: recent progress", *Expert Systems with Applications*, Vol. 184, 115537, doi: 10.1016/J.ESWA.2021.115537.

Kim, J., Doucouliagos, H. and Stanley, T.D. (2019), "Market efficiency in Asian and Australasian stock markets: a fresh look at the evidence", *International Financial Markets*, pp. 382-419.

Kumbure, M.M., Lohrmann, C., Luukka, P. and Porras, J. (2022), "Machine learning techniques and data for stock market forecasting: a literature review", *Expert Systems with Applications*, Vol. 197, 116659, doi: 10.1016/j.eswa.2022.116659.

Lewellen, J. and Resutek, R.J. (2019), "Why do accruals predict earnings?", *Journal of Accounting and Economics*, Vol. 67 Nos 2-3, pp. 336-356, doi: 10.1016/J.JACCECO.2018.12.003.

Downloaded from http://ftp.nowpublishers.com/ajar/article-pdf/9/4/358/9468951/ajar-01-2024-0006.pdf by guest on 15 May 2026

Li, X., Huang, X., Deng, X. and Zhu, S. (2014), "Enhancing quantitative intra-day stock return prediction by integrating both market news and stock prices information", *Neurocomputing*, Vol. 142, pp. 228-238, doi: 10.1016/J.NEUCOM.2014.04.043.

Li, X., Wu, P. and Wang, W. (2020), "Incorporating stock prices and news sentiments for stock market prediction: a case of Hong Kong", *Information Processing and Management*, Vol. 57 No. 5, 102212, doi: 10.1016/J.IPM.2020.102212.

Li, N., Wei, C. and Zhang, L. (2023), "Risk factors in the Indonesian stock market", *Pacific-Basin Finance Journal*, Vol. 82, 102175, doi: 10.1016/j.pacfin.2023.102175.

Lokanan, M., Tran, V. and Vuong, N.H. (2019), "Detecting anomalies in financial statements using machine learning algorithm", *Asian Journal of Accounting Research*, Vol. 4 No. 2, pp. 181-201, doi: 10.1108/AJAR-09-2018-0032.

Malkiel, B.G. (2003), "The efficient market hypothesis and its critics", *Journal of Economic Perspectives*, Vol. 17 No. 1, pp. 59-82, doi: 10.1257/089533003321164958.

Manogna, R.L. and Anand, A. (2023), "A bibliometric analysis on the application of deep learning in finance: status, development and future directions", *Kybernetes*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/K-04-2023-0637.

Nagar, V., Schoenfeld, J. and Wellman, L. (2019), "The effect of economic policy uncertainty on investor information asymmetry and management disclosures", *Journal of Accounting and Economics*, Vol. 67 No. 1, pp. 36-57, doi: 10.1016/J.JACCECO.2018.08.011.

Nallareddy, S., Sethuraman, M. and Venkatachalam, M. (2020), "Changes in accrual properties and operating environment: implications for cash flow predictability", *Journal of Accounting and Economics*, Vol. 69 Nos 2-3, pp. 1-23, doi: 10.1016/J.JACCECO.2020.101313.

Nicolò, G., Santis, S., Incollingo, A. and Polcini, P.T. (2023), "Value relevance research in accounting and reporting domains: a bibliometric analysis", *Accounting in Europe*, pp. 1-36, doi: 10.1080/17449480.2023.2292654.

Nti, I.K., Adekoya, A.F. and Weyori, B.A. (2020), "A systematic review of fundamental and technical analysis of stock market predictions", *Artificial Intelligence Review*, Vol. 53 No. 4, pp. 3007-3057, doi: 10.1007/s10462-019-09754-z.

OECD (2021), "Artificial intelligence, machine learning and big data", *Finance: Opportunities, Challenges, and Implications for Policy Makers*.

OECD (2023), *OECD/INFE 2023 International Survey of Adult Financial Literacy*, OECD, London.

OJK (2023), "Implementasi Artificial Intelligence di Industri Jasa Keuangan", *Otoritas Jasa Keuangan*, 2 February, available at: https://www.ojk.go.id/ojk-institute/id/capacitybuilding/past/1302/implementasi-artificial-intelligence-di-industri-jasa-keuangan (accessed 2 February 2023).

Olorunnimbe, K. and Viktor, H. (2023), "Deep learning in the stock market—a systematic survey of practice, backtesting, and applications", *Artificial Intelligence Review*, Vol. 56 No. 3, pp. 2057-2109, doi: 10.1007/s10462-022-10226-0.

Ozbayoglu, A.M., Gudelek, M.U. and Sezer, O.B. (2020), "Deep learning for financial applications : a survey", *Applied Soft Computing*, Vol. 93, pp. 1-29, doi: 10.1016/J.ASOC.2020.106384.

Pandey, D.K., Kumari, V. and Tiwari, B.K. (2022), "Impacts of corporate announcements on stock returns during the global pandemic: evidence from the Indian stock market", *Asian Journal of Accounting Research*, Vol. 7 No. 2, pp. 208-226, doi: 10.1108/AJAR-06-2021-0097.

Penman, S. and Zhang, X.J. (2020), "A theoretical analysis connecting conservative accounting to the cost of capital", *Journal of Accounting and Economics*, Vol. 69 No. 1, 101236, doi: 10.1016/J.JACCECO.2019.101236.

Picasso, A., Merello, S., Ma, Y., Oneto, L. and Cambria, E. (2019), "Technical analysis and sentiment embeddings for market trend prediction", *Expert Systems with Applications*, Vol. 135, pp. 60-70, doi: 10.1016/J.ESWA.2019.06.014.

Downloaded from http://ftp.nowpublishers.com/ajar/article-pdf/9/4/358/9468951/ajar-01-2024-0006.pdf by guest on 15 May 2026

Prasad, K. and Prabhu, N. (2020), "Does earnings surprise determine the timing of the earnings announcement? Evidence from earnings announcements of Indian companies", *Asian Journal of Accounting Research*, Vol. 5 No. 1, pp. 119-134, doi: 10.1108/AJAR-04-2019-0023.

Qian, Y., Li, Z. and Yuan, H. (2020), "On exploring the impact of users' bullish-bearish tendencies in online community on the stock market", *Information Processing and Management*, Vol. 57 No. 5, 102209, doi: 10.1016/J.IPM.2020.102209.

Santika, E.F. (2023), "Sederet Nilai Kerugian Korban Penipuan Berkedok robot trading, AGT Paling Besar", *Databoks*, 9 March, available at: https://databoks.katadata.co.id/datapublish/2023/03/09/sederet-nilai-kerugian-korban-penipuan-berkedok-robot-trading-agt-paling-besar (accessed 14 October 2023).

Shynkevich, Y., McGinnity, T.M., Coleman, S.A., Belatreche, A. and Li, Y. (2017), "Forecasting price movements using technical indicators: Investigating the impact of varying input window length", *Neurocomputing*, Vol. 264, pp. 71-88, doi: 10.1016/J.NEUCOM.2016.11.095.

Tsafack, G., Becker, Y. and Han, K. (2023), "Earnings announcement premium and return volatility: is it consistent with risk-return trade-off?", *Pacific-Basin Finance Journal*, Vol. 79, 102029, doi: 10.1016/j.pacfin.2023.102029.

Tsileponis, N., Stathopoulos, K. and Walker, M. (2020), "Do corporate press releases drive media coverage?", *The British Accounting Review*, Vol. 52 No. 2, 100881, doi: 10.1016/J.BAR.2020.100881.

Wang, H.-C., Hsiao, W.-C. and Liou, R.-S. (2023), "Integrating technical indicators, chip factors and stock news for enhanced stock price predictions: a multi-kernel approach", *Asia Pacific Management Review*. doi: 10.1016/j.apmrv.2023.10.001.

Weng, B., Ahmed, M.A. and Megahed, F.M. (2017), "Stock market one-day ahead movement prediction using disparate data sources", *Expert Systems with Applications*, Vol. 79, pp. 153-163, doi: 10.1016/j.eswa.2017.02.041.

Weng, B., Lu, L., Wang, X., Megahed, F.M. and Martinez, W. (2018), "Predicting short-term stock prices using ensemble methods and online data sources", *Expert Systems with Applications*, Vol. 112, pp. 258-273, doi: 10.1016/J.ESWA.2018.06.016.

Xu, Y., Zhang, Y., Liu, P., Zhang, Q. and Zuo, Y. (2024), "GAN-Enhanced nonlinear fusion model for stock price prediction", *International Journal of Computational Intelligence Systems*, Vol. 17 No. 1, p. 12, doi: 10.1007/s44196-023-00394-4.

Yaya, O.S., Adekoya, O.B., Vo, X.V. and Al-Faryan, M.A.S. (2024), "Stock market efficiency in Asia: evidence from the Narayan–Liu–Westerlund's GARCH-based unit root test", *International Journal of Finance and Economics*, Vol. 29 No. 1, pp. 91-101, doi: 10.1002/ijfe.2676.

Zhao, D. and Li, K. (2022), "Bounded rationality, adaptive behaviour, and asset prices", *International Review of Financial Analysis*, Vol. 80, 102037, doi: 10.1016/j.irfa.2022.102037.

Appendix

The appendix for this article can be found online.

Supplementary material

The supplementary material for this article can be found online.

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