IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 6, December 2025, pp. 5231~5239
ISSN: 2252-8938, DOI: 10.11591/ijai.v16.i6.pp5231-5239

Exploring the influence of soft information from economic news on exchange rate and gold price movements

Rahardito Dio Prastowo, Indra Budi, Amanah Ramadiah, Aris Budi Santoso, Prabu Kresna Putra
Faculty of Computer Science, Universitas Indonesia, Depok, Indonesia

Article Info

Article history:

Received Jul 16, 2024
Revised Oct 5, 2025
Accepted Oct 18, 2025

Keywords:

Economic news sentiment
Exchange rate
Gold price movements
Granger causality
Multiple linear regression

ABSTRACT

Information on business conditions is an important concern for market players and regulators. Hard information relates to easily validated characteristics such as production levels and employment conditions. In contrast, soft information such as consumer and public perceptions—is subjective and difficult to verify. Although previous studies on hard and soft information mainly focus on microeconomics and banking, current developments in big data and machine learning enable broader applications in financial market analysis. This study combined VADER sentiment analysis and support vector machine (SVM) classification (accuracy=85%) to analyze economic news, followed by Granger causality and multiple linear regression to examine causal effects and predictive relationships. The findings reveal that negative news sentiment and the Indonesian Rupiah (IDR) exchange rate influence each other, while positive sentiment has no causal impact on the exchange rate. Both negative and positive sentiments affect gold prices, whereas gold price movements do not influence sentiment. Regression analysis shows that negative sentiment has a stronger effect in decreasing the IDR exchange rate than positive sentiment, with the model explaining approximately 20% of the variance. Integrating sentiment and exchange rate data enhances the predictive model for gold price forecasting and highlights the asymmetric roles of positive and negative news in financial dynamics.

Corresponding Author:

Rahardito Dio Pratowo
Faculty of Computer Science, Universitas Indonesia
Margonda Raya, Depok, West Java 16424, Indonesia
Email: rahardito.dio@ui.ac.id

1. INTRODUCTION

Both now and in the future, business conditions will always be an important concern for market players and regulators as a basis for determining policy [1]. Two types of information can be used in forecasting, "hard" information in the form of real data that can be obtained directly, such as production levels and employment conditions. In contrast, "soft" information is data usually obtained from the perceptions of consumers and the general public [2]. Even though discussions related to hard information and soft information have previously been widely discussed in the context of microeconomics, especially banking, technological developments have encouraged the use of this concept in financial markets and institutions outside banking [3].

Hard information has properties that can be directly validated and generally agreed upon by various parties, such as demographic data [4]. Another example is financial report data, which banks commonly used to provide loans to small businesses [5]. Another characteristic of hard information is that it is verifiable and has assessment standards used by people [6], resulting in specific information and clear answer [7]. Meanwhile, soft information is data that can be interpreted differently and requires more effort to verify its value [4].

Advances in big data technology in recent years have enabled the transformation of qualitative data into quantitative data [8], especially in financial technology, which has opened up the possibility of utilizing soft information to be converted into hard information to become more efficient [9]. Filomeni *et al.* [10] examined how to integrate soft information consisting of pre-defined questionnaires and sentiment analysis from loan application texts into statistical data to predict corporate default, which shows a significant impact in increasing predictive ability when integrating these data. In a broader context, news headline sentiment has begun to be widely applied and is considered more efficient in measuring investor sentiment. Investor sentiment is a part that cannot be left out when carrying out price prediction analysis for a commodity in addition to indicators such as price index, exchange rate, and production levels [11]. Apart from that, several studies have also proved a strong relationship between news and social media information on investor sentiment, the volume of a commodity on the market, and asset prices by utilizing text mining and classification techniques [12].

It has been proven that macroeconomic news sentiment can be used to analyze daily exchange rate movements, one of which is research conducted by Mao *et al*. [13], where the research integrates news sentiment with the prediction model to find out whether news sentiment can improve the performance of models. Analysis of the relationship between news sentiment and movements in the value of other economic indicators has also been carried out, one of which is the price of gold, where this analysis shows that negative sentiment has more influence on gold price responses [14]. Based on the research, there is a gap for further examination that focuses on the differences in the influence of positive and negative sentiment on macroeconomic news on exchange rates and gold prices. Apart from that, other potential research is related to previous research, which integrated soft information to improve the quality of predictive analysis compared to previously only utilizing hard information, regarding the impact of integrating news sentiment with the exchange rate and its relationship with gold price movements.

2. METHOD

Predictive analysis of an exchange rate often uses time series methods to determine the price trend of a currency. Machine learning is used to increase speed and efficiency, and sentiment analysis is integrated to increase predictive capabilities, as research conducted by Xueling *et al.* [15] The study used the CNN method to extract local features from the text, combined with LSTM to carry out trend exchange rate analysis. Mao *et al*. [13] conducted a study on predicting complex exchange rate movements using CNN-LSTM and transformer models combined with BERT-based news sentiment, showing that long-term news effects can enhance prediction accuracy. Predictive analysis of gold prices that integrates news sentiment factors has also been widely carried out. Junjie and Mengoni [16] used Pearson correlation to compare the relationship between 1-day and 5-day news sentiment and gold price movements.

In this study, the authors aimed to determine news sentiment's impact on the exchange rate and gold price movement. The authors used the Granger causality analysis to find out whether a time series variable can be used to predict other time series variable, such as research carried out by Jiang *et al.* [17], who used Granger causality to study the effect of variable crude oil prices on the exchange rate, this research shows that a significant causal impact between crude oil prices and the exchange rate will only occur when the value of a currency is at a certain extreme condition. Granger causality analysis has also been carried out on gold price movements, where the research was carried out to study the impact of the spread of COVID-19 on gold price movements. The research shows a significant response to the gold price movement from the increase in COVID-19 cases, but no causal relationship was found when the opposite test was carried out [18].

Furthermore, multiple linear regression analysis was conducted to investigate the influence of Indonesian Rupiah (IDR) exchange rate and economic news sentiment on gold prices as the dependent variable. This method was used to assess whether sentiment, as a form of soft information, could enhance the predictive ability of models typically based on hard information. In addition, this study examines whether there is a difference between the impact of negative and positive sentiment. Research conducted by Abdou *et al.* [19] used linear regression analysis to analyze the influence of Twitter sentiment by comparing three regression models, which shows that there is a weak correlation between Twitter sentiment and gold prices. Another research was conducted by Jianyi *et al.* [20], which analyzed the condition of COVID-19 on gold prices. The results showed that the COVID-19 case could be used to explain gold price movements.

Figure 1 shows the research methodology used by the authors to answer the research questions. Three types of data were collected: economic news sentiment data, IDR exchange rate, and gold price movements. Before the causality analysis, sentiment analysis was carried out on news data to classify the positive and negative sentiment. The causality analysis is carried out to assess the impact of economic news sentiment on the IDR exchange rate and gold price movement. After that, a regression analysis is carried out to determine the effect of economic news sentiment on the model used to predict gold prices.

2.1. Data collection

The authors use DetikFinance as an online media source to obtain news data related to the economy in Indonesia because DetikFinance is considered an online news media platform with many readers in Indonesia. The authors scraped the data using the beautiful soup library in the Python programming language from January 1, 2020 to April 30, 2024. Beautiful Soup is a library that can extract HTML and XML data [21]. The other two data were obtained by downloading datasets from trusted sources. Specifically, the authors downloaded data from investing.com to obtain the IDR exchange rate against USD and gold price movements. These datasets are visualized in Figure 2, which presents the trends of both variables over time.

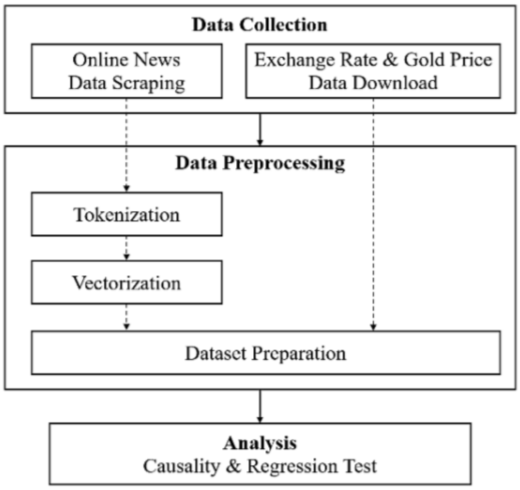

Figure 1. Research methodology

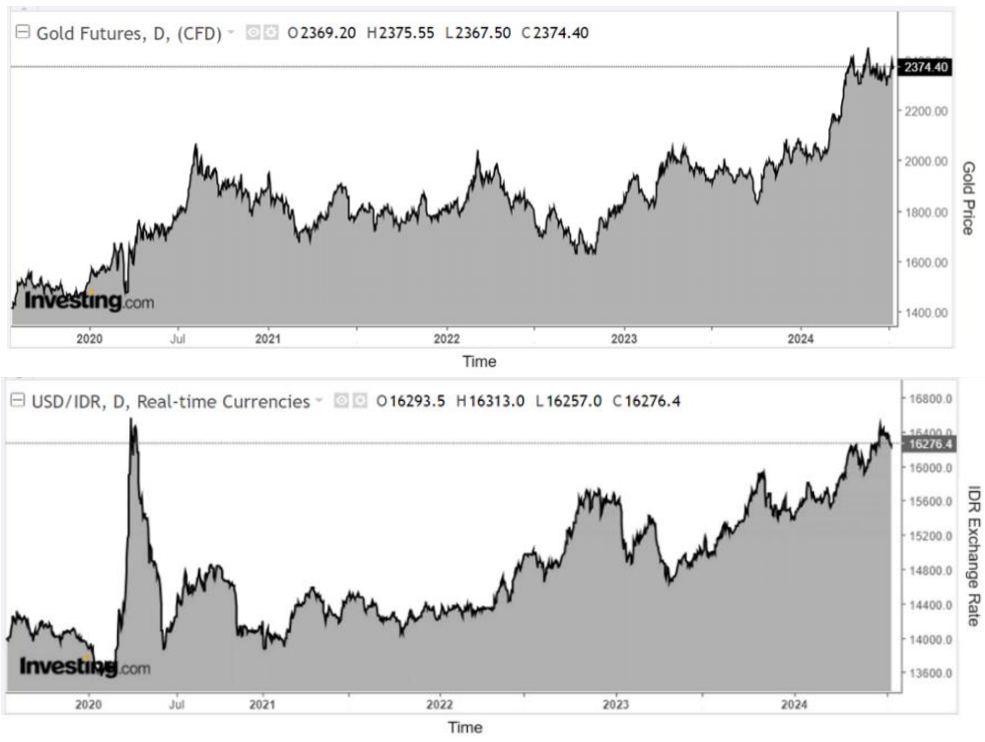

Figure 2. IDR exchange rate and gold price movement chart (investing.com)

2.2. Sentiment analysis

The authors used a sentiment analysis tool called VADER, which is generally used to carry out semantic scoring for social media with the basic sentiment lexicon [22]. The sentiment results with values close to +1 are positive, values close to -1 are negative, and values around -0.5 to 0.5 are neutral [23]. This study combines VADER with the support vector machine (SVM) machine learning algorithm, similar to the approach used in [22], [23] SVM is used to classify previously vectorized data using the TF-IDF method, which results from changing text data into a numerical representation [24].

Based on the results of classification modeling carried out with SVM, Table 1 shows the classification report from the model with the scores of precision, recall, F1-score, and accuracy to measure the classification performance [25]. The precision score shows that correct positive predictions were 83% (negative and neutral labels) and 87% (positive labels) of the total positive predictions. The recall score shows that the correct positive predictions were 78% (negative label), 87% (neutral label), and 89% (positive label) of the total actual positives. The F1-score shows the harmonized value of precision and recall, with all values being above 85%, and the overall accuracy of the model shows a value of 85%. Figure 3 displays a confusion matrix graph, which indicates that the numbers showing conformity are significantly more than the numbers showing nonconformity.

Table 1. SVM classification report

Sentiment label	Precision	Recall	F1-score
Negative	0.83	0.74	0.78
Neutral	0.83	0.87	0.85
Positive	0.87	0.89	0.88
Accuracy			0.85

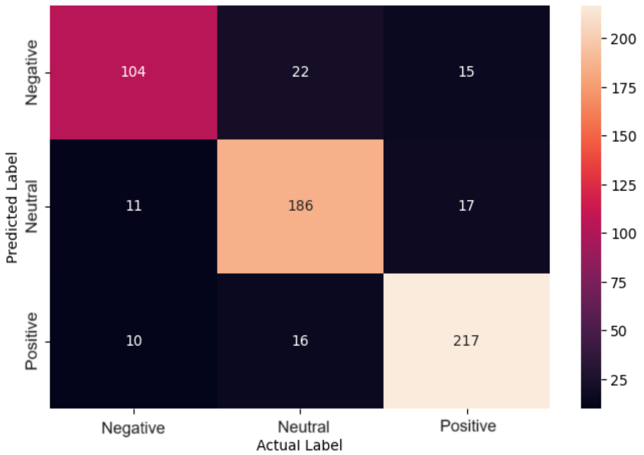

Figure 3. Lags on granger causality tests

2.3. Granger causality analysis

Using the Granger causality method, the author analyzes how news sentiment influences exchange rates and gold prices and vice versa. This technique is commonly applied for time series analysis in various scientific disciplines [26]. Granger causality tests whether one time series can be used to predict another time series [27]. Therefore, this study uses lags 1, 2, and 3 as lag periods to assess how news sentiment affects the exchange rate and gold price. Lags are the delay period in the observation that is influenced, but the distance of these lags cannot be the same for different time series data [26]. Figure 4 further illustrates some of the lags considered in this study.

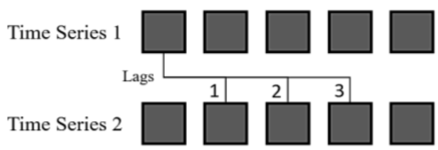

Figure 4. Lags on granger causality tests

2.4. Regression analysis

The author carried out further analysis regarding the ability of news sentiment to make predictions through integrated modeling with exchange rate data to predict gold prices, as previous research stated that soft information could improve the quality of predictions from models created using hard information [10]. Linear regression analysis is a statistical analysis that is generally used for predictive analysis and to analyze the relationship between the dependent variable and one or more independent variables [28]. By integrating news sentiment with exchange rates, the author uses a multiple linear regression model where there are two or more independent variables [29].

3. RESULTS AND DISCUSSION

The authors began the data analysis process by observing trends in the news sentiment data that had been generated. The data is displayed as a line graph in Figure 5. This figure does not indicate a downward or upward trend for negative and positive sentiment throughout the period used. However, there was an increase immediately followed by a decrease in the news with positive and negative sentiment in mid-2020 and early 2021.

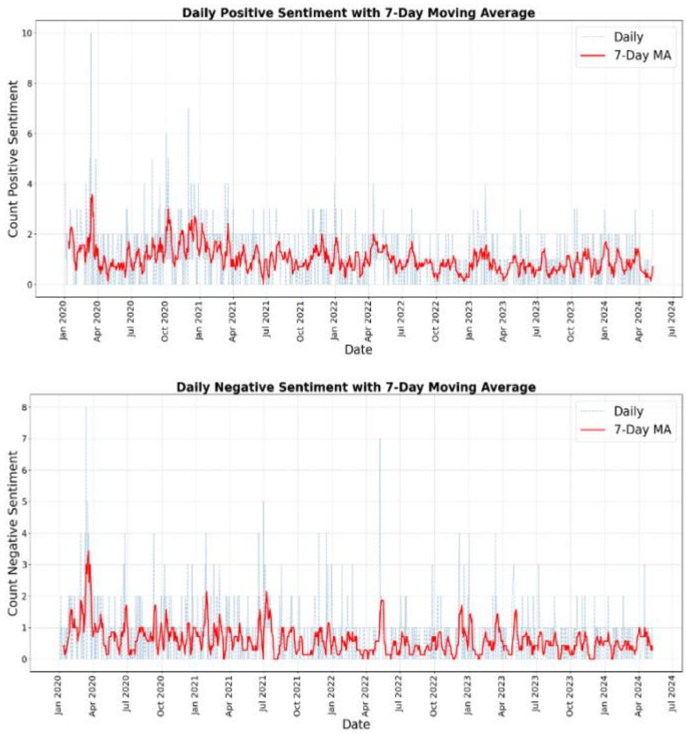

Figure 5. Daily positive and negative news sentiment

3.1. Causality between news sentiment and IDR exchange rate

Based on the Granger causality test that has been done, the p-value shows a statistically significant "causal" relationship if the p-value <0.05, which means news sentiment causes changes in IDR exchange rate. In contrast, the p-value indicates a "non-causal" relationship if the p-value is > 0.05, which means the news sentiment does not cause changes in IDR exchange rate. Table 2 shows the results of the Granger causality test between news sentiment and IDR exchange rate using lags of 1, 2, and 3 days. Apart from that, the direction of the arrow is used to show the direction of causality of the test carried out.

The "Variables" column consists of the direction of the causality test between news sentiment and IDR exchange rate, and the "Lag" column consists of 3 values of lag that have been used in this study. The "p-value" column consists of causality test results, where based on the results in the Table 2, it can be said that 5 relationships show p-value < 0.05 (H2, H5, H6, H9, H10). This indicates that negative news sentiment shows a causal relationship to the IDR exchange rate and vice versa, even though there was a non-causal relationship at lag 1 (H1). In contrast, the positive new sentiment shows a non-causal relationship to the IDR exchange rate and vice versa with p-value > 0.05 (H3, H4, H7, H8, H11, H12).

Table 2. Results for granger causality test between news sentiment with IDR exchange rate

Code	Variables	Lag	p-value	Causality
H1	(-) Sentiment – IDR Rate	1	0.0595	non-causal
H2	IDR Rate – (-) Sentiment	1	1.59e-05	causal
H3	(+) Sentiment – IDR Rate	1	0.1538	non-causal
H4	IDR Rate – (+) Sentiment	1	0.0912	non-causal
H5	(-) Sentiment – IDR Rate	2	0.0015	causal
H6	IDR Rate – (-) Sentiment	2	0.0014	causal
H7	(+) Sentiment – IDR Rate	2	0.0511	non-causal
H8	IDR Rate – (+) Sentiment	2	0.3688	non-causal
H9	(-) Sentiment – IDR Rate	3	0.0041	causal
H10	IDR Rate – (-) Sentiment	3	0.0142	causal
H11	(+) Sentiment – IDR Rate	3	0.0836	non-causal
H12	IDR Rate – (+) Sentiment	3	0.5518	non-causal

3.2. Causality between news sentiment and gold prices

Table 3 shows the results of the Granger causality test carried out by the authors in analyzing the causality relationship between news sentiment and gold price. Based on the results, it can be said that there were 5 relationships that show p-value < 0.05 (H13, H15, H17, H19, H21). This indicates that news sentiment shows a causal relationship to the gold price, both negative and positive sentiment, even though there was a non-causal relationship at Lag 3 (H23), while the gold price shows non-causal relationship to the news sentiment with p-value > 0.05 (H14, H16, H18, H20, H22, H24), both negative and positive sentiment.

3.3. Regression analysis between news sentiment and IDR exchange rates with the gold price

In the next analysis process, the authors carried out statistical analysis using multiple linear regression to test the relationship between one dependent variable and several independent variables. In this study, the dependent variable is the gold price, while the independent variables consist of news sentiment and the IDR exchange rate. Table 4 shows the results of testing with multiple linear regression.

Table 3. Results for granger causality test between news sentiment with gold price

Code	Variables	Lag	p-value	Causality
H13	(-) Sentiment – Gold Price	1	1.23e-04	causal
H14	Gold Price – (-) Sentiment	1	0.5013	non-causal
H15	(+) Sentiment – Gold Price	1	2.25e-03	causal
H16	Gold Price – (+) Sentiment	1	0.5649	non-causal
H17	(-) Sentiment – Gold Price	2	0.0003	causal
H18	Gold Price – (-) Sentiment	2	0.7318	non-causal
H19	(+) Sentiment – Gold Price	2	0.0160	causal
H20	Gold Price – (+) Sentiment	2	0.7222	non-causal
H21	(-) Sentiment – Gold Price	3	0.0020	causal
H22	Gold Price – (-) Sentiment	3	0.6296	non-causal
H23	(+) Sentiment – Gold Price	3	0.0961	non-causal
H24	Gold Price – (+) Sentiment	3	0.7219	non-causal

Table 4. Results for regression analysis between news sentiment and IDR exchange rate on gold price movements

	Estimate	Std. error	t value	Pr(>|t|)
	Negative sentiment & IDR exchange rate			
(Intercept)	365.788690	97.810362	3.740	0.000194 ***
sent_negative	-21.215032	4.321684	-4.909	1.06e-06 ***
IDR	0.101696	0.006585	15.444	< 2e-16 ***
Adj. R-squared	0.1977			
p-value	< 2.2e-16			
	Positive sentiment & IDR exchange rate			
(Intercept)	358.554030	98.309433	3.647	0.000278 ***
sent_negative	-15.053169	4.024521	-3.740	0.000194 ***
IDR	0.102149	0.006616	15.441	< 2e-16 ***
Adj. R-squared	0.1977			
p-value	< 2.2e-16			

The first part of Table 4 displays the regression analysis results with negative sentiment and the IDR exchange rate as independent variables and the gold price as the dependent variable with p-value <0.05, indicating that the negative sentiment and the IDR exchange rate significantly affect the model. The second part of Table 4 displays the regression analysis results with positive sentiment and the IDR exchange rate as independent variables and the gold price as the dependent variable with a p-value < 0.05, also indicating that positive sentiment and the IDR exchange rate significantly affect the model. Meanwhile, the adjusted R-squared value of 0.1977 shows that the model can explain 19% of the variation in the dependent variable.

4. CONCLUSION

This study aimed to determine the effect of soft information from economic news sentiment on the IDR exchange rate and gold price from January 1, 2020 to April 30, 2024. First, the authors carried out sentiment analysis using the VADER lexicon method and validated it using the SVM model. In addition, data related to the IDR exchange rate and gold price were obtained from Investing.com. The Granger causality test revealed that negative news sentiment significantly affects the IDR exchange rate, while positive sentiment shows no significant influence. In contrast, both positive and negative sentiments impact gold prices, but the gold price does not significantly affect news sentiment. These findings indicate that negative sentiment plays a stronger role in currency fluctuations, while gold prices respond to overall sentiment trends. Additionally, multiple linear regression analysis confirmed that economic news sentiment and the IDR exchange rate significantly influence gold prices. This suggests that both factors can be integrated into predictive models for gold price forecasting. Further research can explore the findings from this study, especially regarding the underlying reasons for the difference between negative and positive sentiment influence on the exchange rate or another economic indicator. Other findings related to the multiple linear regression model for predicting gold prices have the potential for further research regarding other economic indicators that can be used to improve the independent variables' ability to explain the dependent variable.

ACKNOWLEDGMENTS

This study was conducted under the auspices of the University of Indonesia, and we are especially thankful for the academic support and facilities provided.

FUNDING INFORMATION

This study was carried out independently without any financial support from external institution or funding body.

AUTHOR CONTRIBUTIONS STATEMENT

To promote transparency and proper attribution of work, this study uses the Contributor Roles Taxonomy (CRediT) to specify the contribution of each author.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Rahardito Dio Prastowo	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Indra Budi	✓	✓		✓	✓			✓		✓		✓		
Amanah Ramadiah	✓	✓		✓	✓			✓		✓		✓		
Aris Budi Santoso	✓	✓		✓				✓		✓	✓			
Prabu Kresna Putra	✓	✓		✓				✓		✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that this study was carried out without any commercial or financial involvement that could be interpreted as a potential conflict of interest.

INFORMED CONSENT

This study did not involve direct interaction with human participants or data obtained from any specific institution. Only publicly available secondary data were used. Therefore, informed consent was not required.

ETHICAL APPROVAL

As this study did not involve human subjects, institutional data, or any confidential or proprietary information, ethical approval was not applicable.

DATA AVAILABILITY

The data that support the findings of this study are openly available in DetikFinance at https://finance.detik.com and Investing.com at https://www.investing.com.

REFERENCES

[1] A. H. Shapiro, M. Sudhof, and D. J. Wilson, "Measuring news sentiment," *Journal of Econometrics*, vol. 228, no. 2, pp. 221–243, Jun. 2022, doi: 10.1016/j.jeconom.2020.07.053.
[2] M. F. Hsu, T. M. Chang, and S. J. Lin, "News-based soft information as a corporate competitive advantage," *Technological and Economic Development of Economy*, vol. 26, no. 1, pp. 48–70, Jan. 2020, doi: 10.3846/tede.2019.11328.
[3] J. M. Liberti and M. A. Petersen, "Information: Hard and soft," *Review of Corporate Finance Studies*, vol. 8, no. 1, pp. 1–41, Mar. 2019, doi: 10.1093/rcfs/cfy009.
[4] S. Estrin, S. Khavul, and M. Wright, "Soft and hard information in equity crowdfunding: network effects in the digitalization of entrepreneurial finance," *Small Business Economics*, vol. 58, no. 4, pp. 1761–1781, Apr. 2022, doi: 10.1007/s11187-021-00473-w.
[5] D. Tsuruta, "Can banks monitor small business borrowers effectively using hard information?," *Accounting and Finance*, vol. 60, no. 4, pp. 4291–4330, Dec. 2020, doi: 10.1111/acfi.12544.
[6] S. N. Ali, N. Haghpanah, X. Lin, and R. Siegel, "How to sell hard information," *The Quarterly Journal of Economics*, vol. 137, no. 1, pp. 619–678, 2022, doi: 10.1093/qje/qjab024.
[7] H. Li, "Embedded microprocessor wireless communication data collection aids in early warning of default risk for internet finance bank customers," *Journal of Sensors*, vol. 2021, pp. 1-10, 2021, doi: 10.1155/2021/1679907.
[8] M. Caron and O. Muller, "Hardening Soft Information: A Transformer-Based Approach to Forecasting Stock Return Volatility," in *2020 IEEE International Conference on Big Data*, Dec. 2020, pp. 4383–4391, doi: 10.1109/BigData50022.2020.9378134.
[9] T. Sheng, "The effect of fintech on banks' credit provision to SMEs: Evidence from China," *Finance Research Letters*, vol. 39, Mar. 2021, doi: 10.1016/j.frl.2020.101558.
[10] S. Filomeni, U. Bose, A. Megaritis, and A. Triantafyllou, "Can market information outperform hard and soft information in predicting corporate defaults?," *International Journal of Finance and Economics*, vol. 29, no. 3, pp. 3567–3592, 2024, doi: 10.1002/ijfe.2840.
[11] Y. Li, S. Jiang, X. Li, and S. Wang, "The role of news sentiment in oil futures returns and volatility forecasting: Data-decomposition based deep learning approach," *Energy Economics*, vol. 95, Mar. 2021, doi: 10.1016/j.eneco.2021.105140.
[12] A. Tadphale, H. Saraswat, O. Sonawane, and P. R. Deshmukh, "Impact of news sentiment on foreign exchange rate prediction," in *2023 3rd International Conference on Intelligent Technologies (CONIT),* Hubli, India, 2023, pp. 1-8, doi: 10.1109/CONIT59222.2023.10205534.
[13] Y. Mao, Z. Chen, S. Liu, and Y. Li, "Unveiling the potential: Exploring the predictability of complex exchange rate trends," *Engineering Applications of Artificial Intelligence*, vol. 133, Mar. 2024, doi: 10.1016/j.engappai.2024.108112.
[14] M. Lukauskas, V. Pilinkiene, J. Bruneckiene, A. Stundziene, A. Grybauskas, and T. Ruzgas, "Economic Activity forecasting based on the sentiment analysis of news," *Mathematics*, vol. 10, no. 3461, Sep. 2022, doi: 10.3390/math10193461.
[15] L. Xueling, X. Xiong, and S. Yucong, "Exchange rate market trend prediction based on sentiment analysis," *Computers and Electrical Engineering*, vol. 111, Oct. 2023, doi: 10.1016/j.compeleceng.2023.108901.
[16] Z. Junjie and P. Mengoni, "Spot gold price prediction using financial news sentiment analysis," in *2020 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology*, Dec. 2020, pp. 758–763, doi: 10.1109/WIIAT50758.2020.00117.
[17] Y. Jiang, Y. S. Ren, S. Narayan, C. Q. Ma, and X. G. Yang, "Heterogeneity dependence between oil prices and exchange rate: Evidence from a parametric test of Granger causality in quantiles," *North American Journal of Economics and Finance*, vol. 62, Nov. 2022, doi: 10.1016/j.najef.2022.101711.
[18] R. Gautam, Y. Kim, E. Topal, and M. Hitch, "Correlation between COVID-19 cases and gold price fluctuation," *International Journal of Mining, Reclamation and Environment*, vol. 36, no. 8, pp. 574–586, 2022, doi: 10.1080/17480930.2022.2077542.
[19] M. Abdou, M. Shaltout, A. Godah, K. Sobh, Y. Eid, and W. Medhat, "Gold price prediction using sentiment analysis," in *20th Conference on Language Engineering, ESOLEC 2022*, 2022, pp. 41–44, doi: 10.1109/ESOLEC54569.2022.10009529.
[20] Y. Jianyi, W. Chenyang, H. Yupeng, and L. Zicheng, "Research on the relationship between covid-19 epidemic and gold price trend based on linear regression model," in *IEEE 9th Joint International Information Technology and Artificial Intelligence Conference 2020*, 2020, pp. 1796–1798, doi: 10.1109/ITAIC49862.2020.9338828.
[21] H. Bhoir and K. Jayamalini, "Web crawling on news web page using different frameworks," *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, vol. 7, no. 4, pp. 513–519, Aug. 2021, doi: 10.32628/cseit2174120.
[22] A. Borg and M. Boldt, "Using VADER sentiment and SVM for predicting customer response sentiment," *Expert Systems with Applications*, vol. 162, Dec. 2020, doi: 10.1016/j.eswa.2020.113746.
[23] D. Marutho, Muljono, S. Rustad, and Purwanto, "Sentiment analysis optimization using vader lexicon on machine learning approach," in *2022 International Seminar on Intelligent Technology and Its Applications: Advanced Innovations of Electrical Systems for Humanity*, 2022, pp. 98–103, doi: 10.1109/ISITIA56226.2022.9855341.
[24] S. Jaiswal, S. Srivastava, S. Garg, and P. Singh, "Effect of news headlines on gold price prediction using NLP and deep learning," in *2023 International Conference on Artificial Intelligence and Applications (ICAIA) Alliance Technology Conference (ATCON-1),* Bangalore, India, 2023, pp. 1-6, doi: 10.1109/ICAIA57370.2023.10169488.
[25] R. Cheruku, K. Hussain, I. Kavati, A. M. Reddy, and K. S. Reddy, "Sentiment classification with modified RoBERTa and recurrent neural networks," *Multimedia Tools and Applications*, no. 83, pp. 29399–29417, Sep. 2023, doi: 10.1007/s11042-023-16833-5.
[26] A. Shojaie and E. B. Fox, "Granger causality: a review and recent advances," *Annual Review of Statistics and Its Application*, vol. 9, pp. 289–319, Nov. 2021, doi: 10.1146/annurev-statistics-040120.
[27] C. Yang, K. Xiao, Y. Ao, Q. Cui, X. Jing, and Y. Wang, "The thalamus is the causal hub of intervention in patients with major depressive disorder: Evidence from the Granger causality analysis," *NeuroImage: Clinical*, vol. 37, Jan. 2023, doi: 10.1016/j.nicl.2022.103295.

[28] J. H. Jan and A. K. Gopalaswamy, "Identifying factors in currency exchange rate estimation: a study on AUD against USD," *Journal of Advances in Management Research*, vol. 16, no. 4, pp. 436–452, Oct. 2019, doi: 10.1108/JAMR-09-2018-0084.
[29] M. Flores-Sosa, E. León-Castro, J. M. Merigó, and R. R. Yager, "Forecasting the exchange rate with multiple linear regression and heavy ordered weighted average operators," *Knowledge-Based Systems*, vol. 248, Jul. 2022, doi: 10.1016/j.knosys.2022.108863.

BIOGRAPHIES OF AUTHORS

Rahardito Dio Prastowo is a student in the Master of Information Technology program at the University of Indonesia. He is also an associate researcher at the National Research and Innovation Agency of the Republic of Indonesia. His research focuses on social listening, social impact analysis, and social media analytics, with the aim of exploring the application of information technology to analyze social behavior and support the formulation of public policy and corporate strategy. He can be contacted at email: rahardito.dio@ui.ac.id or raha012@brin.go.id.

Indra Budi is a distinguished researcher and academic whose pioneering work in computer science and artificial intelligence spans diverse domains such as natural language processing, machine learning, and data mining. With a keen focus on enhancing human-computer interaction, his ResearchGate profile highlights a prolific array of publications and collaborations that underscore his dedication to innovative approaches. He is also a respected faculty member at UI's Department of Computer Science, where his insights and expertise significantly contribute to shaping the evolving landscape of AI research and application. He can be contacted at email: indra@cs.ui.ac.id.

Amanah Ramadiah is a proficient Data Science Lead at FNA, driving Suptech solutions for Asia-Pacific central banks and co-developing Central Bank Digital Currency simulations. Also, as an adjunct faculty member at Universitas Indonesia, her interdisciplinary expertise encompasses computer science, finance, and economics, focusing on systemic risk and digital currencies. A visiting scholar at the Bank of England and IMF, she holds a Ph.D. and M.Sc. from University College London and a B.Sc. from Universitas Indonesia. She can be contacted at email: amanah.ramadiah06@ui.ac.id.

Aris Budi Santoso is a skilled software engineer and data analytics trainer with a Master's in Information Technology from the University of Indonesia. He works as an App Developer at the Ministry of Finance, Indonesia, and excels in full-stack development, web technologies, and software architecture. With a meticulous problem-solving approach, he delivers high-quality solutions and actively contributes to innovative projects. Proficient in Java and Python, he is a proactive collaborator who remains committed to staying updated with industry trends. He can be contacted at email: aris.budi@ui.ac.id.

Prabu Kresna Putra is an accomplished researcher in computer science and technology. He works at the National Research and Innovation Agency's Center for Geospatial Research. With a master's degree in Information Technology from the University of Indonesia. His specialized research spans data mining, social media analytics, and spatial analytics. Proficient in software development and artificial intelligence, his impactful advancements resonate across professional platforms, solidifying his dedication to excellence as a prominent researcher. He can be contacted at email: prabu.kresna@ui.ac.id.