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Machine Learning-Based Sentiment Analysis as a Dynamic Early Warning Sign for Financial Distress in Property and Real Estate Companies

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ABSTRACT

This study investigates the integration of sentiment analysis from social media and digital news portals as predictors of financial distress in Indonesian property companies. Intensifying industrial competition in 2024, as reported by KPPU data, has led to shrinking market shares and declining profits. Companies failing to compete face heightened risks of financial distress, necessitating more proactive monitoring tools. Unlike traditional models relying solely on financial ratios, this research innovates by using investor sentiment as an early warning sign, utilizing advanced crawling techniques like Tweet Harvest and high-performance analysis through RapidMiner. Research methods **a** total of 1,965 tweets and 602 news articles (2020–2023) were extracted and classified using Naïve Bayes. The relationship between sentiment and financial health (Altman Z-Score) was analyzed using ordinal logistic regression. Results both social media sentiment (p=0.029) and news sentiment (p=0.042) significantly influence financial health. Positive sentiment on platform X shows the strongest predictive power (Exp(B)=3.907) in identifying "healthy" companies. Conclusion **i**nvestment sentiment is a robust early warning indicator. Positive investor sentiment significantly reduces the probability of financial distress, offering a dynamic real-time monitoring tool for regulators and investors in a competitive market.

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INTRODUCTION

Amidst technological disruption and global economic volatility, competitive advantage is no longer merely a growth strategy but a critical defense mechanism (Erayanti, 2019) The consistent escalation of the Business Competition Index, which peaked at 4.95 in 2024, signals a structural shift in the Indonesian economy toward a hyper-competitive ecosystem (KPPU, 2024). This environment compels the elimination of conventional business models in favor of innovation-based resilience. Historically, accelerating business competition risks triggering market fragmentation, where a drastic decline in market share can undermine cash flow stability and drive firms toward financial distress (Arifiana & Khalifaturofi'ah, 2022). As market pressures erode profit margins and threaten operational sustainability, the implementation of financial distress prediction models becomes a crucial early warning system to indentify potential financial failure before a company reaches the point of bankruptcy (Elizabeth Inge Pratiwi & Elsa Imelda, 2022).

Financial health serves as the fundamental foundation for business entity sustainability; however, a phenomenon of profitability degradation has plagued the property sector (Chen & Chen, 2020). This is evidenced by the decline in net profit of PT Bumi Serpong Damai Tbk and the increase in operating expenses at PT Agung Podomoro Land Tbk. In 2023, the profit of PT Bumi Serpong Damai Tbk fell to IDR 2.25 trillion, a 1.33 percent decrease from the IDR 2.65 trillion recorded in 2022 (Hidayat, 2024). By the end of December 2022, the net loss of PT Agung Podomoro Land Tbk widened. Based on the company's financial statements, the gross profit of PT Agung Podomoro Land Tbk—after deducting direct costs and cost of goods sold—amounted to IDR 2.26 billion, bringing the total to IDR 1.16 trillion, indicating significant structural vulnerability.(News, 2023) When profit margins are eroded and cash flows contract, companies enter a financial distress risk zone which, if not mitigated, leads to insolvency.

As a sector highly sensitive to macroeconomic dynamics, the property industry frequently encounters price volatility risks and policy changes that directly threaten the stability of issuer financial performance. An entity's inability to mitigate these risks can accelerate financial deterioration into a phase of financial distress, which, if undetected early, will result in bankruptcy (Mahastanti & Utami, 2022). The urgency of early detection is paramount as a protective instrument for stakeholders; for instance, investors can execute timely exit strategies, creditors can secure their receivables through preventive actions, and regulators can intensify supervision. Thus, developing a responsive prediction model is not merely a managerial requirement but an essential mechanism to maintain the stability of the investment ecosystem in the property market (Shiller, 2017).

The limitations of traditional mathematical models, which rely solely on retrospective accounting data, create a predictive gap in detecting real-time financial distress. Amidst volatile market dynamics, the integration of investor sentiment analysis through the social media platform X and news article narratives becomes a crucial instrument offering prospective information dimensions not captured in conventional financial reports (Dunham & Garcia, 2021). The synergy between fundamental indicators and public sentiment enables the formation of a more responsive early warning model, where market perception fluctuations can serve as leading indicators of potential financial health degradation and future bankruptcy risks (Al Qamar Ze & Juanda, 2023).

Investor sentiment represents a critical psychological determinant that directly mitigates fluctuations in issuer performance within the property sector. Fundamentally, this sentiment is constructed through a convergence of internal financial performance, industry prospects, and macroeconomic and political stability (Griffith et al., 2020). In the digital era, sentiment volatility is accelerated by massive information flows through social media platforms like Twitter (X), which provide real-time public opinion data. For market participants, utilizing opinion analysis on current social media is no longer optional but a strategic instrument in predicting market reactions and minimizing investment risks against global and domestic economic dynamics (Sul et al., 2017).

Although liquidity, leverage, and profitability ratios are empirically capable of predicting financial distress, conventional accounting models often demonstrate limited accuracy (Giovanni et al., 2020). For example, the Altman model has been recorded to have an accuracy level of only 58%, with a margin of error reaching 31%. This accuracy gap indicates a need for predictive instruments that are more dynamic and extend beyond historical financial statement data (Sembiring & Sinaga, 2022). Therefore, this research offers novelty through an integrative approach that combines accountancy-based financial data analysis with real-time investor sentiment analysis from Twitter and news articles (Qu, 2023). By synergizing fundamental indicators and public opinion, this model is expected to provide a more responsive and comprehensive early detection system for mitigating corporate financial failure risks.

Building upon this premise, the novelty of this study lies in its systematic integration of real-time digital narratives and fundamental financial data through a robust computational workflow. This research employs an automated data acquisition process using Tweet Harvest to extract high-velocity social media discourse, which is subsequently processed through RapidMiner’s advanced analytics platform. By utilizing RapidMiner’s machine learning operators, this study implements sophisticated text mining and classification algorithms to transform unstructured investor sentiment into quantifiable risk indicators. This approach allows for a more rigorous synergy between behavioral data and accounting ratios, significantly enhancing the model's predictive power and offering a more technologically advanced framework for financial distress detection in the property sector.

This study examines the correlation between investor sentiment and the probability of financial distress by positioning sentiment analysis as a proactive early warning system. Departing from traditional models, this approach utilizes content from the social media platform Twitter and news articles as data sources believed to possess predictive value regarding a firm's financial health before it reaches a crisis or bankruptcy phase. The primary premise is that public opinion volatility and digital information flows reflect the real conditions of issuers more dynamically. Consequently, by analyzing these investor perceptions, companies can identify symptoms of financial anomalies earlier to implement precise strategic corrective measures.

METHOD, DATA, AND ANALYSIS

This study employs a quantitative approach that integrates sentiment analysis and econometric modeling to predict corporate financial health.(Al Qamar Ze & Juanda, 2023) The methodology is systematically structured, beginning with targeted data acquisition, followed by text preprocessing, sentiment classification using machine learning, and culminating in statistical testing via ordinal logistic regression (Basuki & Prawoto, 2016).

The research population comprises all property and real estate companies listed on the Indonesia Sharia Stock Index (ISSI) during the 2020–2023 observation period. Sample selection was conducted using purposive sampling to ensure data representativeness aligned with the research objectives (Sugiyono, 2013). The inclusion criteria were defined as follows: (1) issuers listed on the ISSI throughout the study period with complete financial reports; (2) issuers exhibiting negative volatility, characterized by significant stock price declines; and (3) issuers with sufficient sentiment information available on the X platform and digital news portals. Based on these criteria, eight property sector issuers were selected: ASRI, BKSL, BSDE, CTRA, LPKR, LPCK, PWON, and SMRA.

Data Crawling

The data acquisition process involved a dual-stream crawling strategy to capture both informal and formal market discourse. Primary social media data was harvested from the X platform using the Tweet Harvest tool, targeting specific keyword (e.g., $ASRI, $BSDE) and filtering for Indonesian-language content while excluding retweets to ensure sentiment originality, which yielded 1,965 relevant tweets (Rajan & S.P.Victor, 2014). Simultaneously, secondary data was gathered from the Detik.com news portal using a customized Python-based web scraper in a Google Colab environment, utilizing keywords such as company names and industry terms like "PT Alam Sutera Realty Tbk" and "ASRI" to retrieve 602 news articles.

Data Implementation Process

Raw data underwent a rigorous preprocessing pipeline in RapidMiner software to transform unstructured text into a machine-readable format (Wongkar & Angdresey, 2019). This stage included:

1. Cleansing to removal of noise such as hashtags, mentions, symbols, URLs, and duplicate entries.
2. Case Folding, sandardizing all text characters into lowercase.
3. Tokenization, segmenting text into individual words based on non-letter criteria, resulting in 2,848 regular attributes.
4. Filtering, applying word length filters (2–25 characters) and Stop-word Removal to eliminate Indonesian conjunctions that lack substantive meaning.

Sentiment Labeling and Classification

This research implemented a hybrid labeling strategy to ensure high accuracy. Manual labeling was initially conducted to establish the ground truth, capturing complex linguistic nuances and sarcasm. The dataset was then partitioned into 60% training data and 40% testing data. The Naïve Bayes Classifier algorithm was utilized for automated labeling (Samsir et al., 2021). This supervised learning model was trained using the manual labels and a pplied to the testing set through the Apply Model and Union operators. This process generated a consistent classification of sentiment into three categories: Positive, Negative, and Neutral (Ramadhan & Setiawan, 2019).

Analysis and Predictive Modeling

Classified sentiment results were integrated with financial health indicators measured by the Altman Z-Score model (Resfitasari et al., 2022). An Ordinal Logistic Regression model was applied to test the predictive power of sentiment variables X_1 (Platform X) and X_2 (News Articles). The analysis used the Likelihood Ratio Test for model fit and Nagelkerke R-Square for variance explanation (Algifari, 2000). The use of sentiment as an early warning sign represents an innovation over traditional models relying exclusively on historical financial ratios.

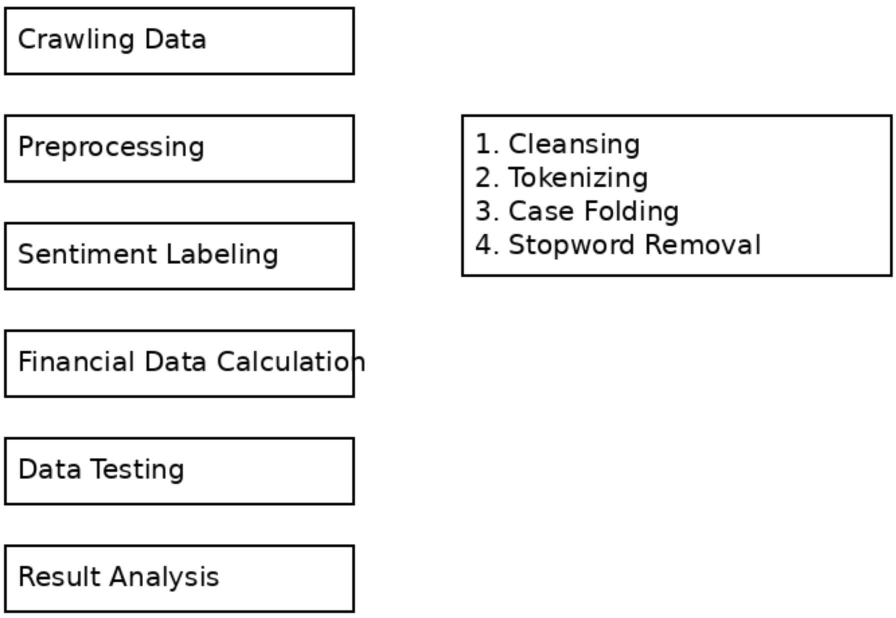

Figure 1. System Design Model

RESULTS AND DISCUSSION

Data Acquisition and Tools

This study employs a hybrid sentiment analysis approach, utilizing the Python programming language for data extraction and preprocessing, alongside RapidMiner for advanced sentiment modeling. The dataset comprises primary data in the form of public opinions (tweets) extracted from the social media platform X (formerly Twitter) and secondary data consisting of news articles sourced from detik.com.

Social Media Data Crawling (X Platform)

Primary data collection was conducted through web crawling techniques using Python within the Google Colab environment. The observation period spanned four years, from January 1, 2020, to December 31, 2023. Data extraction focused on specific property sector issuers using a combination of entity names and stock tickers as keywords, including: ASRI, BKSL, BSDE, CTRA, LPKR, LPCK, PWON, and SMRA.

A total of 1,965 tweets were successfully retrieved, filtered specifically for domestic localization (Indonesia) to ensure relevance to the local market context. The raw data were archived in .csv format to maintain structural integrity. Subsequently, a systematic labeling process was performed to classify each entry into predefined sentiment categories, resulting in a robust dataset ready for testing within the financial distress prediction model.

News Article Data Extraction

To supplement social media insights, secondary sentiment data were gathered from Detik.com. This source was selected to capture formal narratives and informative public discourse regarding corporate reputation and property market trends. Similar to the social media phase, data were collected via Python-based web crawling on Google Colab, targeting the same sample entities (ASRI, BKSL, BSDE, CTRA, LPKR, LPCK, PWON, and SMRA). The observation remained consistent with the four-year study period (2020–2023), yielding 602 relevant news articles. These textual data were converted into .csv format and integrated with the Twitter dataset. The integration of these two distinct data sources aims to provide a comprehensive multidimensional perspective, enhancing the accuracy of predicting a company's financial condition through sentiment signals.

Data Implementation and Processing Workflow

The data implementation phase follows a structured pipeline, beginning with the partitioning of the crawled dataset into training and testing sets. To facilitate accurate classification, the data undergoes a rigorous preprocessing stage. The training data is manually labeled into positive and negative sentiment classes. Subsequently, both datasets are subjected to feature selection and preprocessing before being integrated into a Naïve Bayes classification model. The final output of this system is the classified sentiment result, which serves as a predictive indicator.

Data Preprocessing

The raw dataset is imported into RapidMiner for systematic refinement. This stage is crucial for reducing noise and improving the computational efficiency of the algorithm. The preprocessing consists of the following four steps:

1. Cleansing, initial step involves the removal of redundant or irrelevant information. Specific elements targeted for deletion include hashtags, mentions (@), special symbols, emoticons, excessive whitespace, and duplicate entries. This ensures that the model focuses solely on the textual content.

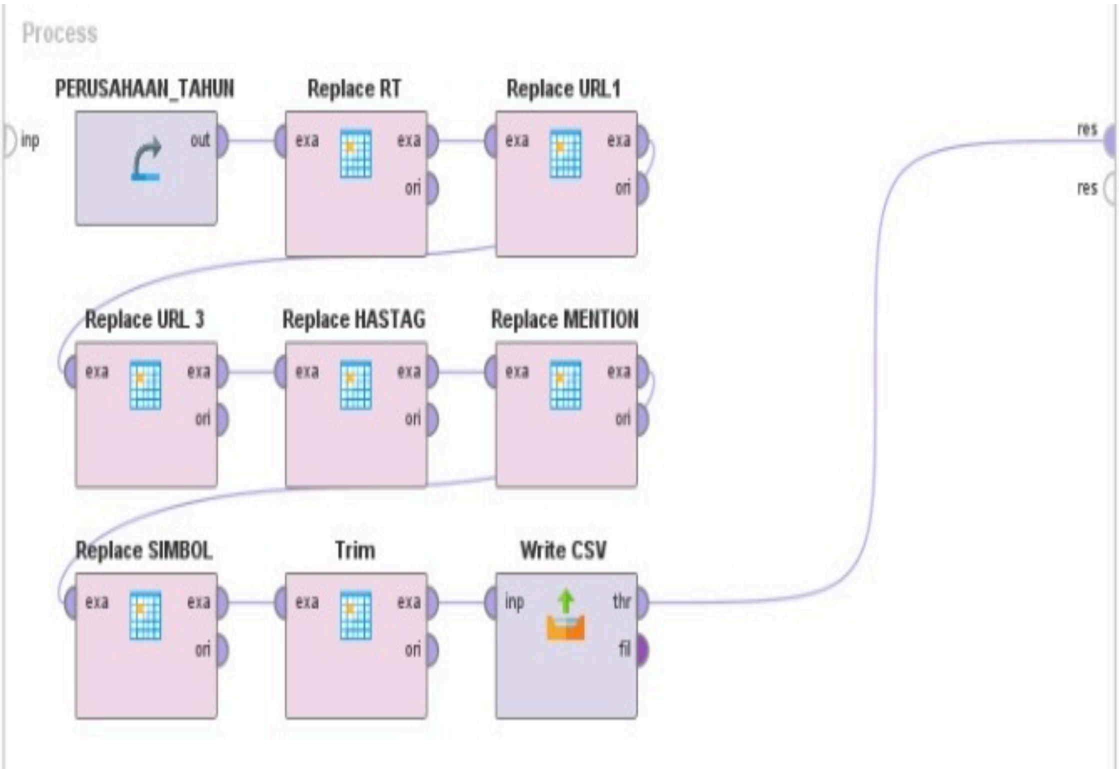

Figure 2. Data Cleaning Proses

Source: Created by Author, 2026

2. Tokenization In this phase, the text strings are decomposed into smaller, meaningful units known as tokens (words or phrases). This process identifies the linguistic origins of the data, resulting in a structured set of 2,848 regular attributes.
3. Case Folding: To ensure uniformity, all characters in the text documents are converted into lowercase. This prevents the algorithm from treating the same word as two different entities due to capitalization variances (e.g., "Pasar" vs "pasar").
4. StopWord Removal: This step filters out frequently occurring words that lack significant semantic value, such as conjunctions and prepositions (e.g., "dan," "atau," "yang"). Removing these terms narrows the focus to "feature-heavy" words that carry sentiment weight.

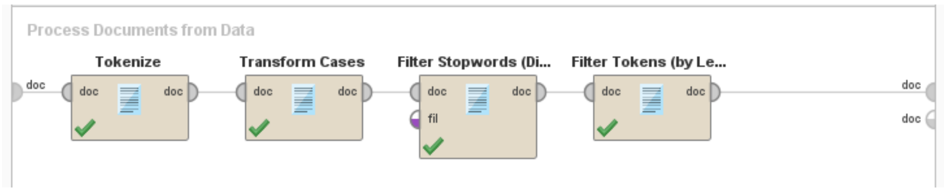

Figure 3. Data Tokenization, Case Folding, StopWord Removal Proses

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Sentiment Labeling Process

The labeling process was conducted using a hybrid approach to classify 1,965 tweets and 602 news articles into positive, negative, and neutral categories. Manual labeling was first applied as the ground truth to address semantic ambiguity and sarcasm that are difficult to detect automatically. The dataset was then partitioned (data splitting) with a proportion of 60% training data to build the model using the Naive Bayes Classifier algorithm and 40% testing data for performance validation. This procedure ensures the reliability of the dataset before it is integrated into the logistic regression analysis. The automated labeling stage was performed utilizing the Naïve Bayes Classifier algorithm through RapidMiner software. This procedure began with training the model (training model) based on the manual labeling results as a machine learning reference.

Figure 4. Sentiment Labeling Process

Source: Created by Author, 2026

Once the model was established, the testing data was processed using the Read CSV operator, filtered through missing values parameters to ensure that only unlabeled data were processed.

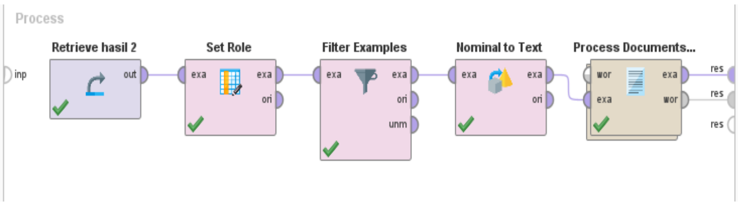

Figure 5. Training Data Modeling Proses

Source: Created by Author, 2026

The testing data modeling stage aims to automatically assign sentiment labels to unclassified data. This procedure begins by employing the Read CSV operator in RapidMiner software, followed by filtering using the parameters "sentiment is missing" and "description is not missing" to ensure input validity. The data is then converted through the Nominal to Text operator before entering the feature extraction stage within the Process Document From Data operator. Inside this operator, four primary sub-processes are performed: (1) Tokenize based on non-letter criteria, (2) Transform Cases for lowercase uniformity, and (3) Filter Tokens (by Length) with a range of 2–25 characters to reduce noise. Subsequently, the Union operator is used to integrate the testing dataset with the previously constructed training model. To maintain data consistency, empty values are addressed using the Replace Missing Values operator with a constant value of 0. The process concludes with the application of the Apply Model operator, where the Naïve Bayes algorithm executes automated labeling based on the training data patterns, producing an output of consistent positive, negative, and neutral sentiment classifications.

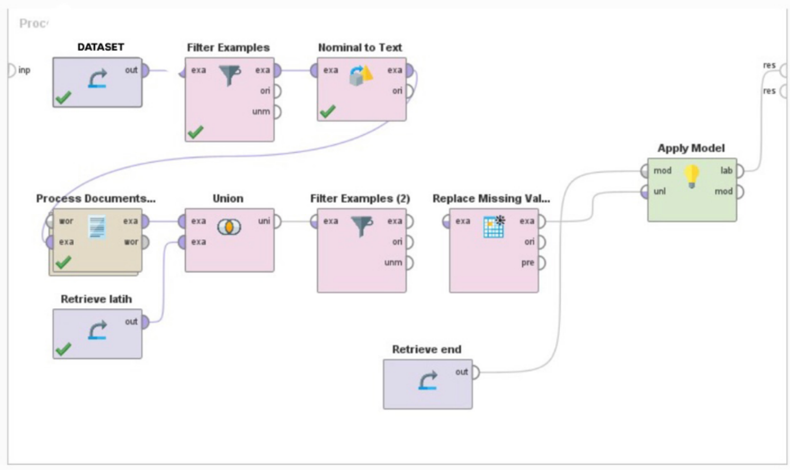

Figure 6. Automated Labeling Process Using the Naive Bayes Algorithm
Source: Created by Author, 2026

Figure 6 shows the automated labeling process flow using the Naive Bayes algorithm in sentiment analysis. This process begins with the data crawling stage, where text data is collected from various sources. Next, the data enters a preprocessing stage, which includes cleansing, tokenizing, case folding, and stopword removal to ensure the data is clean and ready for analysis. After preprocessing, the processed data is used in the sentiment labeling stage using the Naive Bayes algorithm. This algorithm works by calculating the probability that a text falls into a specific sentiment category (e.g., positive, negative, or neutral) based on word frequency and the probability distribution obtained from the training data. The results of this labeling are then used in the financial data calculation stage to link sentiment to the economic or financial variables being analyzed. Data testing is then conducted to verify the accuracy of the classification model used. The final stage is result analysis, where the test results are analyzed to draw conclusions regarding model performance and the implications of the sentiment labeling results.

Financial Data Calculation

The company's financial health is measured using the Altman Z-Score model as the dependent variable. Data is sourced from the annual reports of issuers listed on the Indonesia Stock Exchange (Putri & Maulana, 2023), analyzed through the following formulation:

$$\boxed{Z = 1,2\,X_1 + 1,4X_2 + 3,3\,X_3 + 0,6\,X_4 + 1,0\,X_5}$$

Corporate health classification is determined based on the following score thresholds:

Healthy Zone : Z > 2, 99

Grey Zone : 1,81 < Z < 2,99

Distress Zone : Z < 1,81

Tabel 2. Altman Z Score Result

Company Code	Altman Z-score	Information	Codee
ASRI	0,079334605	Terindikasi	-1
	0,341790962	Terindikasi	-1
	0,720359743	Terindikasi	-1
	0,687867128	Terindikasi	-1
BKSL	0,065139063	Terindikasi	-1
	0,393190144	Terindikasi	-1
	0,288987533	Terindikasi	-1
	0.589805505	Terindikasi	-1
BSDE	0,99002755	Terindikasi	-1
	1,125741164	Zona Grey	0
	1,244841305	Zona Grey	0
	1,317675221	Zona Grey	0
CTRA	0,830927754	Terindikasi	-1
	1,037810544	Zona Grey	0
	1,119236678	Zona Grey	0
	1,173615916	Zona Grey	0
LPCK	-0,779153108	Terindikasi	-1
	0,545900352	Terindikasi	-1
	1,362770563	Zona Grey	0
	1,336571399	Zona Grey	0
LPKR	1,617989202	Zona Grey	1
	2,26593974	Zona Grey	1
	0,459895029	Zona Grey	-1
	0,451735543	Zona Grey	-1
PWON	1,548033014	Zona Grey	0
	1,711416279	Zona Grey	1
	1,61444712	Zona Grey	1

Company Code	Altman Z-score	Information	Codee
	1,28908211	Zona Grey	0
SMRA	0,584195664	Terindikasi	-1
	0,785676935	Terindikasi	-1
	0,767141885	Terindikasi	-1
	0,768143106	Terindikasi	-1

Data source: Author's data processing results, 2026

From the table of results of the Altman Z score model calculation above, it can be concluded that from the entire sample of 8 companies in the period 2020 to 2021, there were a total of 18 data that indicated financial distress/unhealthy, 10 data that were in the gray area and 4 data that did not indicate financial distress/healthy.

Table 3. Ordinal Logistic Regression Analys

Analys Component	Indicator	Statistic Value	Sig. (p-value)
Model Fitting Information	X^2 (Chi-Square)	14,719	0,000***
Goodness-of-Fit	Pearson	6,305	0,789
	Deviance	8,191	0,789
Pseudo R-Square	Cox and Snell	0,369	
	Nagelkerke	0,435	
	McFadden	0,245	
Parallel Lines	Chi-Square	14,719	0,000
Parameter Estimates	**Variabel**	**Estimate**	**Sig.**
Threshold	[y = -1,00]	0,079	0,877
	[y = 0,00]	3,266	0,000***
Location	X_1	1,363	0,029**
	X_2	0,980	0,042**

Data source: Author's data processing results, 2026

The overall regression model is declared fit or feasible, as it demonstrates a significance value of 0.001 ($p < 0.05$) in the Likelihood Ratio test. This is further supported by the significance values of Pearson (0.789) and Deviance (0.610), both of which are greater than 0.05, indicating that the model is consistent with empirical data. The Nagelkerke R-Square value of 0.435 indicates that the independent variables (X_1 and X_2) explain 43.5% of the variance in the dependent variable. Variable X_1 has a positive and significant effect on the probability of higher dependent variable categories (\beta = 1.363; p = 0.029). Similarly, variable X_2 has a positive and significant effect on the probability of higher dependent variable categories (\beta = 0.980; p = 0.042).

Statistical tests show a significance value of $p = 0.000$ ($p < 0.05$), leading to the rejection of the null hypothesis. This proves that both the X sentiment variable and the news article sentiment variable simultaneously have a significant effect on the company's financial distress level. Partially, the X sentiment variable ($p = 0.029$) and the news article sentiment variable ($p = 0.042$) significantly influence the company's financial distress, as the significance values for both variables are lower than \alpha = 0.05. The regression coefficients for X sentiment (1.363) and news article sentiment (0.980) indicate a positive relationship with the company's financial condition. The odds ratio (Exp(B)) values of 3.907 for X sentiment and 2.664 for news sentiment indicate that every one-unit increase in sentiment increases the probability of the company being in the 'healthy' category by 3.9 times and 2.6 times, respectively. This improvement in sentiment significantly contributes to the reduction of financial distress risk and enhances the company's chances of moving into a more stable category.

DISCUSSION

This study aims to analyze the influence of social media sentiment and online news on the prediction of financial distress in the property sector in Indonesia. Based on the results of the ordinal logistic regression test, it was found that these two data sources have a significant influence, both simultaneously and partially, on the company's financial health condition as measured by the Altman Z-Score. The regression analysis demonstrates that social media sentiment on platform X exerts a significant positive influence on the financial distress of companies listed on the Indonesia Sharia Stock Index (ISSI) for the 2020-2023 period, evidenced by a p-value of 0.029 ($p<0.05$).

These findings suggest that the escalation of negative digital sentiment acts as a catalyst for financial instability through two primary transmission channels: the erosion of consumer trust, which triggers sales volatility, and reputational degradation, which prompts conservative investment behavior and aggressive stock sell-offs. This phenomenon aligns with behavioral finance theory (Sisbintari, 2018) and corroborates the empirical evidence provided by (Mengelkamp et al., 2016), reinforcing the premise that unstructured social media data serves as a potent predictor of corporate credit risk and insolvency. Consequently, this study emphasizes the critical necessity for Sharia-compliant firms to integrate digital reputation management into their risk mitigation strategies to safeguard liquidity and ensure long-term financial resilience against perception-based external shocks.

This study finds that news article sentiment significantly influences the financial distress of companies listed on the Indonesia Sharia Stock Index (ISSI) for the 2020-2023 period, as evidenced by a partial test significance value of 0.042 ($p<0.05$). The empirical evidence suggests that news sentiment serves as a critical information signal; while positive coverage bolsters investor confidence and share prices, negative news acts as a precursor to financial instability by triggering liquidity constraints and reputational damage. This is exemplified by the Meikarta case, where legal and regulatory scandals led to a massive sell-off and hindered the firm's ability to access capital markets (Ahdiat, 2023). These findings align with the research of (Nikkinen & Peltomäki, 2020) regarding the impact of information dissemination on crash fears, as well as (Zhao et al., 2022) assertion that integrating sentiment tone features from news publications is highly effective for financial distress prediction. Ultimately, the results underscore that for Sharia-compliant firms, news sentiment is not merely a reflection of public opinion but a tangible risk factor that directly correlates with corporate solvency.

The main findings of this study indicate that the X sentiment variable (X_1) has a regression coefficient of 1.363, while the news sentiment (X_2) is 0.980. The Odds Ratio (Exp(B)) values, which reach 3.907 and 2.664 respectively, indicate that every one-unit increase in positive sentiment on the X platform increases the chances of a company being in the "healthy" category by nearly fourfold. This proves that public opinion on social media tends to be a more sensitive leading indicator of changes in financial conditions compared to formal news. Social media captures investor expectations and concerns in real-time, while news on portals like Detik.com is often informative and confirmatory of events that have already occurred.

The results of this study reinforce the Investor Sentiment theory, which states that public perception can influence market value and corporate funding accessibility, which ultimately impacts financial stability. The use of a hybrid method with the Naive Bayes algorithm for sentiment classification proved effective, as seen from the regression model's ability to explain 43.5% of the data variance (based on the Nagelkerke R-Square value). Although Twitter data is often considered "noisy," the systematic preprocessing including cleansing, tokenizing, and stopword removal has successfully extracted relevant sentiment signals to support technical predictions such as the Altman Z-Score. Specifically for property issuers such as ASRI, BKSL, and SMRA which, during the research period (2020-2023), showed indications of financial distress (low Z-Score), a correlation with the developing public narrative was observed (Pradana et al., 2020). These findings provide managerial implications that companies must not only focus on fundamental performance but also proactively manage corporate communications and digital reputation. For investors, this model can serve as an additional Early Warning System (EWS) instrument beyond traditional financial statement analysis.

CONCLUSION AND SUGGESTIONS

This study concludes that the integration of sentiment analysis based on social media and digital news portals serves as a significant predictor in classifying the financial health of property companies in Indonesia. Based on the ordinal logistic regression analysis, public sentiment variables from the X platform (Twitter) and news article sentiment both simultaneously and partially exert a significant positive influence on the level of financial distress, as measured by the Altman Z-Score model.

The primary findings indicate that public sentiment on the X platform possesses a stronger influence (Exp(B)=3.907) compared to sentiment from news articles (Exp(B)=2.664). This suggests that every one-unit increase in positive sentiment increases a company's odds of being in the "financially healthy" category by 3.9 times. These results reinforce the Efficient Market Hypothesis (EMH), demonstrating that non-financial information and public opinion evolving in digital spaces effectively reflect a company’s fundamental condition. Furthermore, the use of the Naïve Bayes algorithm proved effective in automated labeling with adequate accuracy to support predictive analysis of financial distress risks. Based on these findings and the limitations identified, several directions for future research are proposed. First, regarding methodology, future researchers are encouraged to explore the use of Deep Learning algorithms, such as Long Short-Term Memory (LSTM) or BERT (Bidirectional Encoder Representations from Transformers), to enhance sentiment classification accuracy, particularly in capturing linguistic nuances, sarcasm, and complex local dialects on social media. Second, as this study is limited to the property sector, the generalizability of the results could be enhanced by expanding the sample scope to other industrial sectors and extending the observation period to encompass various phases of the economic cycle. Third, the integration of macroeconomic variables such as interest rate fluctuations, inflation rates, and property sector regulatory policies should be considered as control variables to strengthen the model's predictive power. Finally, from a practical standpoint, regulators and investors are advised to integrate unstructured text data analysis as a component of an early warning system to monitor the financial stability of issuers more dynamically and in real-time within the digital era.

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REFERENCE

Ahdiat, A. (2023). *Terseret Kasus Meikarta, Ini Keuangan Lippo Cikarang 5 Tahun Terakhir*. databoksks.https://databoks.katadata.co.id/properti/statistik/cdd26c632c81aa7/terseret-kasus-meikarta-ini-keuangan-lippo-cikarang-5-tahun-terakhir

Al Qamar Ze, A., & Juanda, J. (2023). Pengaruh Herding Behavior, Media, Interaksi Sosial Dan Advocate Recommendation Terhadap Keputusan Investasi Dengan Sentimen Investor Sebagai Variabel Intervening. *International Journal of Science and Society*, *1*(2), 1–9.

Algifari. (2000). *Analisis Regresi, Teori, Kasus dan Solusi*. BPFE-YOGYA.

Arifiana, R., & Khalifaturofi'ah, S. O. (2022). the Effect of Financial Ratios in Predicting Financial Distress in Manufacturing Companies. *Jurnal Riset Bisnis dan Manajemen*, *15*(2), 103–108. https://doi.org/10.23969/jrbm.v15i2.5838

Basuki, & Prawoto. (2016). *Analisis Regresi dalam Penelitian Ekonomi dan Bisnis (Dilengkapi dengan Aplikasi SPSS &Eviews)*. RajaGrafindo.

Chen, C., & Chen, C.-D. (2020). Financial distress prediction model: The effects of corporate governance indicators. *Journal of Forecating*, *39*(8), 1238–1252. https://doi.org/https://doi.org/10.1002/for.2684

Dunham, L. M., & Garcia, J. (2021). Measuring the effect of investor sentiment on financial distress. *Managerial Finance*, *50*(12), 1834–1852. https://doi.org/10.1108/MF-02-2021-0056

Elizabeth Inge Pratiwi, & Elsa Imelda. (2022). Hubungan Kausalitas antara Sentimen Investor dan Pasar Keuangan Indonesia. *Jurnal Ekonomi*, *27*(03), 182–201. https://doi.org/10.24912/je.v27i03.872

Erayanti, R. (2019). Pengaruh Likuiditas, Profitabilitas dan Leverage terhadap Prediksi Financial Distress. *Jurnal Riset Akuntansi & Perpajakan (JRAP)*, *6*(01), 38–51. https://doi.org/10.35838/jrap.v6i01.393

Giovanni, A., Utami, D. W., & Yuzevin, T. (2020). Leverage dan Profitabilitas dalam Memprediksi Financial Distress Perusahaan Pertambangan Periode 2016-2018. *Journal of Business and Banking*, *10*(1), 151. https://doi.org/10.14414/jbb.v10i1.2292

Griffith, J., Najand, M., & Shen, J. (2020). Emotions in the Stock Market. *Journal of Behavioral Finance*, *21*(1), 42–56. https://doi.org/10.1080/15427560.2019.1588275

Hidayat, K. (2024). *Bumi Serpong (BSDE) Profit Drops 20.04% in 2023, Check Out Its Stock Recommendations*. kontan.co.id. https://english.kontan.co.id/news/bumi-serpong-bsde-profit-drops-2004-in-2023-check-out-its-stock-recommendations#:~:text=Bumi Serpong (BSDE) Profit Drops,Check Out Its Stock Recommendations

KPPU. (2024). *CEDS Unpad : Tingkat Persaingan Usaha Indonesia Tahun 2023 Meningkat*. UNPAD. https://kppu.go.id/blog/2024/01/ceds-unpad-tingkat-persaingan-usaha-indonesia-tahun-2023-meningkat/

Mahastanti, L. A., & Utami, A. D. (2022). Perbandingan Tingkat Akurasi Model Prediksi Financial Distress pada Perusahaan Sektor Property dan Real Estate. *AFRE (Accounting and Financial Review)*, *5*(1), 50–63. https://doi.org/10.26905/afr.v5i1.7526

Mengelkamp, A., Wolf, S., & Schumann, M. (2016). Data driven creation of sentiment dictionaries for corporate credit risk analysis. *AMCIS 2016: Surfing the IT Innovation Wave - 22nd Americas Conference on Information Systems*, *2015*, 1–9.

News, I. (2023). *Financial Statements Full Year 2022 of APLN*. https://www.indopremier.com/ipotnews/newsDetail.php?jdl=Financial_Statements_Full_Year_2022_of_APLN&news_id=417051&group_news=RESEARCHNEWS&news_date=&taging_subtype=APLN&name=&search=y_general&q=Financial Statements&halaman=1

Nikkinen, J., & Peltomäki, J. (2020). Crash Fears and Stock Market Effects: Evidence From Web Searches and Printed News Articles. *Journal of Behavioral Finance*, *21*(2), 117–127. https://doi.org/10.1080/15427560.2019.1630125

Pradana, M. G., Nurcahyo, A. C., & Saputro, P. H. (2020). Pengaruh Sentimen Di Sosial Media Dengan Harga Saham Perusahaan. *Edutic - Scientific Journal of Informatics Education*, *6*(2), 67–77. https://doi.org/10.21107/edutic.v6i2.6992

Putri, M. A., & Maulana, H. Z. (2023). Memprediksi kebangkrutan menggunakan Altman Z-Score pada perusahaan manufaktur sektor makanan dan minuman. *Jurnal Cendekia Keuangan*, *2*(2), 55. https://doi.org/10.32503/jck.v2i2.3431

Qu, S. (2023). A study on the impact of investor sentiment on corporate financial stress based on data mining. *International Conference on Big Data Economy and Information Management (BDEIM)*, 845–850. https://doi.org/10.1145/3659211.3659357

Rajan, A. P., & S.P.Victor. (2014). CRAWLING TWITTER DATA. *Journal of Research in Computer Application &Management*, *4*(9).

Ramadhan, D., & Setiawan, E. B. (2019). Analisis Sentimen Program Acara di SCTV pada Twitter Menggunakan Metode Naive Bayes dan Support Vector Machine. *e-Proceeding of Engineering*, *6*(2), 9736–9743. https://openlibrarypublications.telkomuniversity.ac.id/index.php/engineering/article/view/10708

Resfitasari, E., Taofik Muhammad Gumelar, Andini Ulhaq, & Nina Rusmayanti. (2022). Analisis Prediksi Financial Distress Dengan Metode Altman Z-Score Pada PT. Waskita Karya Tbk. *Jurnal Aktiva : Riset Akuntansi dan Keuangan*, *3*(3), 131–140. https://doi.org/10.52005/aktiva.v3i3.123

Samsir, Irmayani, D., Edi, F., Harahap, J. M., Jupriaman, Rangkuti, R. K., Ulya, B., & Watrianthos, R. (2021). Naives Bayes Algorithm for Twitter Sentiment Analysis. *Journal of Physics: Conference Series*, *1933*(1). https://doi.org/10.1088/1742-6596/1933/1/012019

Sembiring, S., & Sinaga, H. W. C. (2022). Analisis Akurasi Model Altman, Grover, Springate, Zmijewski Dalam Memprediksi Kondisi Financial Distress (Studi Empiris Pada Perusahaan Ritel Yang Terdaftar Di Bursa Efek Indonesia. *Jurnal Riset Akuntansi & Keuangan*, *8*(2), 299–311. https://doi.org/10.54367/jrak.v8i2.1662

Shiller, R. J. (2017). Narrative economics. *American Economic Review*, *107*(4), 967–1004. https://doi.org/10.1257/aer.107.4.967

Sisbintari, I. (2018). Sekilas Tentang Behavioral Finance. *Jurnal Ilmiah Administrasi Bisnis dan Inovasi*, *1*(2), 88–101. https://doi.org/10.25139/jai.v1i2.814

Sugiyono. (2013). Metode Penelitian Kuantitatif, Kualitatif, dan RND. In *Alfabeta* (1 ed.).

Sul, H. K., Dennis, A. R., & Yuan, L. I. (2017). Trading on Twitter: Using Social Media Sentiment to Predict Stock Returns. *Decision Sciences*, *48*(3), 454–488. https://doi.org/10.1111/deci.12229

Wongkar, M., & Angdresey, A. (2019). Sentiment Analysis Using Naive Bayes Algorithm Of The Data Crawler: Twitter. *Proceedings of 2019 4th International Conference on Informatics and Computing, ICIC 2019*, 1–5. https://doi.org/10.1109/ICIC47613.2019.8985884

Zhao, S., Xu, K., Wang, Z., Liang, C., Lu, W., & Chen, B. (2022). Financial distress prediction by combining sentiment tone features. *Economic Modelling*, *106*(April 2021), 105709. https://doi.org/10.1016/j.econmod.2021.105709