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Page : 353 - 365

Layoff Sentiment on Indonesian Twitter: Naïve Bayes Benchmarks and Human Resource Communication Strategy

Ihda Khairunisa Ikrima^{1*}, Amalia Rizky Mulyana²

¹Politeknik Negeri Bandung, Indonesia, ²Universitas Padjadjaran, Indonesia *Corresponding Email: <u>ihda.ikrima@polban.ac.id</u>

ABSTRACT

In 2022, widespread workforce reductions in Indonesia precipitated extensive public discourse on social media platforms, particularly Twitter. While organizational downsizing is frequently adopted as a strategic response to economic uncertainty, empirical evidence suggests it may adversely affect corporate reputation and stakeholder trust, especially when communication is inadequate. This study examines public sentiment toward layoffs by analyzing tweets containing the Indonesian term "PHK" from November to December 2022. Employing automated sentiment classification and social network analysis, the research identifies sentiment distribution and thematic patterns in user-generated content. Findings reveal a sentiment distribution of 40% neutral, 37% negative, and 23% positive, with negative sentiment predominantly associated with job insecurity and neutral discourse reflecting informational reporting. These results align with existing literature on the reputational risks of downsizing. The study advocates for proactive stakeholder mapping, empathetic communication, and real-time sentiment monitoring. Timely dissemination of factual updates and responsive engagement may mitigate reputational damage and prevent sentiment drift. Strategic communication before, during, and after workforce restructuring is essential to preserve organizational legitimacy and minimize adverse market reactions.

Keywords : Workforce reduction, public sentiment, social media analysis, organizational communication, reputational risk

A. INTRODUCTION

The global economic landscape has witnessed a surge in organizational downsizing, particularly in response to financial volatility and shifting market conditions. From technology giants like Meta, Amazon, and Alphabet to traditional sectors such as telecommunications (BT Group, Vodafone) and finance (UBS, Citigroup), workforce reductions have become a widespread strategic response to overexpansion, rising operational costs, and uncertain macroeconomic conditions (Intellizence, 2023; CNBC, 2024). According to a 2023 McKinsey & Company report, over 1,200 major companies worldwide announced layoffs, affecting more than 240,000 employees in the first half of the year alone, with the technology sector accounting for nearly 60% of these reductions (McKinsey, 2023).

Ihda Khairunisa Ikrima, Amalia Rizky Mulyana

These cuts were often framed as necessary measures to enhance operational efficiency, streamline hierarchies, and ensure long-term sustainability amid declining revenues and investor pressure. While firms often justify layoffs as strategic measures to enhance operational efficiency and ensure long-term sustainability, empirical evidence suggests inconsistent outcomes. Atkins & Favreau (2022) demonstrate that while plant closures are associated with positive long-term performance, layoff announcements tend to generate negative market reactions, including declines in firm value. Similarly, a McKinsey (2023) global survey found that only 23% of downsizing initiatives led to sustained improvements in profitability, underscoring the strategic risks of poorly executed workforce reductions. These findings challenge the assumption that layoffs are a reliable path to organizational resilience and suggest that financial logic alone is insufficient to ensure long-term success.

Downsizing initiatives frequently fail to deliver sustained financial improvements and may adversely affect organizational reputation and stakeholder trust (Schulz & Johann, 2018). In this context, real-time public sentiment has emerged as a critical indicator of reputational risk. Social media platforms, particularly Twitter, offer a valuable source of unstructured data for sentiment analysis, enabling researchers to capture immediate public reactions and assess the socio-economic implications of corporate restructuring (Benedetto & Tedeschi, 2016; Rathore et al., 2017; McGregor, 2019).

In Indonesia, mass layoffs have become increasingly prevalent, particularly within the startup ecosystem, where rapid expansion fueled by venture capital has been followed by abrupt contractions amid tightening global funding conditions. Between January and December 2022, at least 37 startups, including GoTo, Shopee, Traveloka, and Ruangguru, implemented workforce reductions, collectively affecting over 10,000 employees (Kompas, 2022; DetikInet, 2022). hese reductions were largely attributed to the withdrawal of global venture capital funding, rising inflation, and the strengthening of the US dollar, which increased operational costs for dollar-denominated startups (Aryono, 2022; Fadhilah, 2022). The phenomenon gained significant traction on social media, with hashtags such as #PHK trending during major layoff announcements.

Scholars have further attributed these workforce reductions to structural inefficiencies, including overstaffing, excessive compensation packages, and unsustainable operational expenditures (Fadhilah, 2022). Fadhilah (2022), criticized the management behavior of startups that engaged in lavish spending and office designs resembling global tech firms, despite limited revenue streams. Industry experts further suggest that many firms initiated preemptive downsizing to navigate anticipated economic headwinds in 2023 (Aryono, 2022). This preventive approach reflects a shift from growth-at-all-costs to survival-oriented strategies, particularly among startups that had previously relied on continuous funding rounds.

The public response to these layoffs was swift and visible on digital platforms. Given Indonesia's position as the fifth-largest Twitter market globally, with 18.45 million users in 2022 (Rizaty, 2022), the platform serves as a significant public forum for expressing opinions on corporate decisions. This digital engagement provides a unique opportunity to analyze how local stakeholders perceive and respond to organizational restructuring, particularly in emerging economies where labor dynamics and public sentiment may differ from Western contexts.

Despite growing interest in the financial and operational impacts of downsizing, there remains a notable gap in research examining public sentiment in non-Western, high-growth economies. Existing literature predominantly focuses on managerial perspectives, stock market reactions, and internal organizational outcomes, with limited integration of real-time social media analytics to assess external stakeholder perceptions (Landsman & Stremersch, 2020; Schulz & Johann, 2018). While sentiment analysis tools such as WEKA and Netlytic are increasingly used in social media research, few studies have systematically examined how these tools can inform strategic communication and human resource policies during organizational crises.

Moreover, there is a lack of studies that incorporate Twitter-based sentiment analysis into managerial decision-making frameworks surrounding layoffs. Most research treats sentiment as a post-hoc metric rather than a proactive input for communication strategy (Al Olaimat et al., 2022). This disconnect limits organizations' ability to anticipate public backlash, adjust messaging, or redesign layoff implementation strategies in response to evolving sentiment dynamics. As digital discourse increasingly shapes brand perception and consumer behavior, the absence of systematic mechanisms to translate sentiment into actionable managerial insights represents a critical shortfall in contemporary downsizing literature.

This study addresses this gap by conducting a sentiment analysis of Twitter discourse surrounding mass layoffs in Indonesia during the peak period of 2022. By combining computational text analysis with a management-oriented framework, the research aims to inform strategic communication and human resource policies that mitigate reputational damage, enhance stakeholder trust, and support more socially responsible downsizing practices. The findings contribute to both academic discourse and practical management by demonstrating how real-time social listening can be integrated into organizational decision-making, particularly in dynamic, digitally connected markets.

B. THEORETICAL

Layoffs, Performance, and Reputation

Research shows that collective layoffs often depress demand-side outcomes and brand equity, indicating that long-term gains are not consistent and depend on context and execution (Landsman & Stremersch, 2020). Manufacturers also experience varied post-layoff effects on channel relationships and operations, reinforcing heterogeneous

Ihda Khairunisa Ikrima, Amalia Rizky Mulyana

performance trajectories rather than uniform improvements (Atkins & Favreau, 2022). Corporate reputation is fragile under downsizing, further underscoring that outcomes are contingent and reputationally risky rather than reliably value-creating (Schulz & Johann, 2018).

Public Perception and Social Listening

Given these heterogeneous outcomes, monitoring stakeholder sentiment is strategically valuable, as public reactions mediate reputational and market responses to layoff events (Landsman & Stremersch, 2020). Scholarship on reputation management emphasizes social networking platforms as scalable, near-real-time sources for perception tracking and issues management, making social listening a practical complement to traditional research (Al Olaimat et al., 2022). Integrating social listening with marketing levers (e.g., messaging and promotions) helps align responses with sentiment dynamics observed around layoff announcements.

Sentiment Analysis and Netlytic Social Network Analysis

Sentiment analysis is a technique in natural language processing (NLP) that determines whether the sentiment expressed in a piece of text is positive, negative, or neutral (Aftab et al., 2023). It helps extract subjective information by analyzing the context and tone of the text. This method can be applied to data from various sources, such as social media comments, news articles, customer reviews, and others (Aftab et al., 2023). According to Gupta et al. (2017), the purpose of sentiment analysis is to categorize data accurately into various sentiment classes. A sentiment class is a set of entities that want to be identified into a classification of two sentiment classes (positive and negative) or a classification of three sentiment classes (positive, negative, and neutral) (Gupta et al., 2017).

Netlytic is a tool for cloud-based data collection and analysis of social media such as Twitter, YouTube, and Facebook to obtain information from interactions and to form clusters on social media (Rohimi, 2021). Twitter sentiment classification studies provide robust methodological baselines, with Naïve Bayes frequently used as a fast, transparent benchmark for short-text polarity detection (Atsqalani et al., 2022; Syahputra et al., 2022). International work reports competitive accuracy for Naïve Bayes on Twitter data using TF-IDF features, providing a replicable baseline for domain-specific tasks such as layoff discourse (Wahyuni et al., 2021).

Integrating Sentiment Analytics into Human Resource Communication Strategy

Despite growing recognition of social media as a barometer for public sentiment, its integration into strategic management decisions, particularly during organizational restructuring, remains underdeveloped. While studies acknowledge that layoffs trigger reputational risks and demand-side consequences (Landsman & Stremersch, 2020), managerial responses are often reactive rather than informed by real-time stakeholder feedback. Current frameworks in human resource management and corporate

communication tend to rely on traditional surveys, internal audits, or delayed media analysis, which lack the immediacy and granularity offered by social listening tools (Al Olaimat et al., 2022). This disconnect limits organizations' ability to anticipate public backlash, adjust messaging, or redesign layoff implementation strategies in response to evolving sentiment dynamics. As digital discourse increasingly shapes brand perception and consumer behavior, the absence of systematic mechanisms to translate Twitter-based sentiment into actionable managerial insights represents a critical shortfall in contemporary downsizing literature.

While technical studies validate the use of tools like Netlytic and machine learning classifiers such as Naïve Bayes for sentiment detection (Atsqalani et al., 2022; Wahyuni et al., 2021), these methods are rarely positioned as decision-support systems within management theory. Research has yet to establish clear pathways for how sentiment analytics can inform communication protocols, timing of announcements, or employee severance policies during downsizing. The integration of computational social science with strategic management remains fragmented, with few studies proposing frameworks that link sentiment trends to specific Human Resource or Public Relation interventions (Schulz & Johann, 2018).

C. METHODOLOGY

This study employed a two-stage approach to analyze Indonesian public sentiment regarding mass layoffs, focusing on a high-activity period in late 2022 when the topic of layoffs was especially viral on Twitter. Data were collected from Twitter using keywords related to layoffs ("PHK") over three time points in November and December 2022, aligning with peak public attention on the issue. The timing was strategically chosen because sentiment analysis depends on capturing real-time public discourse, and this period represented the most substantial and relevant dataset available for analysis, reflecting stakeholder reactions as events unfolded at scale.

Text Mining

Sentiment Analysis

Labelling

Training

Set

Testing Set

Testing Set

Hable au

Machine Learning

Picture I. Process research methods

Source : Permana et al., 2021

Ihda Khairunisa Ikrima, Amalia Rizky Mulyana

Data collection utilized the Twitter API and the Python programming language to retrieve relevant tweets. Standard text preprocessing techniques were applied, including stopword removal, tokenization, and stemming, to ensure the data's quality and analytical validity. For sentiment classification, the Naïve Bayes algorithm was implemented using the WEKA software, which is recognized for its effectiveness in classifying short-text social media data. The modeling process followed common practice by splitting the dataset into training (70%) and testing (30%) subsets, with manual validation performed to ensure classification accuracy. By focusing on the 2022 dataset, the study leverages a real-time, event-driven public reaction benchmark essential for understanding the reputational and managerial consequences of mass layoffs in Indonesia.

D. RESULT AND DISCUSSION

In this study, an analysis of public opinion was conducted regarding the phenomenon of the massive layoffs that occurred in 2022. Throughout the year, 120,000 global startup employees have been victims of layoffs (Dewi, 2022). In Indonesia, Shopee is a startup that accounts for 3% of its 6,232 employees (Dewi, 2022). Conversations regarding layoffs begin to pick up on social media. As of November 18, 2022, there were 473,000 tweets with hashtag #RIP Twitter following Elon Musk's policy of laying off employees. The period of late 2022 was selected based on the unprecedented visibility and activity regarding mass layoffs on Indonesian Twitter. This timeframe aligns with a major viral phenomenon in which the term "PHK" (layoffs) spiked dramatically due to global and domestic tech sector announcements. For sentiment analysis, data must represent real-time public discourse when public attention is at its peak; the selected dates correspond to the most comprehensive and representative dataset available. This just-in-time sampling provides a robust context to assess genuine public reactions at the height of stakeholder concern in Indonesia.

Sentiment Analysis Using WEKA

The sentiment analysis conducted in this study leveraged Twitter data related to mass layoffs ("PHK") collected during a period of intense public discourse in late November and early December 2022, using JupyterLab on the Anaconda Navigator application. In total, 29,333 tweets were analyzed, reflecting a real-time snapshot of stakeholder reactions at the peak of event virality. This focus on the 2022 dataset was deliberate: sentiment analysis provides the greatest managerial value when it captures public attitudes during active, high-impact periods, enabling organizations to respond to real-world communication needs.

Standard data preparation techniques, ncluding stopword removal, tokenization, and stemming, were used to clean the dataset and extract key themes. The most frequent keywords such as PHK, RT, mass, work, employee, Indonesia, and threat indicated widespread discussion not only about the layoffs themselves, but also their broader reputational and operational risks.

ANACONDA NAVIGABOR

ANACON

Figure 2. The text mining process from Twitter

Source: data processed 2025

The extract words are connected and grouped based on their values through the map-reduction stage. From the results of grouping words at the map-reduce stage, 100 words were most often used based on the number of tweets and word frequencies. The first rank is the word most often used, namely "PHK" followed by "RT" and "mass". The word "PHK" is used the most, with a word frequency of 20,389 times and a tweet frequency of 19,384 times. After the word "PHK", the next most frequently used word is "RT", with a word frequency of 16,151 times and a tweet frequency of 16,101 times, which indicates that the conversation is dominated by re-posting of articles containing the phenomenon of termination of employment. Apart from these two words, other words that often appear are related to "mass", "work", "employee", "Indonesia", "threat", and others.

A total of 10,381 cleaned tweets were classified using the Naïve Bayes algorithm (WEKA), with a 70:30 split between training and testing data as per empirical best practice (Gholamy et al., 2018). Sentiment was manually labeled as positive (+1), neutral (0), or negative (-1) for supervised machine learning validation, resulting in a model accuracy of 81.39%. Data classification was performed using a per-perception multilayer process (Permana et al., 2021). An overall accuracy of 81.39% with 18.61% misclassification is consistent with Naïve Bayes functioning as a reliable short-text baseline for Twitter monitoring, supporting operational dashboards while warranting care for edge cases in ambiguous posts (Alabid & Katheeth, 2021). The sentiment split 39.7% neutral, 36.9% negative, 23.3% positive underscores a predominance of impartial or concerned reactions, with negative sentiment reflecting anxiety and reputation fragility, and positive sentiment tied to messages of compensation or support.

Table I. Summary of The Result

Metric	Value
Total Tweets Analyzed	29,333
Sentiment Distribution	39.7% Neutral, 36.9% Negative, 23.3% Positive
Model Accuracy (WEKA)	81.39%

Ihda Khairunisa Ikrima, Amalia Rizky Mulyana

Metric	Value
Top Keywords	PHK, RT, mass, work, employee, Indonesia, threat
Most Active Accounts	cnbcindonesia, angelatabitha, hestyratnas, with cnbcindonesia forming the largest cluster

Source: data processed 2025

A sentiment split of roughly 40% neutral, 37% negative, and 23% positive mirrors literature showing that collective layoff announcements often trigger demand-side and reputational headwinds, though effects vary by context and communication choices (Landsman & Stremersch, 2020). Positive sentiment is associated with compensation after layoffs, negative sentiment with anxiety about finding a new job, and neutral sentiment with notification of the number of layoffs. Previous studies show that layoff announcements depress sales and worsen price and advertising elasticities (Landsman & Stremersch, 2020). Implying that evidence spikes in negative sentiment into measurable commercial pressure if not mitigated correctly. Announcement features and firm context moderate these effects; neutral sentiment represents a movable middle that targeted communications can shift away from negativity toward understanding and acceptance. Downsizing's effect on reputation fragility emphasizes that motive, timing, and prior layoffs shape perception (Schulz & Johann, 2018); aligning with observed negativity around employment insecurity and highlighting why transparent rationale and process fairness matter.

Comparison of Sentiment Analysis Using Netlytic

Netlytic is a community-supported social network and text analysis tool for automatically summarizing and visualizing public conversations online on social media. Sentiment analysis on Netlytic was performed automatically by retrieving data from a Twitter account synchronized with the Netlytic account. However, there are limitations to the free account because it can only analyze a maximum of 2,500 datasets, and keywords can be searched directly using the Indonesian language filter.

Netlytic can show a word cloud of the most used layoff-related words. The word "PHK" ranks first with 2,372 posts, followed by the word "Government" with 602 posts and the word "Thousand" with 575 posts. Besides finding the words with the highest frequency used, Netlytic can also show the account with the highest number of posts along with the relationship between accounts that make up a cluster. Based on the analysis results, it can be seen that the @cnbcindonesia account is the account with the most posts, reaching 16.9%, followed by the @angela_tabitha account (14.5%), and @hestyratnas account (10.8%). The @cnbcindonesia account had the largest cluster, with many other Twitter users joining the conversations posted by that account. The @angela_tabitha account posts information on how to disburse JKP BPJS Ketenagakerjaan funds to employees who have been laid off, so they are reposted quite

often. Netlytic can also perform sentiment analysis on Twitter text. The results of the sentiment analysis using Netlytic are shown in Figure 14.

Netlytic's sentiment classification shows that most Twitter users feel good about the keyword "layoffs"; other users feel bad, disappointed, and neutral. The weakness of using Netlytic is that there is no manual validation of the prediction results, so the accuracy of the sentiment analysis results cannot be known.

FEELINGS (GOOD) (Posts:24 | Terms:24)

TASTE (Posts:14 | Terms:14)

TIME (Posts:9 | Terms:9)

FEELINGS (BAD)...

Figure 3. The results of sentiment analysis using netlytic

Source: data processed 2025

A positive-leaning distribution could reflect narratives about severance, redeployment, or policy support; however, automated lexicon rules may also misread sarcasm, idioms, or code-switching in Indonesian layoff discourse (Kurniawan, 2022; Rahaman et al., 2021). The presence of "bad," "disappointed," and "neutral" categories indicates a mixed conversation typical of event-driven topics, but without ground truth the class proportions cannot be trusted as definitive (Rahaman et al., 2021).

Human Resource Communication Strategy

Negative sentiment concentrates on job-search anxiety concrete commitments on severance, outplacement, and reskilling should be communicated early and repeatedly, leveraging the observed positive sentiment around compensation and support (Landsman & Stremersch, 2020). Neutral sentiment, information-heavy discourse presents an opportunity window; aligning message cadence with factual updates can prevent drift toward negativity observed after layoff announcements. Commercial consequences vary with announcement design, integrate social listening into pre-briefing, announcement, and post-announcement phases to test framing, monitor backlash, and adapt tactics within the first 72 hours (Landsman & Stremersch, 2020).

A three-phase strategy that integrates empathetic communication, stakeholder-specific mitigation, and real-time social listening can materially reduce reputational, demand-side, and operational risks from layoffs announcements (Atkins & Favreau, 2022; Alabid & Katheeth, 2021; Landsman & Stremersch, 2020; Schulz & Johann, 2018). The action could taken as managerial implication, including:

Ihda Khairunisa Ikrima, Amalia Rizky Mulyana

- 1. Pre-annoucement: Map stakeholders and likely impact pathways; design a message architecture that emphasizes clear business rationale, process fairness, and concrete support; prepare demand-side stabilizers anticipating adverse shifts in price and advertising elasticities after layoff; stand up a social listening baseline on Indonesian Twitter using a transparent classifier to track sentiment and topics before disclosure.
- 2. Announcement: orchestrate synchronized and empathetic communications across executive; time disclosures to minimize rumor cascades and immediately publish FAQs; monitor near-real-time sentiment and topics; set explicit escalation thresholds for negative spikes and for narratives around fairness, leadership credibility, and job support.
- 3. Post-announcement (72 hours until 30 days): counter misinformation quickly and sustain a cadence of factual updates to prevent neutral discourse drifting toward negativity that can depress sales; protect innovation capacity by retaining critical roles and preserving; maintain public reporting on transition outcomes (placements, reskilling completions) to rebuild reputation through visible follow-through resource slack where possible, acknowledging trade-offs in innovation outputs

E. CONCLUSION

This study analyzed public sentiment toward mass layoffs in Indonesia during late 2022 using Twitter data and multiple analytical tools, including WEKA and Netlytic. The findings reveal a sentiment distribution of approximately 39.7% neutral, 36.9% negative, and 23.3% positive, with key themes centered on compensation, job insecurity, and government responsibility. While WEKA provided a validated, accurate classification (81.39% accuracy), Netlytic highlighted the influence of media accounts and support narratives, particularly around severance policies. Google Trends complemented these insights by identifying regional search patterns and company-specific layoff interest, such as Ruangguru and GoTo.

However, this study has limitations. The data is confined to Twitter, which may not fully represent broader public opinion across other platforms like Instagram, TikTok, or traditional media. Additionally, automated sentiment tools, especially, Netlyticlack manual validation and may misinterpret sarcasm or cultural nuances in Indonesian discourse. The temporal scope is also limited to a single high-activity period, which, while strategically chosen, may not reflect long-term sentiment evolution.

During the announcement phase, the news shoulde be delivered During the announcement phase, the news should be delivered in person or via video to avoid impersonal methods, with acknowledgment of the emotional impact and appreciation expressed for employees' contributions. Clear, factual information on severance, outplacement, and next steps must be published immediately, while sentiment is monitored in real time to detect and respond to negative spikes. In the post-

announcement phase, organizations should sustain engagement through regular factual updates to prevent neutral discourse from turning negative, quickly counter misinformation, and highlight positive outcomes such as successful job placements or reskilling completions. Sharing progress on transition support demonstrates accountability and aids in rebuilding organizational reputation. By integrating sentiment analytics into each phase, companies can shift from reactive to proactive reputation management, recognizing that public response to layoffs is not fixed, it can evolve from negative to neutral or even positive when handled with transparency, empathy, and strategic foresight, underscoring that how layoffs are communicated is as critical as why they occur.

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Ihda Khairunisa Ikrima, Amalia Rizky Mulyana

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