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# When Newsroom Tears Go Viral: A Sentiment Analysis of Public Response to Media Layoffs in Indonesia

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ABSTRACT

The recent phenomenon of layoffs (PHK) in the Indonesian media industry has triggered an emotional public response, especially when the event involves figures who have built close relationships with audiences. This study aims to analyze public sentiment towards the viral farewell moment of KompasTV presenter Gita Maharkesri, as a symbol of the humanitarian crisis in the media workplace. Data was collected from 2,238 user comments on the Antaranews YouTube video using a crawling technique using the YouTube Data API v3 and analyzed using a Python-based Big Data Analytics approach in Google Colab. The results show that the majority of comments are neutral (73.1%), followed by positive comments (14.1%) and negative comments (12.8%). Positive comments reflect a strong parasocial relationship, characterized by words such as "semangat," "terima kasih," and "terembus," while negative comments are often critical of the media presentation, with keywords such as "exaggerated," "PHK," and "bohong." The temporal distribution shows a spike in interactions in the first two days after the video aired, then a gradual decline. Correlation analysis between words reveals clusters of discourses of empathy and criticism coexisting. This study concludes that public responses to media layoffs are not merely emotional but also reflect a social awareness of job instability in the digital age. These findings underscore the importance of ethical and empathetic crisis communication in the new media landscape and demonstrate the crucial role of sentiment analysis as a tool for understanding collective public opinion.

## 1. Introduction

In the last decade, the global media industry has undergone significant transformation due to digitalization and changes in information consumption behavior (Abdullah, 2020, 2021a; Enli et al., 2019; Enli & Syvertsen, 2016). The development of digital technology has shifted audience preferences from conventional media to digital platforms (Abdullah et al., 2025). This condition has led to a decline in advertising revenue and forced many media companies to make efficiency, including mass layoffs (Kholili et al., 2024; Yessenbekova, 2018; Abdullah, 2021b; Born, 2003; Pecheranskyi et al., 2023; Tapsell, 2015; Vázquez-Barrio et al., 2021). Even according to According to the Indonesian Press Council, at least 1,200 media workers were laid off between 2023 and 2024, and there will reportedly be more layoffs at major media outlets such as*Kompas TV, CNN Indonesia, Republika,*and*TVRI (Fauziah & Fikri, 2025)*

This phenomenon is not only happening in developed countries, but also in Indonesia, where several major media companies have announced layoffs in response to economic pressures and changes in the media landscape (Indra, 2025; IFJ, 2020; Puspa, 2024).

One of the cases that attracted public attention was the mass layoffs at Kompas TV in early 2025, which was marked by the emotional moment of farewell of presenter Gita Maharkesri (Tomorrow, 2025; Subaharianto, 2025). The farewell video went viral on the YouTube platform, sparking a wave of empathy and discussion on social media (ANTARA News, 2025). The public's reaction to this event reflects the emotional closeness between the audience and media figures, and shows how digital media has become a space for people's collective expression of social issues (Cohen & Holbert, 2021; Horton & Richard Wohl, 1956; Houston et al., 2019; Jayus et al., 2025; Liebers & Schramm, 2025).

The emotional closeness between the audience and the media figure is known as the parasocial relationship, which is a one-way relationship formed through regular interactions between the audience and the media figure (Gregg, 2018). In the digital context, this relationship is increasingly intensified because the audience can interact directly through comments, likes, and shares (Johnson & Lee, 2023). Studies show that parasocial relationships can influence audience perceptions and behaviors, including in response to events that befall their favorite media personalities (Sumaiyah et al., 2025; Cohen, 2006; Cohen & Holbert, 2021; Dibble et al., 2016; A. M. Rubin et al., 1985)

Sentiment analysis of audience comments on digital platforms, such as YouTube, is an effective method for understanding the public's emotional response to certain events. This technique allows researchers to identify patterns of emotions, opinions, and perceptions that develop in society (Chalkias et al., 2023). Several studies have applied sentiment analysis to evaluate public reactions to social issues, including layoffs, using a variety of approaches, such as lexicon-based and machine learning (Abdullah et al., 2025; Abiola et al., 2023; Cheng et al., 2023; Diantoro et al., 2023)

Although sentiment analysis has been widely used in various contexts, research that specifically examines public responses to layoffs in the Indonesian media industry through digital platforms is still limited. Most studies focus on news analysis or data from platforms such as Twitter, while YouTube as a rich source of data on audience comments has not been explored much in this context (Baqach & Battou, 2023; Chunqiong et al., 2025; Sukmayadi, 2019; Widyatama et al., 2025; Yu & Yang, 2024)

In addition, studies on the emotional impact of layoffs on media figures and how it affects parasocial relationships with audiences are also still minimal. In fact, understanding these dynamics is important to design effective communication strategies in dealing with crises in the media industry. Previous research has shown that termination of a media personality can trigger a strong emotional reaction from the audience, which in turn can affect the image and reputation of a media company (Gabriel et al., 2018; Cohen & Holbert, 2021; Rubin et al., 1985).

In the Indonesian context, where the media has an important role in shaping public opinion, understanding the emotional response of audiences to layoffs in the media industry is becoming increasingly relevant. Moreover, with the increasing use of digital media, platforms such as YouTube have become the main space for people to express their opinions and emotions on social issues (Wollmer et al., 2013; Razali et al., 2021; Sahut et al., 2022)

Therefore, this study aims to analyze public sentiment towards layoffs in the Indonesian media industry, focusing on the Kompas TV case and the viral farewell video of Gita Maharkesri on YouTube. Using sentiment analysis techniques on audience comments, this study will identify patterns of emotions and opinions that develop, as well as evaluate how parasocial relationships influence the public's response to the event (Bond & Calvert, 2014; Breves & Van Berlo, 2025; Horton & Richard Wohl, 1956; Liebers & Schramm, 2025; Ravi & Patki, 2025; Xu et al., 2023).

The results of this research are expected to contribute to understanding the dynamics of the relationship between media and audiences in the digital era, as well as provide insight for media companies in designing communication strategies that are more empathetic and responsive to crises. In addition, this research can also serve as a basis for future studies that want to explore more about parasocial relationships and public emotional responses to social issues on digital platforms (Auter & Palmgreen, 2000; Cohen, 2006; Cohen & Holbert, 2021; Dibble et al., 2016; R. B. Rubin & McHugh, 1987).

Thus, this research not only contributes to the development of communication science and sentiment analysis, but also has practical implications for the media industry in facing challenges in the digital age full of dynamics and complexity (Abdullah, 2020, 2021b, 2021a).

## 2. Method

This study adopts a Big Data Analytics approach with a focus on Sentiment Analysis to understand the public response to layoff events in the media industry, specifically audience comments on a video titled "*Kompas Sport Pagi Pamit, tangis Presenter mengiringi Perpisahan (Kompas Sport Pagi Goodbye, Presenter's Tears Accompany Farewell)*" on the ANTARANEWS YouTube channel (ANTARA News, 2025). Comment data is collected using the YouTube Data API v3 in a Google Colab environment based on the Python programming language. This scraping technique has proven effective in collecting large numbers of comments from YouTube videos for public opinion analysis (Adhikari et al., 2023; Alsanoosy & Alqarni, 2023; George & Baskar, 2024; Lee & T. N. Nguyen, 2023a; Li et al., 2018; Nahas et al., 2024; Sui, 2022; Surana et al., 2026; Thakkar & Patel, 2015).

Table 1. Source of Datasets

| Content Title | Platform | Subscribe | Comment | Viewers |
|---|---|---|---|---|
| *Kompas Sport Pagi Pamit, tangis Presenter mengiringi Perpisahan (Kompas Sport Morning Goodbye, Presenter's Cry Accompanies Farewell)* | www.youtube.com/ @antaranews | 203 thousand | 2238 | 812 K |

Furthermore, a dataset of 2,238 comments was processed in Google Colab with Python scripts using various libraries for crawling and sentiment analysis (Google Colab, 2026). Pre-processing includes text cleanup, normalization, tokenization, and feature extraction using NLP techniques. Sentiment analysis is carried out through lexicon-based methods such as VADER or TextBlob as well as light machine learning such as Naïve Bayes, SVM, and Random Forest, which were previously used in YouTube or social media studies with high-accuracy results (Jayus et al., 2025; Kumar & Agrawal, 2026; Mustakim et al., 2021; Lee & T. N. Nguyen, 2023b; Qi & Shabrina, 2023; Ribeiro et al., 2016; Saifullah et al., 2021; Thakkar & Patel, 2015).

Table 2. Python Library

| Yes | Library Python | Functions in the Methodological Process |
|---|---|---|
| 1 | googleapiclient.discovery | Access YouTube Data API v3 for video comment scraping (Google for Developers, 2026; Li et al., 2018) |
| 2 | Pandas | Store and manage comment datasets in DataFrame format |
| 3 | nltk, Literary | Text pre-processing: tokenization, stop-word removal, Indonesian stemming |
| 4 | fatherSentiment / TextBlob | Lexicon-based sentiment analysis (positive-negative-neutral) on English/Indonesian comments |
| 5 | Scikit-Learn | Machine learning implementation for sentiment classification: Naive Bayes, SVM, Random Forest |
| 6 | matplotlib, seaborn, wordcloud | Visualization of sentiment distribution, wordcloud of dominant topics, and comment data patterns |

Validity and reproducibility are maintained with complete documentation in the Google Colab notebook. The visualization of the results of the analysis was carried out using Python libraries such as matplotlib, seaborn, and wordcloud, which are commonly used in social media big data research to explore the distribution of sentiment and word patterns (George & Baskar, 2024; Lee & T. N. Nguyen, 2023b; Li et al., 2018; Hajiali, 2020; El Alaoui et al., 2018).

## 3. Result and Discussion

### 3.1. Distribution of Public Sentiment towards Presenter Farewell Video

Normative analysis of 2,238 comments on the farewell video of KompasTV presenter Gita Maharkesri shows that the majority of comments are classified as neutral, which is 1,636 comments or around 73.1% of the total comments analyzed. Meanwhile, positive comments amounted to 315 comments (14.1%) and negative comments were recorded as many as 287 comments (12.8%). This distribution shows that even though the video touches on the emotional aspect, most of the audience chooses to give responses that are informative, normative, and even emotionally ambiguous.

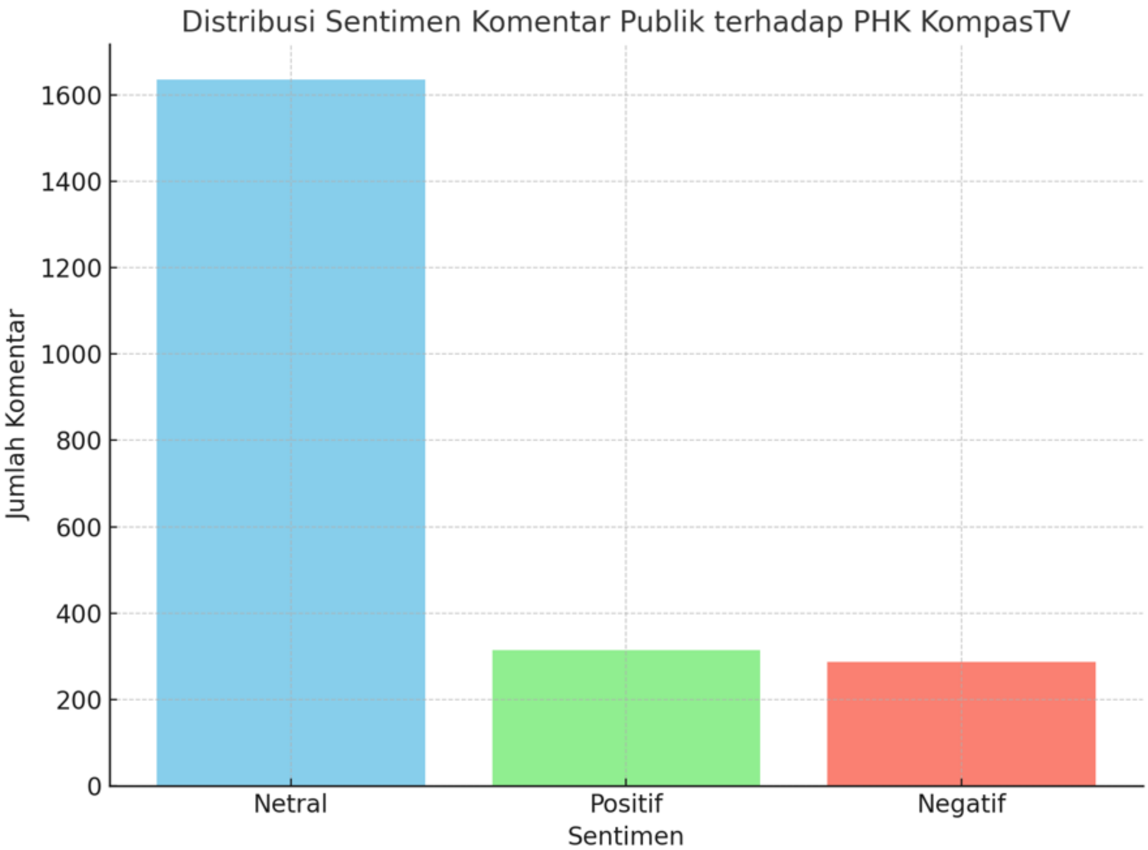


Figure 1. Distribution of Public Comment Sentiment on KompasTV's Layoff

These findings are in line with research Yu & Yang (2024) which states that in social events with a high emotional dimension, the distribution of public sentiment tends to remain dominated by neutral comments due to the existence of social norms in digital public spaces that prioritize objectivity or mere passive observation without explicit opinions. However, the relatively balanced number of positive and negative comments indicates a split audience response to this phenomenon, a pattern that was also observed in the study (Gabriel et al., 2018) when the public responds to media figures who have experienced a change in professional status emotionally.

Positive comments that appear in the data generally contain keywords such as "*terharu* [overwhelmed]", "*terimakasih* [thank you]", "*semangat* [Enthusiasm]", and "*sukses* [Success]", which reflects a form of emotional support and empathy towards the presenter. This reinforces the concept of parasocial relationships explained by Horton & Richard Wohl (1956), where audiences experience an emotional attachment to media figures through repetitive one-way interactions. Study Cohen & Holbert (2021) adding that the intensity of this parasocial relationship can be the main determinant of the emergence of positive sentiments in the context of separation or crisis.

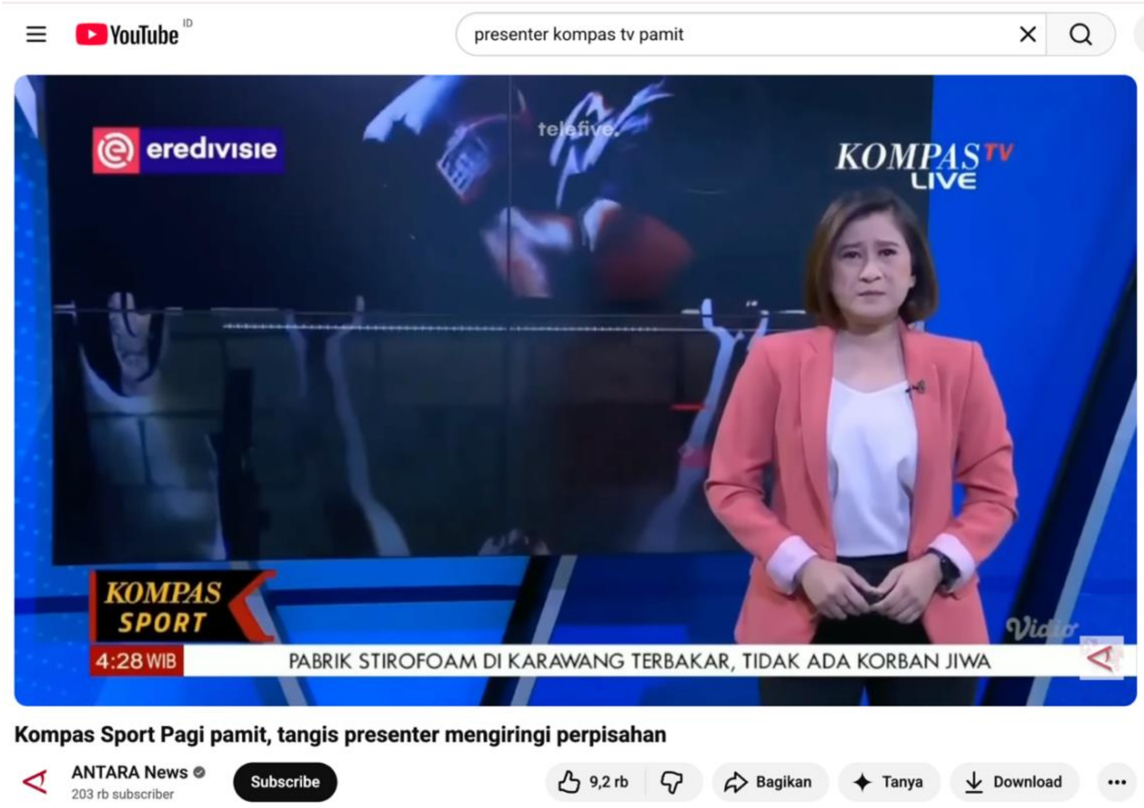


Figure 2. Screenshot of Antara News Youtube Channel

On the other hand, negative comments indicate dissatisfaction, cynicism, and criticism of media companies. Words like " *lebay* [overacting]", "*bohong* [*lie*]", "*sedih* [sad]", and "*PHK* [layoff]" dominate this category. This shows that some audiences not only respond emotionally to presenters but also make critical assessments of media management policies. This suggests that responses to events such as media layoffs are not monolithic, but rather complex and layered as described in the affective communication approach in digital media studies (Eyal & Cohen, 2006; Liebers & Schramm, 2025).

The relatively balanced distribution between positive and negative comments also indicates the existence of a discourse dynamic that not only revolves around empathy for individuals but also encompasses the systemic aspects of the media industry. In this context, sentiment analysis serves not only as a quantitative tool, but also as an early indicator of the climate of public opinion towards employment practices in the media, particularly in the era of digital transition and economic crisis.

### 3.2. KompasTV Presenter and Netizens, Emotional Response

One of the most prominent findings in the analysis of public comments on the viral farewell video of KompasTV presenter Gita Maharkesri was the many expressions of empathy, emotion, and emotional attachment from the audience. In the positive comments category, various expressions such as "*semangat selalu mbak Gita* [a passion for Gita],", "*terharu sampai nagis* [overwhelmed to the point of crying]", and "*terimakasih sudah menemani pagi saya selama ini* [Thank you for accompanying me in the morning all this time]" shows that the presenter is not just a conveyor of information but has formed a symbolic and emotional relationship with the public. This reflects the power of parasocial relationships, which are one-way relationships between audiences and media figures that feel real even though they are not direct (Cohen, 2006; Horton & Richard Wohl, 1956; Liebers & Schramm, 2025).


Figure 3. World Cloud Positive Comments for KompasTV Presenters

This closeness is also driven by the intensity of presenters' presence in the audience's private space over the years, especially through daily programs such as "*Kompas Sport Pagi*". In the context of television media, repetition and consistency of the figure on screen create the illusion of interpersonal relationships. Cohen & Perse, (2003) It is said that parasocial relationships can have an emotional effect equivalent to real relationships, especially when there is a separation, loss, or crisis. In this study, many commenters conveyed a sense of loss as if they knew Gita personally, as in the comments " *aku ngerasa ditinggalin sahabat pagi-pagi* [I felt like I had left my friend early in the morning]".

In addition to the aspect of emotional connectedness, public comments also reflect a sense of solidarity with the conditions that befell the presenters. In many comments, there are narratives that link the experience of termination to the broader economic reality, such as in the phrase "*semoga mendapatkan pekerjaan lebih baik* [hopefully get a better job], "*PHK itu pahit* [layoffs are bitter]" or "*banyak orang baik di-rumahkan, sedih* [many good people have to be laid off, sad]". This shows that audiences not only respond in terms of personal relationships but also have social awareness of structural injustices in the media industry. This kind of response confirms that parasocial relationships can be triggers for social empathy and collective solidarity (Dibble et al., 2016; Giles, 2002; A. M. Rubin et al., 1985; R. B. Rubin & McHugh, 1987)

This phenomenon is reinforced by the findings Gabriel et al., (2018), which shows that emotional engagement with media figures in the digital age is not limited to entertainment, but can be strongly embedded in political, economic, and even employment contexts. In these cases, the public not only responds to individual grief, but also voices collective grievances against the increasingly unstable world of work. This means that the presenter's tears serve as an emotional symbol of a larger crisis in the media industry and the netizens' response is an expression of personal connectedness as well as structural solidarity.

The emotional response to Gita Maharkesri reflects the dual function of media figures in the digital society: as an object of personal attachment as well as a symbol of the suffering of the working class in an unstable industry. This reaction puts the presenter in a broader symbolic position than just a laid-off worker, but as an emotional touchpoint of a public experiencing collective unease over deteriorating working conditions.

### 3.3. Dominant Keywords in Positive and Negative Comments

Analysis of the dominant words in public comments classified as positive shows that netizens explicitly express their support and empathy for KompasTV presenter, Gita Maharkesri. Words like "*semangat* [Enthusiasm]", "*terharu* [overwhelmed]", "*terimakasih* [Thank you]", "*hebat* [Great]", and "sukses [success]" appears with high frequency in Word Cloud. The dominance of these words confirms that the majority of positive comments emphasize appreciation for the presenter's dedication and the sense of loss over his passing. In the context of parasocial relationships, these words reflect the form of symbolic interaction between the audience and the media figures that they consume on a regular basis (Cohen & Perse, 2003; Horton & Richard Wohl, 1956; Liebers & Schramm, 2025)

On the other hand, analysis of negative comments shows the appearance of words such as "*lebay* [Overacting]", "*bohong* [Lie]", "*sedih* [Sad]", "*PHK* [Layoff]", and "*basi* [Stale]". Prahse as "*lebay* [Overacting]", "*bohong* [Lie]" is widely used to respond to the presenter's emotional expression, suggesting that some audiences consider the aired breakup moment too dramatic or even questionable in its authenticity. While the word " *PHK* [Layoff]" and "*sedih* [Sad]" arises in the context of criticism of media management and empathy for the condition of affected workers. These words reflect the existence of a dimension of structural criticism behind public expression, where the audience not only responds to the personality of the presenter, but also voices dissatisfaction with the work system in the media industry (Ali et al., 2023; Gabriel et al., 2018; Yu & Yang, 2024).

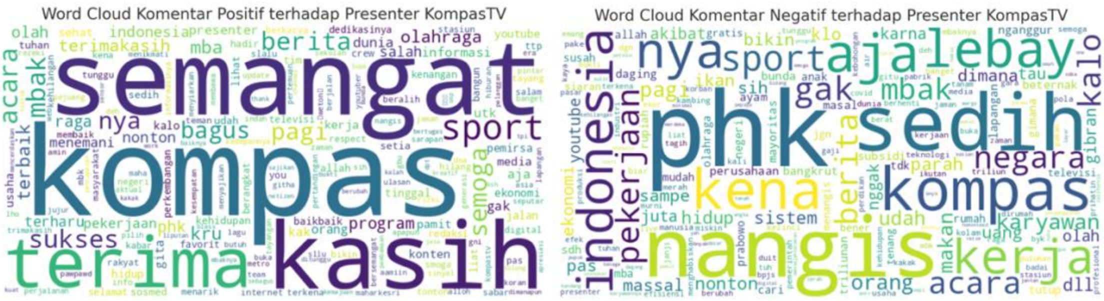


Figure 4. Wordcloud Positive and Negative Comments on Kompas TV Presenter

The presence of the word " *PHK* [Layoff]" in both poles of sentiment confirms that the issue of termination of employment is at the center of public discourse. In positive comments, this word appears in sentences with a tone of sympathy and solidarity, such as "*semoga tetap semangat meskipun kena PHK* [Hopefully keep your spirits up despite being laid off]"; While in negative comments, this word is often juxtaposed with criticism such as " *lebay banget cuma karena di-PHK* [It's just too bad to be slacking off]". This shows that sentiment towards layoffs is ambivalent, can be a source of empathy and cynicism, depending on the ideological position and personal affection of the audience towards the figure in question (Dibble et al., 2016; Eyal & Cohen, 2006)

These findings are in line with the concept of emotional affordance in digital platforms, where audiences are not only consumers of information, but also producers of emotions through comments that can sow collective resonance (Papacharissi, 2015). In this case, comments with empathic keywords can trigger a wave of solidarity, while cynical comments can trigger counter-discourse. This pattern reflects the complexity of digital public spaces that are not singular in interpreting events, but are always plural, fluid, and full of emotional nuances influenced by various social, psychological, and political factors.

The dominant words in public commentary are not just linguistic elements, but also indicators of the structure of social feelings formed in the context of the media crisis. Word Cloud is an effective visual tool for representing the collective emotional configuration of the public, which in this study reflects the mix of parasocial relationships, working-class empathy, and structural criticism of the increasingly fragmented media world.

### 3.4. Comment Time Distribution and Interaction Peaks

In the context of digital media, time is an important variable in reading the pattern of public engagement on issues that touch the emotional realm. The viral phenomenon that accompanied the farewell of KompasTV presenter, Gita Maharkesri, was not only marked by the high number of comments, but also by the rhythm of its distribution within a certain period of time. Therefore, analysis of the distribution of comment time is crucial to understand how the public response to this media layoff event is formed, spread, and finally subsided. A graph of daily interactions gives a clear picture of when audiences are most actively expressing their reactions, as well as how these emotional dynamics are taking place within a specific time frame.

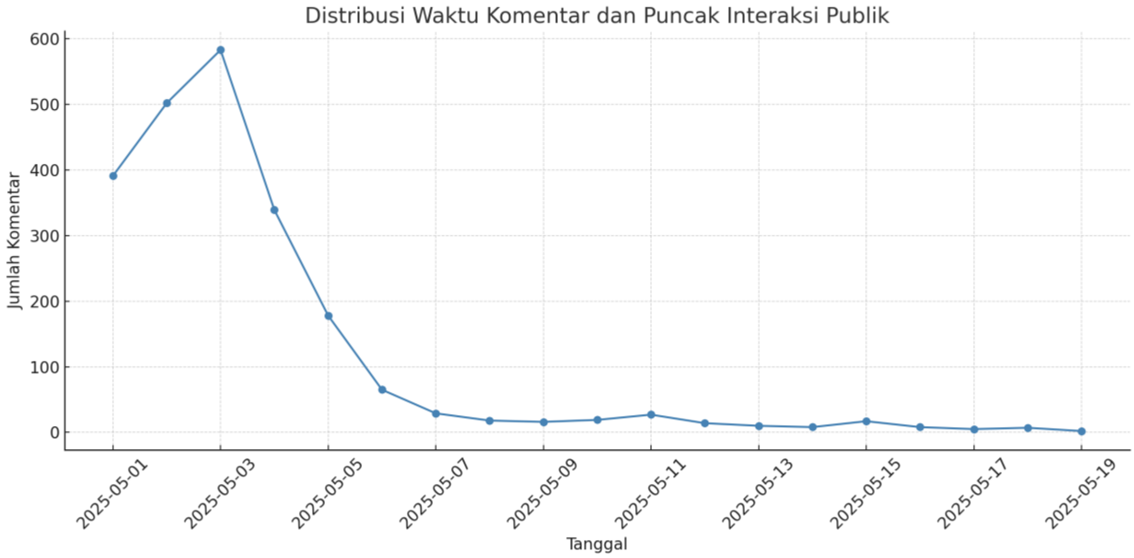


Figure 5. Distribution of Comment Time and Peak of interaction

Analysis of the temporal distribution of comments on the KompasTV presenter's farewell video shows a typical pattern of public engagement from the viral content phenomenon. A graph of interactions by date shows that comments peaked in the first one to two days after the video was uploaded to the ANTARANEWS YouTube channel. After that peak period, there was a sharp decline in the number of daily comments, which continued to decline in the following days. This pattern indicates that public emotions in responding to this kind of content are reactive, fast, and centralized in a short period of time.

This finding is in line with the concept of affective temporal burst put forward by Papacharissi (2015), which is a condition when content that touches public emotions will trigger very high engagement in a short period of time, and then slowly subside as public attention shifts to new issues. In this context, a video that touches on the human side like the tears of a laid off presenter quickly becomes an emotional flashpoint that prompts thousands of people to respond through digital commentary. Study Marwick & Boyd (2011) It also shows that audience engagement with public figures on social media platforms tends to be moment-based, rather than sustainable.

The public's tendency to respond directly emotionally in the near future after a video is uploaded also reinforces the argument that the relationship between audiences and media figures is dynamic and heavily influenced by the momentum of actuality (Abidin, 2018). In this case, the emotional closeness that the audience has to presenter Gita Maharkesri is expressed through comments in a time very close to the events of her last broadcast. As stated in the theory of emotion-based communication, emotional contagion can spread quickly through digital media and create a pattern of collective engagement that is temporary but intense (Ferrara & Yang, 2015; Wilkie et al., 2026; Coviello et al., 2014)

Interestingly, although the intensity of interactions decreased within a few days after the peak of virality, the graph shows that comments remained in small numbers over the next few days. This suggests that even though the viral effects are short-lived, the emotional footprint of the video remains and resonates with a portion of the audience who may have just watched the content on a delayed basis. This corroborates the findings Lu & Hong (2022) that the affective traces of viral content can survive and create a long tail effect in the context of digital social interaction.

The temporal distribution of commentary on this video not only reveals the rhythm of public engagement but also provides an important understanding of how society responds to the personal crises experienced by media figures in a fast-paced digital landscape. The peak of interaction is a reflection of the emotional dispersion of the content, while the distribution tail hints at the persistence of the collective memory of the issue, albeit on a smaller scale.

### 3.5. Heatmap Correlation Between Words and Discourse Patterns

In the study of digital communication, it is important to not only observe sentiment quantitatively, but also to understand how interrelated words form collective meaning in the comment space. One approach that can uncover this dynamic is through the analysis of correlations between words, which are visualized in the form of heatmaps. This technique allows researchers to see thematic clusters that emerge from the frequency and relevance of words used by the public, while uncovering the discourse structures hidden behind individual comments. With this approach, we can track the pattern of how the public builds narratives, express emotions, and formulates opinions communally in response to the issue of viral media layoffs.

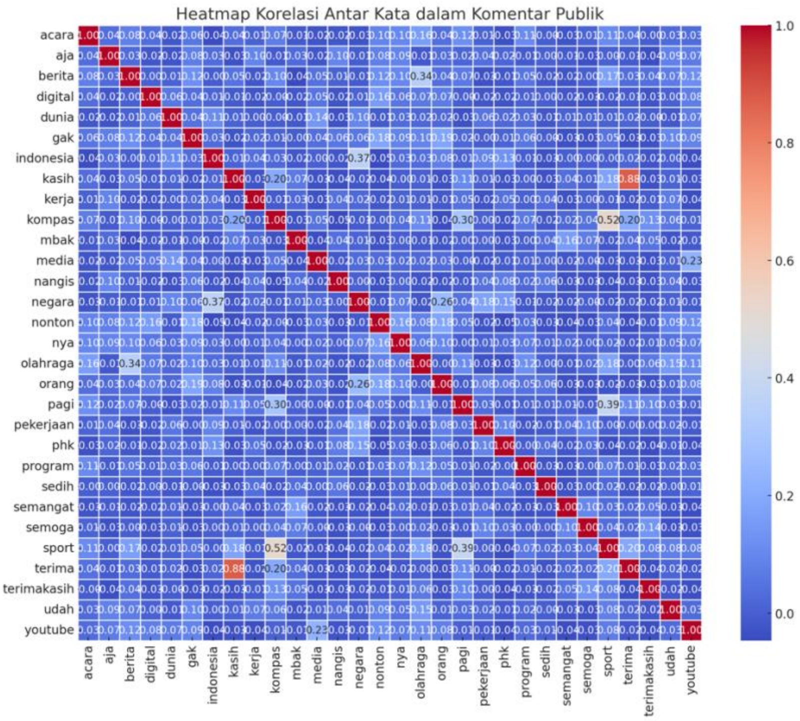


Figure 6. Heatmap Correlation between words in public comments

The visualization in the form of a correlation heatmap between words provides in-depth insight into the structure of public discourse in response to the layoff of KompasTV presenters. From the results of the analysis, it can be seen that there are a number of words that consistently appear together in comments, forming a cluster of meanings that mark certain topics or nuances in public conversation. For example, the word "*PHK* [layoffs]" shows a strong correlation with words like "*kerja* [work]," "*sedih* [sad]," and "*kasihan* [pity]," suggesting a realm of discourse centered on empathy for the plight of workers who have lost their jobs.

On the other hand, there are also groups of words such as "*terima* [receive]", "*kasih* [love]", "*presenter* [presenter]", and "*Kompas*" that are correlated with each other, forming an appreciative narrative of the figure of Gita Maharkesri and the programs that she has been presenting. This shows that public comments are not only reactive but also contain a dimension of genuine appreciation for the presenter's contributions. This cluster is a representation of parasocial discourse that is full of emotions and attachment (Cohen & Perse, 2003; Horton & Richard Wohl, 1956)

This correlation pattern confirms that the comments that emerge are not stand-alone entities, but rather part of a network of collective meanings. Words not only serve as individual expressions, but also as social constructs that spread and reinforce each other. In this context, the heatmap functions like a semantic map that shows the path of the spread of public opinion ranging from empathy, criticism, to a sense of loss all mixed in one digital discourse space (Gerlitz & Rieder, 2013; Papacharissi, 2015)

Correlation also indicates the existence of narrative tension. For example, the emergence of a relationship between the words "*bohong* [lie]", "*lebay* [Overacting]", and "*drama* [drama]", which tends to mark cynical discourses and skepticism of the authenticity of emotional expressions in the video. This shows how the public not only voices solidarity but also questions the motives and framing of the media. This finding is in line with the concept of discursive contestation Wodak (2009), where the dominant narrative can be refuted by counter-narratives in the social media space.

The word correlation heatmap helps uncover patterns of emotional connectedness and meaning in digital discourse and confirms that the public's response to media layoffs is no single, but rich, complex, and polarized. This technique also expands the role of sentiment analysis from mere measurement of affection to the mapping of collective discourse, which is essential in contemporary communication studies.

### 3.6. Social Implications of Public Reaction to Media Layoffs

Layoffs in the media industry are not only an internal issue for the company, but also trigger a wide public reaction, especially when it involves media figures who are widely known to the public. In the case of the breakup of KompasTV presenter Gita Maharkesri, the public response was not only in the form of emotional sympathy but also contained a deeper social dimension. Through thousands of comments poured out on the YouTube platform, the public not only voiced their feelings, but also showed a collective awareness of the instability of work and structural conditions in the media ecosystem. It is therefore important to further examine the social implications of this phenomenon in the context of digital communication and the relationship between media, audiences, and contemporary work systems.

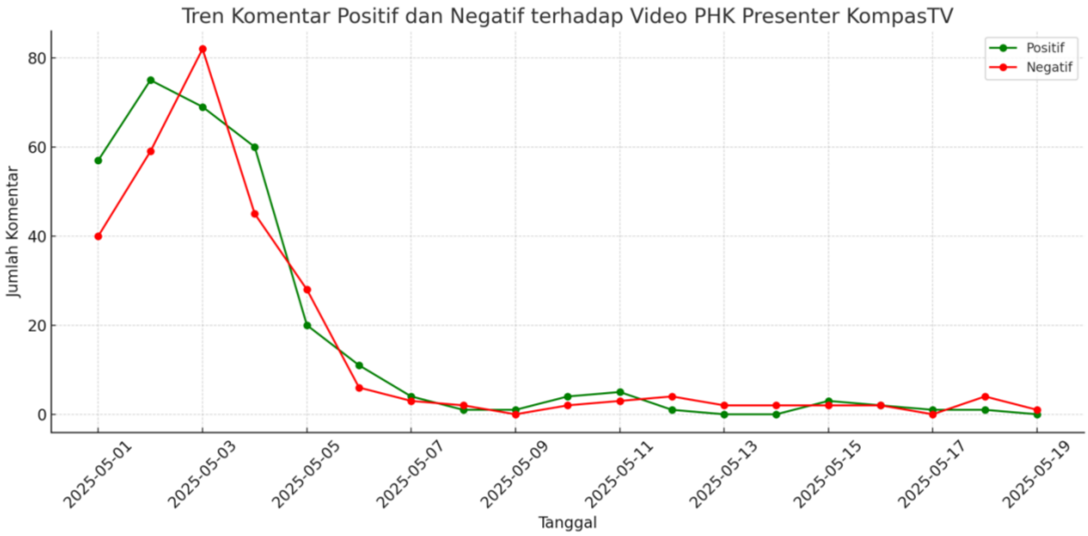


Figure 7. Trends of Positive and Negative Comments on Kompas TV Presenter Videos

The public reaction to Gita Maharketri's farewell video not only reflects an emotional individual expression but also shows the structure of social solidarity in the face of the employment crisis in the media industry. The phenomenon of empathic comments that flooded the viral video reflected the community's collective awareness of the vulnerability of media workers' positions, as well as voicing criticism of the work system that was considered unfair. In this context, digital platforms act as a space for public expression that allows feelings of loss, empathy, and cynicism towards media management to manifest openly and massively (Marwick & Boyd, 2011; Papacharissi, 2015).

The positive comments that are full of support and appreciation show that media figures like Gita Maharkesri are not only seen as professional presenters, but also as representatives of the humanist face of the world of work that is being threatened by digital disruption and corporate efficiency. When the public writes "*semangat terus Mbak Gita* [Keep spirit, Gita] " or "*Terimakasih sudah menemani pagi kami selama ini* [Thank you for accompanying us in the morning all this time]", they not only greet individuals, but also maintain personal meaning in an increasingly impersonal work structure. This shows that parasocial relationships are not only a matter of media psychology, but also a support for digital solidarity in an unstable work era (Cohen, 2006; Giles, 2002).

Instead, negative comments that contain words such as " *lebay* [Overacting]", "*Drama*", or "*Stale*", and *"basi* [Stale]", indicates resistance to the emotional narrative presented by the media. This shows that not all the public internalizes the separation narrative in the same way. Some see it as an exaggerated construction of the media, and some even voice dissatisfaction with the news structure that is considered manipulative. This phenomenon illustrates the fragmentation of emotions in the digital public space, where sympathy and cynicism can coexist in a single thread of discussion (Chouliaraki, 2006; Wodak, 2009).

The social implications of this phenomenon are very important for the world of communication, especially in the context of the sustainability of the media industry. The public response to the layoff event is an indicator of public trust in media institutions, as well as underlining the importance of building crisis communication that focuses not only on corporate reputation, but also on the empathic and humanitarian dimensions. In addition, this reaction shows that the public is now increasingly literate about employment practices in the media industry and is ready to voice their dissatisfaction directly in the digital space (Ferrara & Yang, 2015; Yu & Yang, 2024).

The public reaction to the layoff of the KompasTV presenter became more than just a momentary emotional response. It is a reflection of the growing social consciousness in the digital media ecosystem, which is influenced by affective relations, the value of justice, and the sophistication of technology platforms. For the media industry, this phenomenon serves as a reminder that any policy that impacts human capital will not only be recorded by internal media, but will also be responded to, tested, and reinterpreted by the public through millions of meaningful digital comments.

### 3.7. Public Discourse Mapping: Scatter Comment Plots Based on Sentiment

The two-dimensional scatter plot visualization based on *Principal Component Analysis* (PCA) provides a comprehensive spatial mapping of the representation of public comments related to the viral moment of the KompasTV presenter's farewell. Each point in this scatter plot represents a single netizen's comment, which has been processed through TF-IDF vectorization transformation and then reduced in dimension to two main components using PCA. The color of the dots reflects sentiment: green for positive, red for negative, and gray for neutral.

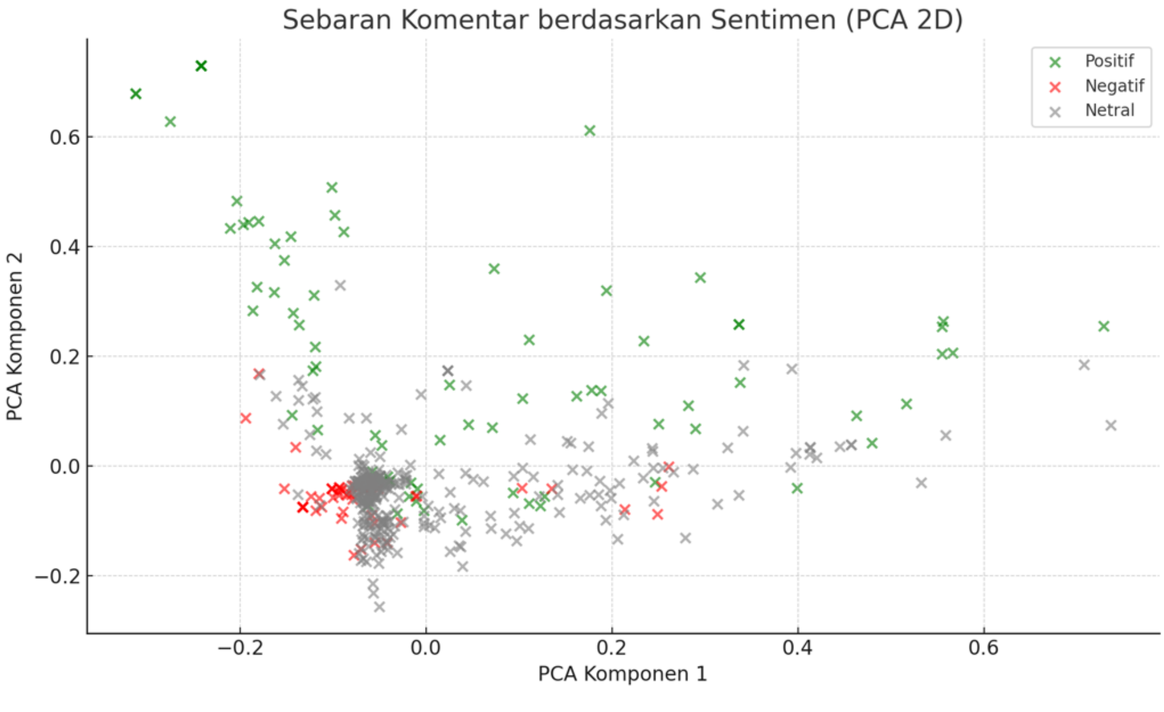


Figure 8. Comment Distribution Based on Comments

The results of this visualization not only show the dissemination of data but also reveal the structure of discourse that is organically formed in the digital space. Although neutral comments dominate quantitatively, their distribution appears to be evenly distributed throughout the vector space. This suggests that neutral comments have a wider variety of vocabulary and semantics, which may include factual expressions, mild observations, or non-emotional reactions. In contrast, the positive comment cluster looks more consolidated and forms a relatively dense cluster. This indicates the similarity of emotions and language used by users in expressing empathy, appreciation, and moral support to presenters affected by layoffs.

On the other hand, negative comments appear to be more widespread and form several different sub-clusters. This shows the heterogeneity of public criticism, ranging from satire against media management, accusations of excessive dramatization, to expressions of distrust of the narrative conveyed. This variation reflects the diverse motives and intentions of criticism, which are not always destructive, but also loaded with an evaluative dimension to media institutions and work culture in the digital age.

Conceptually, this scatter plot emphasizes that public sentiment does not emerge in a vacuum, but rather as part of a collective and complex structure of social discourse. The PCA technique helps extract latent patterns in the comment data, which are not always visible through ordinary linear readings. Thus, this approach not only illustrates the intensity of sentiment, but also maps a vivid and dynamic narrative landscape within the digital space after important events such as media layoffs.

In the context of digital communication studies, these results are relevant to understand how collective emotions and framing discourses are formed spontaneously and spread through social networks. This scatter plot becomes a visual symbol of the interaction between opinions, algorithms, and public empathy in forming a common opinion. This is in line with previous findings on the importance of sentiment analytics as a tool to explore the dynamics of public opinion in depth in an era of intense digital connectivity.

## 4. Conclusion

This research reveals that the viral phenomenon of the farewell of KompasTV presenter, Gita Maharkesri, is not just an ordinary media event, but a symbol of the emotional and social turmoil felt by the public towards the dynamics of employment in the media industry. Through an analysis of 2,238 public comments on the ANTARANEWS YouTube channel, it was found that the majority of comments were neutral, but positive and negative comments appeared in significant numbers and contained emotions, solidarity, criticism, and resistance to the reality of media layoffs.

The distribution of sentiment shows a strong empathic reaction to the presenter figure, which is reinforced by the parasocial relationship between the audience and the media figure. Pharase such as "*semangat* [Enthusiasm]", "*terharu* [overwhelmed]", "*terimakasih* [Thank you]", dominated positive comments, while negative comments showed the emergence of narratives such as *lebay* [overacting]", "*bohong* [*lie*]", "*sedih* [sad]", and "*PHK* [layoff]" that contained criticism of the presentation of emotions and media management policies. This pattern confirms that public discourse is not singular, but rather complex and often contradictory.

Temporal analysis shows that the public reaction was intense in the early days of the video's release, illustrating the rapid and massive nature of emotional engagement. Although interactions are gradually declining, the response has left a significant footprint in the digital public space. The word correlation heatmap also shows the existence of clusters of meaning and discourse, such as word groups that form empathetic narratives and groups that mark cynicism towards the media.

The social implications of this phenomenon are very important. Today's digital society is not only a passive spectator, but also an active actor who helps build discourse and convey a collective voice on employment issues and structural justice. The layoffs of media figures are no longer an internal issue, but a public issue that triggers solidarity and criticism simultaneously, which is recorded and spread through social media widely.

In the end, this study emphasizes that big data-based sentiment analysis can not only capture public emotions but also reveal the structure of social meaning in digital discourse, as well as being a reflection tool for the media industry in building more humane communication in the midst of ongoing digital transformation.

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