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Two-Stage Sentiment Analysis on Indonesian Online News Using Lexicon-Based

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Abstract: The image of a supplier company is often associated with the well-known brand it supplies, and its reputation can be influenced by online news circulation. To maintain a positive image, it is crucial for the company to monitor and manage online news to rectify any false information. Failure to maintain a good company image can lead to customer order loss and even company shutdown. This paper aims to conduct a two-stage sentiment analysis on Indonesian news articles regarding unilateral layoffs by company XYZ. The first stage will analyze sentiment in the circulating news about the layoffs, while the second stage will assess sentiment after the company releases a press release to provide accurate information. The VADER lexicon-based method, utilizing the InSet and SentiStrength_ID Indonesian dictionaries, will be employed to analyze sentiment before and after the press release. This will enable us to compare sentiment and evaluate the effectiveness of the press release and the Indonesian dictionaries in analyzing sentiment in the news. The research findings indicate that the company's press release, aimed at correcting false information, had a positive impact by reducing negative sentiment and generating a more positive sentiment in the second stage. Moreover, the selection of the sentiment analysis dictionary also plays a critical role in determining the sentiment analysis results.

Keywords: InSet, Lexicon, Sentiment, SentiStrength_ID, VADER.

INTRODUCTION

Company XYZ is a manufacturing company that exclusively supplies one brand to a single customer. Any negative perception of the company can adversely affect the brand image it supplies. It is crucial for supplier companies to maintain a positive image and monitor the sentiments surrounding news circulating on online media. Whether positive or negative, news can shape public opinions and impact not only the company's image but also the brands it supplies (Mishra & Samu, 2021).

Brand owners have an interest in safeguarding their trademark image and paying attention to the reputation of their suppliers. Poor suppliers can be replaced with better ones. However, news circulating online about unilateral layoffs by Company XYZ can create a negative and detrimental image for the company, while over ten thousand employees depend on it for their livelihood. The company is obligated to rectify false news by providing accurate information, facts, and evidence (Ferry Sandi, 2023), ensuring that public opinions or sentiments are not swayed by incorrect news and do not adversely affect the company's image and the brands it supplies. The hope is that by providing accurate information to online media, the company can rectify misinformation and improve its image.

The purpose of this study is to assist companies in conducting sentiment analysis on circulating news, determining whether the news has a positive, negative, or neutral sentiment. The results of sentiment analysis will enable companies to correct any erroneous news, such as issuing official

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statements to the media or holding press conferences, as well as evaluating the impact before and after corrections.

The existing papers on sentiment analysis have typically conducted a single sentiment analysis to determine the sentiment score of online news articles—whether they are positive, negative, or neutral. However, these studies have not explored the subsequent stages after an action of press release to assess how the sentiment might be influenced by the press release.

This paper performs a two-stage news article sentiment analysis on a case involving unilateral layoffs by Company XYZ in Indonesian language. The first stage is before the company's official statement, and the second stage is after, enabling us to compare and evaluate the two sentiment analysis results to understand the impact of the company's official statement on public sentiments.

LITERATURE REVIEW

Analysis of news articles to understand people's opinions, thoughts, and impressions about the content is known as sentiment analysis (Alonso, Vilares, Gómez-Rodríguez, & Vilares, 2021). It is the process of collecting and analysing people's opinions, thoughts, and impressions about a specific topic, news, product, subject, or service(Wankhade, Rao, & Kulkarni, 2022). Sentiment analysis, also known as opinion mining, is a research field that examines people's sentiments, opinions, attitudes, and emotions towards various elements (Serrano-Guerrero, Olivas, Romero, & Herrera-Viedma, 2015), including news articles in the media.
There are numerous methods available for conducting sentiment analysis, which can be grouped into five categories, as follow:

Rule-Based: This method employs pre-defined rules to determine the sentiment of words, using a list of positive and negative words and calculating sentiment values in news articles to generate specific sentiment scores (Zahoor & Rohilla, 2020).

Machine Learning: This method utilizes machine learning algorithms to classify news articles based on their sentiments. Some sentiment analysis algorithms in machine learning include Naive Bayes, Support Vector Machines (SVM), and Random Forest (Samizade & Abad, 2018).

Deep Learning: This method employs artificial neural networks to classify news articles based on their sentiments. Common types of artificial neural networks used include Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) (Seo, Kim, Kim, Mo, & Kang, 2020).

Lexicon-Based: This method uses dictionaries of words, phrases, and punctuation marks associated with specific sentiments to determine the sentiment of news articles (Ding, Liu, & Yu, 2008).

Hybrid: The hybrid method in sentiment analysis is an approach that combines multiple sentiment analysis techniques to leverage their individual strengths and overcome their respective limitations. By fusing the power of different methods, the hybrid approach aims to achieve improved accuracy and robustness in sentiment classification(Ray & Chakrabarti, 2022).

Each of these categories has its own advantages and disadvantages, as showed in Table 1 below.

Table 1 Pros and Cons for Each Sentiment Analysis

No	Method	Pro	Cons
1	Rule-Based Approaches	• Simple and easy to implement • Can be customized for specific domain or requirements • Can handle specific linguistic rules. • Transparent and interpretable rules results. • Low computational complexity	• May not capture complex sentiments or context • May not perform well on new or diverse data • Rule creation and maintenance can be labor-intensive and require domain expertise. • Reliant on predefined rules and patterns
	Machine Learning	• Can handle complex sentiments and adapt to different domains	• Requires a large amount of labelled training data

Researchers often choose machine learning, deep learning, and hybrid methods due to their high accuracy in sentiment analysis. However, these methods require large amounts of data for training, testing, and require significant computational resources. In the case of unilateral layoffs where data is limited in articles related to this topic, these methods may be less effective for this research with limited data.

The rule-based approach in sentiment analysis is not well-suited for news articles due to its limitations in capturing the complexity and nuances of language found in such content. News articles often contain sophisticated language, subtle expressions, and varying contexts, which can be challenging for pre-defined rules to handle effectively (Berka, 2020). On the other hand, lexicon-based approach is suitable for news article sentiment analysis due to its ability to handle diverse and complex language found in such content.

Lexicon based approach can handle negations, modifiers, and domain-specific terms, providing a more accurate analysis of sentiments expressed in news articles (Fauziah, Yuwono, & Aribowo, 2021). Moreover, the lexicon-based approach is relatively easy to implement, making it practical for analysing a large volume of news articles in real-time. Its interpretability allows researchers to gain insights into the sentiment patterns of the news content, making it a valuable tool for understanding public opinions and reactions to various topics and events covered in news articles.

Considering pros and cons of sentiment analysis methods in Figure 1 and the characteristic of the case, in this research use lexicon method to measure sentiment analysis in news articles.

The lexicon-based analysis employs VADER (Valence Aware Dictionary and Sentiment Reasoner), a sentiment analysis method for analysing sentiments in news articles. This method uses a lexicon dictionary to assess the sentiment of words within the text, where each word is assigned, a score based on its positivity or negativity. VADER can handle aspects such as emotional intensity, capitalization usage, and punctuation(Neal Dickert et al., 2014).

The existing research on sentiment analysis of online news articles in Bahasa Indonesia typically involves conducting a single stage of analysis to determine the sentiment score of the online news articles, classifying them as positive, negative, or neutral (Ayu, Wijaya, & Mantoro, 2019; Hermanto, Setyanto, & Luthfi, 2021; Muhith & Atastina, 2022; Rustanto & Rakhmawati, 2021; Tri Sakti, Mohamad, & Azlan, 2021; Waspodo, Nuryasin, Bany, Kusumaningtyas, & Rustamaji, 2022; Wiyono, Qodir, & Lestari, 2023; Yu & Han, 2023). However, most researchers have not analysed a second stage to assess the impact of press releases on sentiment. Additionally, some studies have translated Bahasa Indonesia articles into English (Christina & Ronaldo, 2018; Harnikawati, 2021; Mas Diyasa et al., 2021;

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Pamungkas & Putri, 2017) to take advantage of the wider availability of VADER(Hutto & Gilbert, 2014) lexicon dictionaries for measuring sentiment analysis compared to those based in Bahasa Indonesia. These studies have used two Bahasa Indonesia lexicon bases to measure sentiment analysis and compare the results.

Although initially designed for English text, VADER can effectively be applied to Bahasa Indonesia text by modifying the reference lexicon accordingly. There are at least two available Bahasa Indonesia sentiment lexicons: InSet and SentiStrength_ID (Abdillah, Premana, & Bhakti, 2021)which will be used for comparison in the sentiment analysis.

InSet is a Bahasa Indonesia lexicon dictionary created to identify written sentiments or opinions and categorize them as positive or negative. It consists of 3,609 positive words and 6,609 negative words, each with a score ranging from -5 to +5 (Koto & Rahmaningtyas, 2018).

SentiStrength_ID is a Bahasa Indonesia lexicon with 1,729 words, each assigned a score between -5 and +5. Both InSet and SentiStrength_ID have scores ranging from -5 to +5, where -5 represents the highest negative sentiment score and +5 indicates the highest positive sentiment score(Wahid & SN, 2016).

TWO-STAGE SENTIMENT ANALYSIS

The two-stage sentiment analysis involves evaluating two groups of news article related unilateral layoffs by Company. The first group consists of articles before the company's press release, while the second group contains articles published after the press release. By comparing the sentiment analysis results between these two stages, we can observe any changes in sentiment. Additionally, we aim to compare the sentiment analysis outcomes using two different Bahasa Indonesia dictionaries, InSet and SentiStrength_ID.

Data Set

The data used for this research consists of six teen news articles in Bahas Indonesia related to unilateral layoffs published on two main websites: www.tempo.co and www.cnbcindonesia.com. The articles are divided into two groups: the first group as the stage one, consists of six articles before the press release, and the second group as stage two, consists of ten articles after the press release.

Table 2
Data Set: Stage 1 and Stage 2

Two-Stage	CNBC Indonesia	Tempo.co	Total News
Stage 1	2	4	6
Stage 2	7	3	10
Total	**9**	**7**	**16**

Table 2 show the distribution of data from both online media sources into two sentiment stages. The data analysis process is conducted for each group separately.

Sentiment Analysis Steps

The sentiment analysis process begins with the collection of relevant online news articles, which are used as the dataset. These articles are then divided into two stages: pre-press release and post-press release. To prepare the text for analysis, the articles undergo preprocessing, where irrelevant characters are removed, stemming is applied, and sentences are broken down.

Next, sentiment analysis is conducted using VADER Lexicon-based with two different lexicon dictionaries InSet and SentiStrength_ID (Abdillah et al., 2021). These dictionaries help determine the sentiments expressed in the news articles. Finally, the sentiment figures obtained from each stage are compared to observe any changes or differences in sentiment before and after the press release. As a result, these analyses, allowing us to examine the variations in sentiment based on different dictionaries and the timing of press releases.

Sentiment Analysis Evaluation

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The sentiment score of a sentence is determined by adding up the sentiment scores of each word listed in the VADER dictionary (InSet and SentiStrength_ID) within the sentence. Each individual word has a sentiment score ranging from -5 to 5. However, the overall sentiment score of the sentence is normalized to a value between -1 to 1. This allows for a more standardized representation of the sentiment level of the entire sentence, making it easier to interpret and compare across different texts. The normalization use in VADER(Hutto & Gilbert, 2014).

The sentiment score (compound) of a sentence, represented by 'x', is divided by the normalization parameter 'a', which is set to 15 in the equation (1) below.

$$\frac{x}{\sqrt{x^2+15}} \quad (1)$$

As example the sentence “saya lelah hari ini!” in Bahasa, using VADER and SentiStrength_ID lexicon, the output of sentiment analysis is shown as follows:

```
Sentiment: {'neg': 0.523, 'neu': 0.477, 'pos': 0.0, 'compound': -0.5093}
```

This result indicates that the analysed text has a negative score of 0.523, a neutral score of 0.477, and a positive score of 0.0. The 'compound' score is -0.5093, suggesting an overall negative sentiment. The 'compound' score is calculated using normalization rules to combine the positive, negative, and neutral scores into a single value. This score ranges from -1 (very negative) to +1 (very positive), with 0 indicating neutrality.

RESULT

In this research, Python programming is utilized to perform sentiment analysis including data retrieval and extraction from online news articles. As an example, extracting a news articles published on CNBC Indonesia's online media, as demonstrated in the code snippet provided below.

```
# News Article Link
url = "https://www.cnbcindonesia.com/news/20230512184515-4-436981/pabrik-sepatu-adidas-cs-di-tangerang-phk-1400-karyawan"
# Send a request to retrieve the web page content
response = requests.get(url)
html_content = response.text
print(html_content)
...
```

The output of the code above a text in the format of html text format as follow:

```
<!DOCTYPE html>
<html lang="id-ID">

   <head>
   <title>Pabrik Sepatu Adidas Cs di Tangerang PHK 1.400 Karyawan</title>
<link href="https://www.cnbcindonesia.com" rel="dns-prefetch">
        <link href="https://cdn.cnbcindonesia.com" rel="dns-prefetch">
        <link href="https://cdn.detik.net.id" rel="dns-prefetch">
        <link href="https://securepubads.g.doubleclick.net" rel="dns-prefetch">
        <link href="https://cdnstatic.detik.com" rel="dns-prefetch">
        <link href="https://akcdn.detik.net.id" rel="dns-prefetch">
        <link href="https://www.gstatic.com" rel="dns-prefetch">
        <link href="https://www.google-analytics.com" rel="dns-prefetch">
        <link href="https://www.facebook.com" rel="dns-prefetch">
        <link href="https://partner.googleadservices.com" rel="dns-prefetch">
```

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```
    <link href="https://www.googletagmanager.com" rel="dns-prefetch">
    <link href="https://cdn.ampproject.org" rel="dns-prefetch"><meta charset="utf-8">
<meta http-equiv="X-UA-Compatible" content="IE=edge">
<meta http-equiv="Content-Type" content="text/html; charset=UTF-8" />
<meta name="robots" content="max-image-preview:large">
...
```

The data in the HTML format above cannot be used directly as it is raw data and requires initial processing to be ready for sentiment analysis. The data cleaning process is performed using the *Python* module *BeautifulSoup*.

```
# Function to preprocess the text
def preprocess_text(text):
  # Remove HTML tags
  text = BeautifulSoup(text, "html.parser").get_text()
  # Remove non-alphabetic characters
  text = re.sub("[^a-zA-Z]", " ", text)
  # Tokenize the text
  tokens = word_tokenize(text.lower())
  # Remove stop words
  stop_words = set(stopwords.words("indonesian"))
  tokens = [token for token in tokens if token not in stopwords]
  return tokens
```

The data cleaning involves several cleanup stages. First, HTML tags are removed from the HTML format. Second, non-alphabetic characters are removed using regular expressions. Third, tokenization is applied to the text, converting it to lowercase. Additionally, *stopwords* in the Indonesian language are removed using the *stopwords* library, resulting in a clean text of the news articles as follows:

```
Jakarta, CNBC Indonesia - Gelombang pemutusan hubungan kerja (PHK) di industri tekstil belum juga usai. Terbaru, produsen sepatu dari Adidas yakni PT XYZ di Tangerang terus melakukan PHK terhadap ribuan pegawainya. Direktur Utama PT XYZ mengonfirmasi keputusan PHK tersebut."Memang itu terjadi PHK karena order berkurang, jadi mau gak mau mengurangi karena beban perusahaan, kalau ngga, kita gak bisa survive. Dengan berkurang (pegawai PHK) yang lain masih bisa bekerja nih," katanya kepada CNBC Indonesia.
...
```

At this stage, all news articles from both stage 1 and stage 2 have been cleaned up and their sentiment has been measured using VADER and two Indonesian dictionaries. As a result, each news article ID has a sentiment score, grouped into stage 1 (P1) and stage 2 (P2) also dictionary used InSet and SentiStrength_ID.

The sentiment scores are broken down into four categories: negative (neg), neutral (neu), positive (pos), and compound (compound). The neg, neu, and pos scores represent the proportion of the text that falls into each of those categories. The `compound` score is a normalized, weighted composite score that takes into account all of the individual sentiment scores. It ranges from -1 (most negative) to +1 (most positive). Compound score represents the overall sentiment of the news, with a higher score indicating a more positive sentiment and a lower score indicating a more negative sentiment. The `compound` score is useful for determining the overall sentiment of a text of news, especially when the text contains a mix of positive, negative, and neutral sentiments. The results for each article are shown in Table 3. (Hutto & Gilbert, 2014).

Table 3
Sentiment Analysis Result

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			Dictionary							
			InSet				SentiStrength_ID			
Stage	News Media	Article ID	Compound	Negative	Neutral	Positive	Compound	Negative	Neutral	Positive
S1	CNBC	CNBCS11	-0,0002	-0,5300	0,9730	0,4970	-0,9001	-0,1230	0,8150	0,0620
		CNBCS12	0,0000	-0,5120	1,0330	0,4550	-0,9899	-0,1330	0,8230	0,0440
	Tempo	TEMPS11	0,0000	-0,4840	1,1000	0,4160	-0,4588	-0,0550	0,9010	0,0440
		TEMPS12	-0,0001	-0,4900	1,0320	0,4780	-0,8750	-0,0720	0,8890	0,0380
		TEMPS13	-0,0004	-0,5520	1,0750	0,3730	-0,9584	-0,1090	0,8420	0,0480
		TEMPS14	-0,0001	-0,5200	1,0670	0,4130	-0,9517	-0,0720	0,8900	0,0380
S2	CNBC	CNBCS21	-0,0002	-0,5420	1,0230	0,4350	-0,4588	-0,1160	0,7880	0,0960
		CNBCS22	-0,0001	-0,5420	1,0180	0,4400	-0,7906	-0,0890	0,8430	0,0680
		CNBCS23	-0,0002	-0,5290	1,0610	0,4100	0,9432	-0,1020	0,7720	0,1260
		CNBCS24	-0,0007	-0,4680	1,1660	0,3660	0,9060	-0,0740	0,8150	0,1120
		CNBCS25	-0,0002	-0,5240	1,0390	0,4370	-0,2500	-0,1030	0,8140	0,0830
		CNBCS26	-0,0002	-0,5140	1,0610	0,4250	-0,8750	-0,0950	0,8390	0,0660
		CNBCS27	-0,0002	-0,5200	1,0420	0,4380	-0,2500	-0,1030	0,8140	0,0830
	Tempo	TEMPS21	-0,0001	-0,5710	0,9860	0,4430	-0,9953	-0,1290	0,8110	0,0600
		TEMPS22	-0,0003	-0,5430	1,0540	0,4030	-0,9517	-0,0920	0,8710	0,0380
		TEMPS23	-0,0001	-0,5460	1,0340	0,4200	-0,9776	-0,1220	0,8070	0,0710

Table 3 shows the detailed sentiment scores for each article and each stage. Stage 1 includes two news articles from CNBC Indonesia (CNBCP11- CNBCP12) and four news articles from Tempo.co (TEMPP11-TEMPP14). Stage 2 includes seven news articles from CNBC Indonesia (CNBCP21-CNBCP27) and three news articles from Tempo.co (TEMPP21-TEMPP23). All those articles measured both by InSet and SentiStrength_ID.

DISCUSSION

In this study, the sum of the 'compound' sentiment scores will be used to analyse the overall sentiment trend and the magnitude of changes between stage 1 and stage 2. This is more effective in measuring the impact than using an average score. By adding up all the sentiment scores, we can see the total magnitude of changes in sentiment across the dataset. This gives us a better understanding of the overall sentiment trend and can help us identify significant shifts in sentiment.

Sentiment analysis focused on compound score of stage 1 (before press release) and stage 2 (after press release), show in figure 1, where the first column is stage, second column in dark red color as compound, third column in pink color as negative, fourth column in pink color as negative, fifth column in green color as positive, sixth column in gray color as neutral, same color format will be applied to other figures below.

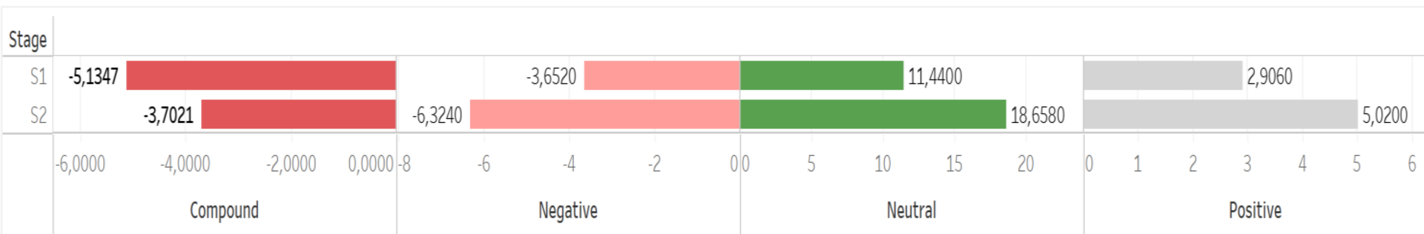

Fig. 1 Sentiment Score Stage 1 and Stage 2

The total sum of compound scores in Stage 1 (S1) is -5.1347, indicating an overall negative sentiment before the press release. In Stage 2 (S2), the total sum of compound scores improved to -3.7021, indicating a positif shift towards a less negative sentiment after the press release.

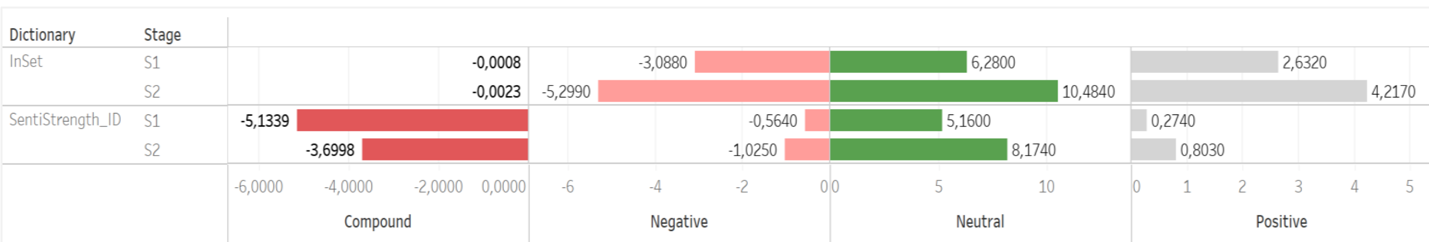

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Fig. 2 Different Dictionary InSet and SentiStrength_ID impact.

The impact of the press release in figure 2 between S1 and S2 using deferens dictionary, InSet and SentiStrength_ID, the analysis revealed different impacts on sentiment depending on the dictionary used. When employing the InSet dictionary, the compound score decreased slightly by 0.0015 from -0.0008 to -0.0023, indicating a slight decline in overall sentiment after the press release. However, there was an increase in the negative score by 2.211 from 3,088 to 5,299 and the neutral score by 4.204 from 6.2800 to 10.4840, suggesting a higher presence of negative and neutral sentiment in stage 2. The positive score also increased by 1.585 from 2.6320 to 4.2170, indicating a higher presence of positive sentiment in stage 2.

Conversely, when using the SentiStrength_ID dictionary, the compound score increased by 1.4341 from -5.1339 to 3.6998, signifying an overall increase in sentiment after the press release. Similar to the InSet dictionary, the negative score increased, suggesting a higher presence of negative sentiment in stage 2. Additionally, the neutral score increased by 3.014 from 5.1600 to 8.1740, and the positive score increased by 0.5290 from 02740 to 0.8030, indicating higher occurrences of neutral and positive sentiment in stage 2.

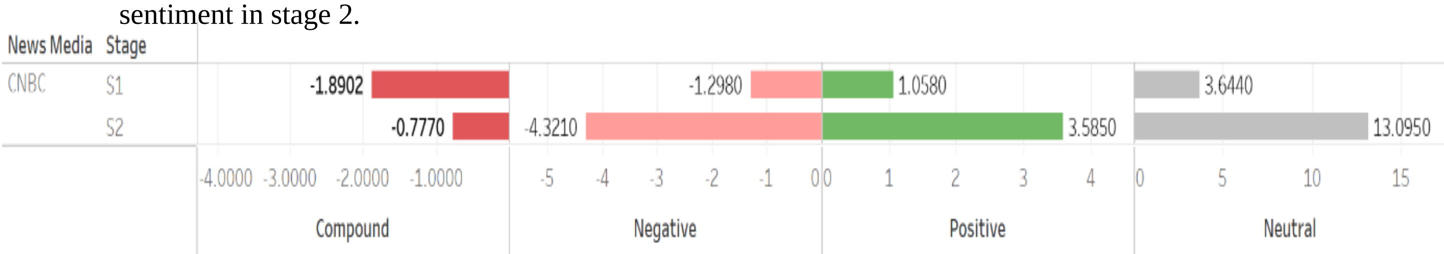

Fig. 3 Different Stage 1 and Stage 2 from CNBC.

In figure 3, the impact of the press release sentiment from deferens source of article reveals interesting fact. During stage 1, CNBC news articles exhibited a notable level of negativity from compound score -1.8902 to -0.7770 increased by 2,6672. However, the press release proved to be effective in mitigating this negativity and improving the overall sentiment for CNBC news articles.

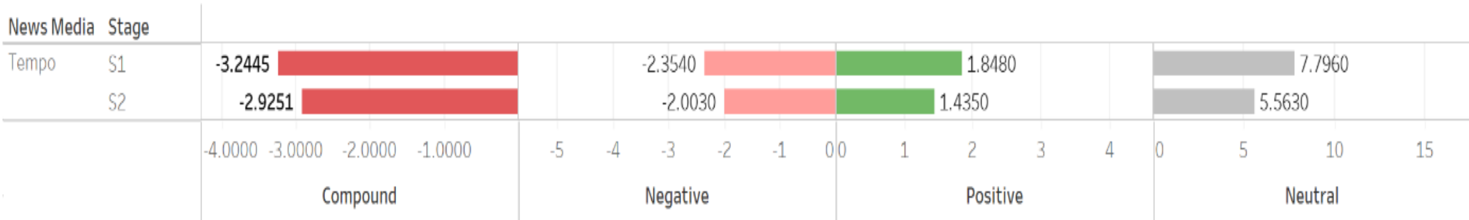

Fig. 4 Different Stage 1 and Stage 2 from Tempo.

On the other hand, Tempo news articles in figure 4 showcased a more positive sentiment overall during stage 1 to stage 2, from compound score -3.2445 to -2.9251 increased by 0,3194.

As the paper aimed to examine the changes in sentiment within news articles from CNBC and Tempo before and after the press release, utilizing the InSet and SentiStrength_ID sentiment dictionaries for analysis. The results revealed that the SentiStrength_ID dictionary demonstrated more significant fluctuations in sentiment polarity compared to the InSet dictionary. In stage 1, CNBC articles exhibited a higher degree of negative sentiment compared to Tempo articles. However, following the press release in stage 2, both news media displayed a decrease in sentiment polarity, with CNBC experiencing a more substantial decrease.

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During stage 2, both CNBC and Tempo news articles demonstrated a positive shift in sentiment in comparison to stage 1. The press release had a slightly positive effect on Tempo news articles, further improving sentiment and approaching a neutral stance. For CNBC news articles, the press release successfully contributed to maintaining a positive sentiment.

The press release played a crucial role in positively impacting sentiment for both CNBC and Tempo news articles. It effectively mitigated the negativity associated with the unilateral layoff news, resulting in an overall improvement in sentiment for both news media. The press release appeared to be particularly effective in enhancing sentiment polarity in CNBC news articles, especially when using the SentiStrength_ID dictionary. However, for Tempo news articles, the press release had a more limited impact on sentiment polarity.

The two-stage sentiment analysis of CNBC and Tempo news articles, utilizing the InSet and SentiStrength_ID dictionaries, provided valuable insights into the sentiment trends surrounding unilateral layoffs. The results drawn from each stage and the effectiveness of the press release were consistent, emphasizing the importance of carefully considering the sentiment analysis dictionary used to ensure accurate insights. To optimize the effectiveness of press releases in managing public image and perception, companies should closely monitor sentiment trends and tailor their communication strategies accordingly.

CONCLUSION

In conclusion, the press release had a positive influence on the sentiment of both news media, offering potential benefits for companies seeking to manage their public image and perception effectively. The choice of sentiment analysis dictionary should be carefully considered to ensure the accuracy of insights. Nevertheless, it is crucial to recognize that sentiment analysis is just one aspect of understanding public reception, and a comprehensive analysis should also encompass factors such as context, content, and public perception.

To sum up, this sentiment analysis provides valuable guidance for companies and organizations in effectively managing their public image during critical events. By utilizing insights derived from sentiment analysis and refining communication strategies, companies can enhance public perception and navigate challenging situations more adeptly. However, it is imperative to acknowledge that sentiment analysis is only one element of a comprehensive approach to comprehend public reception and manage public relations.

For future studies, a more comprehensive understanding of public sentiment dynamics surrounding significant events, such as unilateral layoffs, can be achieved by incorporating additional contextual information and conducting sentiment analysis on a broader range of news articles. Additionally, investigating the impact of diverse communication strategies and press release formats on sentiment may yield valuable insights for companies seeking to improve their public relations efforts. Researchers may also explore alternative methods for measuring sentiment impact and compare the results with those obtained in this study.

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