Tweeting During the Covid-19 Pandemic: Sentiment Analysis of Twitter Messages by President Trump

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In this article, we utilize VADER, a rule-based model, to perform sentiment analysis of tweets by President Donald Trump during the early spread of the Covid-19 pandemic across the United States, making it the worst-hit country in the world. We discover a statistically significant negative correlation between the sentiment of his messages and the number of Covid-19 cases in the United States, indicating an effect on the tone of his tweets as the pandemic took its toll on American lives and economy. Furthermore, we also witness a gradual shift from positive to negative sentiment in his messages mentioning China and coronavirus together.

CCS Concepts: • **Information systems** → Information systems applications;

Additional Key Words and Phrases: Sentiment analysis, VADER, rule-based model, Twitter, Covid-19, Donald Trump

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1 INTRODUCTION

President Donald Trump's Twitter account has been a source of many controversies and breaking news [28]. His frequent use of the micro-blogging site and his influence as President of the United States of America have led to various scientific studies evaluating his Twitter messages [10, 29]. He has been accused of using Twitter to attack and undermine character of his opponents and of sending out negative messages as political strategy [13, 23]. Due to his position, Donald Trump's tweets have significant real-world impact, such as his messages related to U.S.-China trade war negatively affecting S&P 500 returns [6, 7].

Hence, it is not surprising that during the current Covid-19 pandemic, Donald Trump again took to Twitter to discuss the virus outbreak. This phenomenon is not singular to him, however, as Twitter was used by many heads of state to communicate with citizens in helping them understand the nature of the pandemic. For example, a study that looks into the usage of Twitter from November 17, 2019 to March 17, 2020, by leaders from the G 7 countries, discovered 203 Covid-19-related tweets that went viral [24]. Out of these 203 messages, 166 were classified as informative, 48 had web links to government resources, 19 were considered as morale boosting, and 4 were political in nature [24].

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Not only political leaders but also government officials and public agencies around the world utilized Twitter to communicate with the public during the pandemic. They conveyed reassurances by replying to troubling tweets, issuing alerts on progress of virus, and outlining ways to protect against the pandemic [21]. Studies have also discovered that information relating to the latest news about the Covid-19 pandemic and the government's handling of the crises positively affects citizen engagement on social media [9].

Twitter utilization for communication in times of crisis has increased over recent years. Some of the first studies to evaluate Twitter usage during natural disasters looked at user tweets in the course of Japan's earthquake and tsunami of 2011 [1]. Since then, the use of Twitter during natural disasters and crises has continued to rise [20, 27]. Various tools and applications have developed over time that utilized actionable information extracted from Twitter for disaster relief efforts [5, 17]. Furthermore, advancements in natural language processing and machine learning have enabled researchers to automate analysis of large text datasets, created by millions of users [14, 25]. This has led to a rise in research studies employing sentiment analysis to gauge public mood and opinion utilizing Twitter data [8, 15, 30].

In this article, we perform sentiment analysis of messages posted on Twitter by Donald Trump during the ongoing global Covid-19 crisis. To date, the first officially confirmed case of Covid-19 was detected in the United States on January 21, 2020, and Donald Trump mentioned the coronavirus in a tweet for the first time on January 24, 2020 [12, 22]. We gathered all of his tweets for 159 days, starting from January 24, 2020, when he first mentioned coronavirus, to June 30, 2020. These frequent messages offer us a unique understanding of the President of the United States of America as his country led the world in the number of cases and deaths from Covid-19 [12]. We evaluate his messages for the following question:

- Did the rise in Covid-19-related cases and deaths have any impact on the sentiment of tweets by President Donald Trump?

In rest of this article, we discuss methods and data analysis to answer the preceding question.

2 DATA AND METHODS

Data related to Covid-19 cases and deaths in the United States is taken from EU Open Data Portal [12], whereas Donald Trump's tweets are downloaded from Twitter Trump Archive [4]. During these 159 days, President Trump tweeted and retweeted a total of 5,325 times, averaging almost 33.5 messages a day. We can observe from Figure 1 that the frequency of messages by Donald Trump on Twitter has remained fairly consistent. In fact, the linear trend of his tweets remained remarkably stable throughout the 159 days of our analysis. However, it is during this time period, on June 6, 2020, that Donald Trump set a personal record of sending out exactly 200 tweets and retweets in a single day [19].

VADER is utilized for sentiment analysis of Donald Trump's tweets. VADER is a lexicon- and rule-based tool and is specially created to evaluate sentiment social media messages [14]. It is a free open source tool that is available for implementation as a Python package.

VADER has gained popularity recently and is being used in various studies utilizing social media data [15, 26]. Success of the tool has led to its adoption in analyzing sentiment of languages other than English [3]. The model provides output as a proportion of text classified as positive, negative, or neutral sentiment. It also gives a compound score of sentiment for the entire text ranging from -1 to $+1$, with -1 as highly negative and $+1$ as extremely positive.

3 SENTIMENT ANALYSIS

Although the overall frequency of Donald Trump's tweets remained unchanged during the time period of our study, the positive tone of his messages decreased with the spread of Covid-19. We created a time series of his sentiment for 159 days by taking average sentiment of all tweets he created in a day. Figure 2 displays this daily

Fig. 1. Daily tweets by Donald Trump from January 24 to June 30, 2020.

Fig. 2. Daily and 5-day moving average sentiment of tweets by Donald Trump between January 24 and June 30, 2020.

sentiment of messages by Trump on Twitter. We can observe that the trend becomes less positive as the number of cases and deaths related to coronavirus increase. For the time period of analysis, Covid-19 peaked in April, as highest numbers of cases and deaths were recorded on April 26 and April 16, respectively.

We can further observe from the graphs in Figures 3 and 4 an inverse relationship between sentiment of President Trump's tweets and increase in Covid-19 cases and deaths.

To further explore this inverse relationship, we perform correlation analysis to test for significance. We test the three distributions of sentiment, cases, and deaths for normality. The values of skewness, kurtosis, and their respective z-scores are shown in Table 1.

Fig. 3. Daily sentiment of tweets by Donald Trump and daily new Covid-19 cases in the United States between January 24 and June 30, 2020.

Fig. 4. Daily sentiment of tweets by Donald Trump and daily Covid-19-related deaths in the United States between January 24 and June 30, 2020.

Table 1. Skewness and Kurtosis Scores of Sentiment, Cases, and Deaths Distribution

	Skewness	Kurtosis	$z\text{-Test}_{Skew}$	$z\text{-Test}_{Kurt}$
Sentiment	0.131	0.212	0.68	0.55
Cases	0.013	-1.247	0.07	-3.26
Deaths	1.340	2.616	6.98	6.83

Note: The last two columns display the z-test scores of normality for the three distributions. The $z\text{-test}_{Skew}$ and $z\text{-test}_{Kurt}$ between ± 3.29 indicate normally distributed data.

Table 2. Correlation Matrix Between Sentiment of Donald Trump Tweets and Covid-19 Cases and Deaths in the United States

	Daily Cases	Daily Deaths
Daily Tweet Sentiment	-0.198*	-0.056

Note: The asterisk (*) indicates a statistically significant correlation with $p < 0.05$.

The standard error for skewness and kurtosis for the three distributions is 0.192 and 0.383, respectively. For a medium sample size ($300 > n > 50$), we reject null hypothesis at a z-value greater than ± 3.29 [16]. We can observe from Table 1 that sentiment and Covid-19 cases have a z-value less than this threshold indicating both of them as normally distributed. Hence, we apply Pearson correlation, used for correlation analysis of normally distributed data, on sentiment and Covid-19 cases.

However, although distribution of sentiment is normal, we can also see from Table 1 that distribution of Covid-19-related deaths is non-normal as the z-scores for skewness and kurtosis of this distribution are 6.98 and 6.83, respectively, which are above the threshold value of 3.29. Hence, in this case, we utilize a non-parametric Spearman correlation to test for correlation between sentiment and Covid-19-related deaths.

The relationship between sentiment and both Covid-19 cases and deaths is negative. This relationship is statistically significant between sentiment and daily cases with $p < 0.05$. Results of the correlation analysis are shown in Table 2.

Along with this inverse relationship between the rise in daily cases and sentiment, an interesting shift is also observable in Trump's messages mentioning China with the progress of Covid-19. We witness a drastic change in the tone of President Trump's tweets mentioning China and coronavirus together [22]. Initially, his Twitter

Fig. 5. Sentiment of Donald Trump's tweets mentioning China and coronavirus or related terms together.

messages had a positive sentiment toward China when discussing her response to the virus outbreak. His first tweet mentioning coronavirus on January 24 also mentioned China [22]. From the following tweet text, we can observe the extremely positive tone of the message:

China has been working very hard to contain the Coronavirus. The United States greatly appreciates their efforts and transparency. It will all work out well. In particular, on behalf of the American People, I want to thank President Xi!

However, as Covid-19 spread across the United States, taking a high toll on the economy and life, the sentiment of his tweets mentioning China and coronavirus also changed to negative. What follows is his last tweet in our dataset mentioning China and the pandemic, posted on June 30 [2]:

As I watch the Pandemic spread its ugly face all across the world including the tremendous damage it has done to the USA I become more and more angry at China. People can see it and I can feel it!

The last tweet has strong negative connotation and sentiment. We can observe the dramatic about-face in President Trump's sentiment toward China from these two messages [2, 22]. Figure 5 shows this shift in sentiment as a scatter plot of his tweets between January 24 and June 30, in which he mentions China and Covid-19 or related terms together.

4 DISCUSSION

Although the frequency of tweets by Donald Trump remained stable throughout the 159 days of our analysis, the sentiment of his messages was nonetheless affected by the devastation caused by Covid-19. We discovered a statistically significant negative correlation between the sentiment of his tweets and daily new Covid-19 cases. This indicates that his message tone was affected by ravages of the pandemic. We can also observe from Figures 3 and 4 that his sentiment was significantly lower on days that witnessed some of the highest Covid-19 cases and deaths. Covid-19 cases and deaths peaked on April 26 and April 16, respectively, in the United States, and these 2 days are some of very few in the 159-day period of our analysis that have an average negative sentiment of Donald Trump's tweets. Similarly, Covid-19 deaths in the United States reached 100,000 on May 28, and we can

observe from Figure 2 that the sentiment of his tweets remained negative during the time period that this grim milestone was reached.

Finally, the tone of his messages toward China changed dramatically with the spread of Covid-19 in the United States. Donald Trump mentioned China and coronavirus together in several messages, as he built the narrative of China being complicit in hiding the devastating potential of the virus [2, 22]. On March 16, 2020, he used the term *Chinese virus* for the first time, which he used frequently from then on to refer to Covid-19 [18]. Figure 5 shows the sentiment of his tweets mentioning China/Chinese and coronavirus. Donald Trump has been accused of attacking his opponents on Twitter [13]. He is specifically known to employ negativity as rhetoric political strategy [23]. We observe a somewhat similar approach with respect to China, where he tries to employ a de-professionalized and amateurish style in his Twitter communication to appear authentic [11].

5 CONCLUSION

In this article, we evaluate sentiment of tweets by President Donald Trump during the early spread of Covid-19 in the United States. We discover the sentiment of his tweets correlating negatively with an increase in daily Covid-19 cases and observe a drastic change in sentiment toward China from positive to negative. Unfortunately, the pandemic is still far from over and the dynamics of this analysis may very well change in the future.

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