5-1-2022

Sentiment trends in political tweets: a case study of Marjorie Taylor Greene

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A Document Type.
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for Graduation *Cursus Honorum* in the Shackouls Honors College

Mississippi State, Mississippi
May 2022

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Date of Degree: May 13, 2022

Institution: Mississippi State University

Major Field: Communication

Select Appropriate Title: Dr. Holli Seitz

Title of Study: Sentiment trends in political tweets: a case study of Marjorie Taylor Greene

Pages in Study: 41

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Political public relations has changed in recent years with new developments in social media, leading to a greater use of digital communication. This thesis focuses on the wording in Twitter posts. This purpose of this case study is to find the potential effect of tweet sentiment on audience engagement when looking specifically at messages from Marjorie Taylor Greene's professional Twitter account. A sentiment analysis of a sixth-month time span of tweets was created using the Linguistic Inquiry and Word Count (LIWC) system. The variables assigned for tone were averaged for each day and charted on a graph, showing when they trend more negative or positive. These variables were also compared to the average number of retweets, likes, and replies received. The results revealed a negative correlation between positive tone and the number of likes and replies. The implications of these findings are further discussed in this paper.

TABLE OF CONTENTS

CHAPTER I

INTRODUCTION

"Impeach. Convict. Remove." This bold call to action is just one example of the intentional statements that turned the media's attention to Representative Marjorie Taylor Greene. Twitter messages like this have been shared by Greene to her nearly 850,000 followers (*Rep. Marjorie Taylor Greene🇺🇸 (@RepMTG)* | *Twitter*, 2022). Her rise in power has been seen as a sign of President Trump's hold on the Republican party. Just as he did, Greene has utilized social media to interact with the public and share strongly worded messages like this one. Her presence has gripped the media's focus and secured her a spot in Congress representing the state of Georgia (Mosley & Raphelson, 2021).

The topic of my thesis is the impact of sentiment trends in political messaging. In order to research this, I chose to do a case study of one member of Congress's Twitter page, analyzing tweets over a six-month period. Limiting the study to these parameters ensured the dataset would be manageable while also raising questions for potential future research. When choosing which platform to study, the research pointed to Twitter being the best option because of its accessibility, limited word count, and audience engagement features. Additionally, it is a well-established tool for political communication (Fountaine, 2017).

Once the social media platform was selected, the next step was deciding whose account to focus on. Choosing to focus on a member of Congress was intentional, as it kept it to a local level while also allowing for a large reach and audience beyond "small town politics." Initially, I focused on southern states, pulling lists of representatives with various profile information, including gender, race, age, and political party. Each of these factors was used in narrowing my focus. Georgia had a near even split of representatives, with eight Republican representatives and six Democratic representatives. The state has a more diverse demographic than others, which would allow for its representatives to have a wide variety of followers. Once looking at the online profiles of each representative, Marjorie Taylor Greene was chosen because of her active Twitter presence and recurring appearances in the media. The media attention that she receives results in higher audience engagement than her fellow state representatives.

Conducting a case study of a unique figure like Greene provides an analytical framework of one figure, ensuring a manageable dataset for research. This study is interesting as controversial politicians are taking to Twitter to share their thoughts. Greene is one who has often done this, and focusing solely on her can provide an empirically-rich account of a unique individual.

Broad Significance

Throughout my studies of public relations and political science, I have been interested in finding ways to merge the two. Completing a sentiment analysis of the online messages of prominent politicians combined two of my academic interests into one research topic. Previous research has been done on social media usage in politics and campaigns, providing a good background to this study. There is also literature surrounding sentiment analysis and the impact of language. The goal of this thesis is to find any potential effect of tweet sentiment on audience engagement when looking specifically at messages from Marjorie Taylor Greene's professional Twitter account. Greene's controversial public image and divisive media attention causes her to be a unique and interesting subject to focus on. This information can be applied to future research, focusing on online communication strategies and used to determine the best communication practices for this field.

CHAPTER II

LITERATURE REVIEW

Explanation of Political Public Relations

Social media platforms have been embraced by politicians, allowing for increased communication with the public through new methods. This growing acceptance of social media has created new opportunities for dissemination online, particularly in politics, allowing online users to share numerous messages with large audiences and directly respond to what is being viewed. Social media usage has also increased access, participation, and engagement with platform users. The social media communication methods that are being embraced in the political sphere are a practice of political public relations (Fountaine, 2017). Political public relations has been defined by Strömbäck and Kiousis (2011) as

> the management process by which an organization or individual for political purposes, through purposeful communication and action, seeks to influence and to establish, build, and maintain beneficial relationships and reputations with its key publics to help support its mission and achieve its goals. (p. 8)

Much can be learned from the communication methods utilized by politicians and the growth of social media usage. By researching the ways digital campaigning has become more common, one can understand the growing importance of using social media to reach a larger public. Its accessibility can both negatively and positively affect the political realm, allowing anyone to be able to say what they want. It allows for a new method of communication between candidates and the public. As the media continues to evolve throughout time, it is likely that political campaigns will adjust to continue to fit the current society.

Impact of Social Media

Growth of Social Media in Politics

When researching social media usage for political interactions, there are some important topics and questions that must be addressed. First, why is social media being used for politics? Is it important or necessary to use social media? Additionally, which social media sites are being utilized? Before looking at the specific techniques in sharing political messages on social media, it is important to look at the way that it has grown and become a more prominent political tool in recent years. Online communication reaches a more diverse audience because it is not limited to physical contact and geographical areas. This creation of new opportunities for users to reach and engage with new publics in a personal manner has led to online communication becoming more mainstream in politics (Aldrich et al., 2015).

Social media has allowed for political campaigns to become more local (Bright, 2019). Large political figures and organizations can communicate with small publics and individuals about local issues and topics without having to be physically present. This has allowed for many politicians who are geographically confined to reach a large audience, regardless of location (Bright, 2019). This localization of large figures allows the public to see them as a "regular" person, rather than as an official political figure who is disconnected from everyday issues and life. Their online messages become not only something that was reported on by a news outlet, but rather information that can be "liked," "commented" on, and "shared" with their own audiences (Marquart et al., 2020).

Many US adults have been reported as using social media as their primary source of political information, especially during election seasons (Sahly et al., 2019). This shift in how publics seek out and consume political information is reflective of the shifting modern media environment and growing relevance of social media platforms in the political sphere (Marquart et al., 2020). Additionally, social media has been found to offer unique opportunities for political discourse in campaigns, giving direct access to all candidates and often highlighting information that could be excluded from traditional news reports (Hwang, 2013). These benefits of utilizing social media in politics point to the development of new methods and its establishment as a main tool in political communication (Mueller & Saeltzer, 2020).

While social media is being embraced in the field of political communication because of the benefits previously stated, it has also brought unintended effects on politics and public discourse. The use of social media has had a direct role in political polarization, with most of the online political discussion being negative messages. This leads to an increase of separation between partisans (Mueller & Saeltzer, 2020). However, politicians are continuing to share online messages and interact with platform users due to the benefits such as localization and direct engagement.

There are many platforms available for politicians to utilize the localization and interaction with publics that has been discussed. Twitter is a public site, with majority of the user accounts being visible and accessible for all audiences. Twitter has been used for political information gathering more than other platforms because of its accessibility to politicians and the direct communication available. Users do not have to be “friends with” or connected to one another to see messages and engage on the site (Stier et al., 2018). These reasons, in addition to the amount of research available on Twitter, support the choice of focusing on this social media platform for the purpose of this research.

Twitter

To develop an understanding of the specific platform studied in this thesis, this section will introduce Twitter and its basic terminology, in addition to the demographics of its users. Tweets, or messages shared on Twitter, are limited to 280 characters. These brief messages can include links, photos, images, or other outside material to share information beyond what can be said in the tweet itself. Each profile has a feed that includes messages and content from accounts they follow, including what those people reshare. The messages that fill one’s feed determine what types of tweets and accounts are suggested for further connection. In addition to being able to share tweets with your community be retweeting, users can interact with messages with the like and reply features. These three features will be analyzed in addition to the sentient of the tweets selected for this research. The options for open communication have enabled Twitter to be used for learning, gathering, and sharing information, in addition to engaging with politicians and other large-scale users (Logghe et al., 2016).

Since its beginning in 2006, Twitter has gained over 313 million active users worldwide (Fountaine, 2017). Twitter is the most popular site among young adults, but there has been an increase in usage among several different demographic groups (Enli 2016). According to Pew Research (2022), over 80% of US adults between the ages of 18-49 use some form of social media. Facebook and Twitter are the most used of social media sites, with 23% of US adults using Twitter. While Twitter users tend to be members of the younger generation, this platform reaches a large range of users in many age groups and demographic categories. Approximately 42% of U.S. adults ages 18 to 29 are reported as Twitter users, and 27% of U.S. adults ages 30 to 49 using Twitter. Smaller percentages of older age groups are listed as Twitter users, however there is still reported use up to ages 65+. There also was found to be an established Twitter use for various races, genders, and income levels (https://www.pewresearch.org/internet/fact-sheet/social-media/?menuItem=b14b718d-7ab6-46f4-b447-0abd510f4180).

Twitter Usage in Politics

The possibility of attracting new followers and voters through Twitter's open communication channels and wide variety of users has attracted politicians to the platform, encouraging them to share messages directly to their audiences. Younger politicians in young areas are more likely to utilize Twitter when campaigning, leading to changes in traditional campaigning techniques. Research points towards the development and permanence of social media in politics, with the use of Twitter in political campaigns steadily increasing over the past 10 years (Fountaine, 2017).

While Facebook and Twitter are both used in high volumes (Bright, 2019), there literature discussed in this paper focuses on Twitter. Twitter is a form of micro-blogging, which has been defined as "a system of communication or an Internet-based publishing platform that consists of sending short text messages with a maximum length of [280] characters through tools such as Twitter" (Hwang, 2013). Because this form of micro-blogging is highly interactive, politicians have utilized it to adjust their image and expand their reach to new audiences. It allows them to control the narrative directly through short conversation and straightforward messages (Hwang, 2013).

Twitter users are politically active and react directly to messages shared by politicians. Beyond just reaching their followers, this interaction shares these messages with users' own networks. Likes and retweets serve to spread the original message and have often become an incentive and goal in digital campaigning (Mueller & Saeltzer, 2020).

Social Media Engagement

While an online presence has become vital in political campaigning, engagement with an audience ensures the messages have an impact. Audience engagement can be defined as "the level of user participation and interactivity in real time on social media platforms (p. 4)." The level of engagement of an online message can be measured by the number of interactions, such as likes, comments, shares, retweets, etc. (Sahly et al., 2019).

While political campaigns may be looking more towards social media to interact with the public and share their messages, it is important to see if this actual has a positive effect on their audiences' political participation (Gil de Zúñiga, 2012). President Obama was one of the first to successfully utilize social media in his political campaign, leading to social media strategy becoming the new norm in the United States' political world. Audience engagement is easily examined and often used to determine a politician's effectiveness in disseminating messages (Sahly et al., 2019). One way that many campaigns track audience engagement is through the number of retweets and likes that a message shared on Twitter receives (Mueller & Saeltzer, 2020).

Younger generations are utilizing social media platforms as their primary news source, with many Twitter users falling into this demographic. Approximately 75% of people between ages 18 to 29 use social media daily to get news, interacting with friends and strangers to discuss various topics. News platforms are adapting to this shift to nontraditional media, sharing articles, stories, and announcements online for its audience. The way that this younger generation is interacting with media outlets and political figures has been found to directly shape their future political involvement and civic attitudes, leading to more civic engagement. Networked communication logic supports this, enforcing the idea that one's personal interests and peer networks have a direct influence on information interacted with online (Marquart et al., 2020). Because of this, it is vital to understand the audience engagement with the data that is being researched, taking likes, replies, and retweets into account.

Public Perception and Political Credibility

While there are many traits that politicians value, one that is most notable is credibility. Twitter allows for users to share their thoughts and messages directly, controlling the narrative by taking away the middle party. This direct access to the public brings up the question of how credible the message and the speaker may be (Hwang, 2013).

It has been found that a favorable opinion of one's Twitter usage and amount of activity results in greater credibility among young followers. Credibility and attitudes were found to be tied together, each positively affecting the other. When users were familiar with a politician and had already established a positive attitude of their work, they believed their messages to be reliable and trustworthy. In the same way, if one felt that a message was credible due to outside support and endorsements, they tended to have a positive association with the speaker (Hwang, 2013). However, as mentioned previously, social media has led to an increase in partisan separation. What may be credible to one user may not be credible to another due to their prior opinions of issues and association with one political party (Mueller & Saeltzer, 2020).

Sentiment in Tweets

Content analyses of social media posts are often utilized by researchers to further examine messages shared by online users. By conducting a content analysis of social media posts, one can analyze the positive and negative emotion words used to understand the tone of the message and the effect it could have on social media users (Schwartz, 2015). Tweets can be analyzed by multiple different methods for different purposes. You can also label the language used to show a slim or wide variety of emotions (Meo & Sulis, 2017). Understanding these emotions that are shared through language on social media and the effect they have on readers' emotions can positively impact multiple areas of life and allow politicians to strategically share messages, improving their digital campaigns (De Choudhury, 2012).

Message framing is an important social media strategy that many politicians utilize to make their desired perception of a topic salient in an online message. Frame building and the frame effect work together in a framing process to achieve this desired outcome. Politicians are able to construct their desired message and directly share it with the public, removing the "middleman" and directly bypassing news media gatekeeping (Sahly et al., 2019). It is also important to note the decision making when selecting how to say what is being shared. Political groups use precise wording to encourage the readers to act in a desired manner. Action messages use action strategies, such as energizing and encouraging followers to complete the desired task or become involved with their mission. This influential wording strategy can bridge the gap and connect with a larger audience. Not only do users share and interact with messages that align with their beliefs, but also messages that are crafted how they prefer regardless of the content. Politicians can adjust their wording and crafting of messages to what their audience most interacts with (Crow et al., 2021).

Sentiment analysis is a research technique that analyzes a piece of text to determine the sentiment behind it in and understand the meaning of media messages (Jenkin, 2020). Greene's public presence and divisive reputation make her an interesting, yet unique, subject for a case study. The goal of this research project is to find the potential effect of tweet sentiment on audience engagement when looking specifically at messages from Greene's professional Twitter account.

CHAPTER III

METHODOLOGY

Data Collection

Manual Scraping

To gather data for this research project, I manual scraped six months' worth of tweets from Greene's professional Twitter account, @RepMTG. The timeline of messages chosen was from April 2021 through October 2021. This six-month time span covered an active period of message sharing, but also avoided a time where her personal account was banned to ensure that the messages being analyzed were strictly professional. The total number of messages was 199, providing a large enough sample to begin researching but also pointing towards more questions for future research with a larger data set.

The content of each tweet was copied into an excel document, focusing solely on messages that she shared. Tweets that did not include any characters were not chosen for this analysis, as the system used analyzes dictionary words rather than images and videos. Also, messages that were retweeted by Greene without any additional comment were not included, as this study is focusing strictly on her wording rather than the wording of messages she shared. However, if she added her own words to a message that she retweeted, her words were copied and included in the excel document, but the original message from a different user was not included. The document contained columns for retweets, likes, and replies for each of Greene's tweets. The link to the actual tweet was also included, making it easy to refer to the message when analyzing the data.

Before coding the data, various characteristics were found using the averages formula provided by excel. The average word count of Greene's analyzed tweets was ≈20 words per tweet. The average number of retweets was ≈1,179. The average number of likes was ≈4,728, and the average of replies was ≈1,626. The standard deviation of each category was also found: the standard deviation of retweets was 1172.143, likes was 5867.448, replies was 2038.959, positive tone was ≈7.69 and negative tone was ≈8.35.

Calculating Daily Averages

Using the average formula in excel, the averages for retweets, likes, and replies was found for each day. Additionally, the averages for the positive and negative tone variables were found after running the data through the software. The method of finding these variables is explained in detail in the next section. The following image shows a section of the excel document created, containing the data for the month of April and the averages found for each category.

Figure 1

April Data and Averages

A	B	C - retweets	D - likes	E - replies	F	Segment	Affect	tone_pos	tone_neg
4/1/21	#FireFauci	384	1549	467	https://twi	1	0	0	0
4/1/21	#WeWillNc	668	2776	719	https://twi	1	7.69	0	7.69
4/1/21	??NEW BILl	3538	8285	4416	https://twi	1	7.5	5	2.5
4/1/21	Thank you (	934	3483	1444	https://twi	1	7.14	7.14	0
4/1/21		**1381**	**4023.25**	**1761.5**				**3.04**	**2.5475**
4/2/21	Three new (	484	1748	1255	https://twi	1	10	10	0
2-Apr		**484**	**1748**	**1255**				**10**	**0**
4/5/21	#FireFauci	376	1709	1062	https://twi	1	0	0	0
5-Apr		**376**	**1709**	**1062**				**0**	**0**
4/8/21	Welcome a	157	716	364	https://twi	1	20	20	0
4/8/21	Thank you t	327	1379	525	https://twi	1	5	5	0
8-Apr		**242**	**1047.5**	**444.5**				**12.5**	**0**
4/9/21	Beautiful pi	230	2606	632	https://twi	1	7.69	7.69	0
9-Apr		**230**	**2606**	**632**				**7.69**	**0**
4/12/21	The Biden a	1735	5630	1142	https://twi	1	11.54	0	11.54
12-Apr		**1735**	**5630**	**1142**				**0**	**11.54**
4/13/21	This week, I	448	1497	1168	https://twi	1	13.95	6.98	4.65
4/13/21	Thank you (	497	1815	807	https://twi	1	17.65	17.65	0
4/13/21	Glad to sup	468	1887	492	https://twi	1	42.86	42.86	0
4/13/21	Thank you (	451	1484	462	https://twi	1	20	20	0
4/13/21	Thank you f	166	836	292	https://twi	1	14.29	14.29	0
13-Apr		**406**	**1503.8**	**644.2**				**20.36**	**0.93**
4/14/21	Happy birtl	82	607	178	https://twi	1	40	40	0
4/14/21	Beautiful pi	71	822	265	https://twi	1	4.76	4.76	0
4/14/21	Georgia wil	383	1727	1393	https://twi	1	9.09	9.09	0
14-Apr		**178.666667**	**1052**	**612**				**17.95**	**0**
4/15/21	Thanks to B	66	752	367	https://twi	1	5	5	0
15-Apr		**66**	**752**	**367**				**5**	**0**
4/16/21	Thanks to J.	47	407	778	https://twi	1	2.94	2.94	0
16-Apr		**47**	**407**	**778**				**2.94**	**0**
4/19/21	I just went i	5379	19672	4758	https://twi	1	10.34	0	10.34
4/19/21	Today, I file	1912	64414	2585	https://twi	1	12.5	0	12.5
19-Apr		**3645.5**	**42043**	**3671.5**				**0**	**11.42**
4/28/21	Subscribe t	113	378	782	https://twi	1	7.69	0	7.69
28-Apr		**113**	**378**	**782**				**0**	**7.69**
5/5/21	Congratula	106	694	423	https://twi	1	6.06	6.06	0

Linguistic Inquiry and Word Count System

Once the data were compiled, it was run through the Linguistic Inquiry and Word Count (LIWC) Analysis system. LIWC is a reputable and widely used program for analyze text content.

This program was created to "provide an efficient and effective method for studying the various emotional, cognitive, and structural components present in individuals' verbal and written speech samples" (Pennebaker et al., 2015). LIWC has been updated since its original development to include a larger dictionary database and a more modern software design.

The text that is intended to be analyzed by LIWC are referred to as target words, and the words contained in LIWC's dictionary database are dictionary words (Pennebaker et al., 2015). The LIWC Developmental Manual explains its processing operation as

> [accessing] a single text file, a group of files, or texts within a spreadsheet and [analyzing] each sequentially. For each file, LIWC2015 reads one target word at a time. As each target word is processed, the dictionary file is searched, looking for a dictionary match with the current target word. If the target word is matched with a dictionary word, the appropriate word category scale (or scales) for that word is incremented. As the target text file is being processed, counts for various structural composition elements (e.g., word count and sentence punctuation) are also incremented.
>
> For each text file, approximately 90 output variables are written as one line of data to an output file. This data record includes the file name and word count, 4 summary language variables (analytical thinking, clout, authenticity, and emotional tone), 3 general descriptor categories (words per sentence, percent of target words captured by the dictionary, and percent of words in the text that are longer than six letters), 21 standard linguistic dimensions (e.g., percentage of words in the text that are pronouns, articles, auxiliary verbs, etc.), 41 word categories tapping psychological constructs (e.g., affect,

> cognition, biological processes, drives), 6 personal concern categories (e.g., work, home, leisure activities), 5 informal language markers (assents, fillers, swear words, netspeak), and 12 punctuation categories (periods, commas, etc). (p. 2)

For this research project, the excel document containing the collected tweets was run through LIWC for the tone of each message. The categories selected from LIWC's available variables were positive tone and negative tone, in addition to word count for each tweet. The LIWC Manual for Version 22 includes examples of the most frequent words of each category. Examples of positive tone were *good*, *well*, *new*, and *love*, and examples of negative tone were *bad*, *wrong*, *too much*, and *hate* (Boyd et al., 2022). A score was given to each tweet that represented the number of words in each category. If a one-word tweet portrayed a negative tone for its singular text, it was given a score of 1 for 100% negative tone. If a tweet contained five negative words in a 10-word tweet, it was given a score of 0.5 for 50% negative tone.

Data Analysis

After being run through LIWC, a numerical value was given to each tweet for positive and negative tone. These results were averaged for each day and charted on a graph. Four separate graphs were created, comparing the tone variables to each other and to the audience engagement features that were recorded. These graphs and findings will be included in the following chapter with further discussion.

To determine any potential correlation between the message tone and the number of retweets, likes, and replies received, the data were also run through the Statistical Package for Social Sciences (SPSS) software. The results revealed some correlation among various engagement features and the tone of the tweets. These correlation results are included and further discussed in the following chapter.

CHAPTER IV

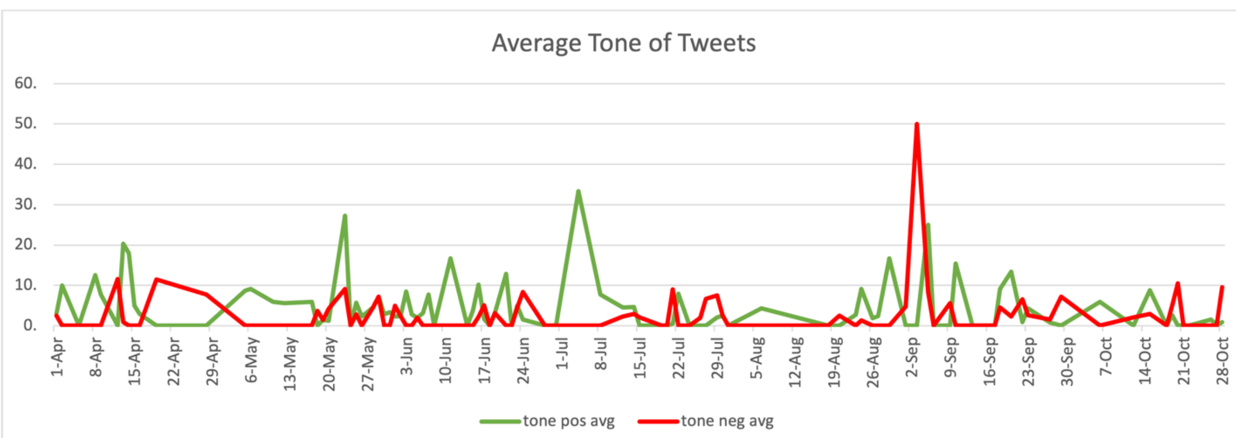
RESULTS

Results

The LIWC analysis provided numerical figures that allowed for graphs to be created and compared. The figures below show the results of LIWC analysis once charted on the graphs. The first graph created (Figure 2) shows a line comparison of tweets with a positive tone and tweets with a negative tone. This first chart enables one to pinpoint the most positive and negative tweets based on the spikes in the graphs.

Figure 2

Graph – Average Tone of Tweets



To further understand what could cause the messages to be labeled negative or positive, the five most negative and five most positive spikes were identified. Because the chart shows the average tone for each day, all the tweets shared on the five days with the largest spikes were included in a table. Table 1 looks at the positive tone spikes, including the content of the tweets for the top five days and the raw and average LIWC tone variables.

Table 1

5 Most Positive Spikes

Date	Tweets for the Day	Individual LIWC Score	Average LIWC Score
July 4, 2021	Happy Independence Day [emoji]!	33.33	33.33
May 23, 2021	Happy Sunday, everyone! Let's work together to END ABORTION in America!	27.27	27.27
July 3, 2021	Happy Independence Day weekend [emoji]!	25	25
September 5, 2021	Happy Sunday, everyone! Let's all work together to END ABORTION in America!	25	25
April 14, 2021	Happy birthday to the @USAFReserve!	40	17.95
	Beautiful picture of the Chattooga County Courthouse in Summerville sent in to my office by DeWayne T. of Chattooga County! #gapol	4.76	
	Georgia will NOT apologize for passing strong election reform laws that require an ID to vote, just like every ballpark requires an ID to pick up tickets at will call. Proud to join @RepJeffDuncan, @SenMikeLee, and the rest of my colleagues on this bill!	9.09	

The first tweet from April 14, 2021, has the highest overall raw score. However, once averaged with the other messages on that day, April 14 had only the fifth largest spike in positive emotion. Each of the days that had a high positive LIWC score had tweets containing the word "happy." This points to happy being a positive tone word, giving these tweets an overall positive score. Other words from these messages that stood out are "beautiful," "strong," and "proud."

Something important to recognize is the similarity between the tweets shared on July 3, 2021, and July 4, 2021. These tweets partly use the same wording but have a significantly different LIWC score. The reasoning for this is the number of words in each text. The tweet on July 3 contains four words, resulting in a lower score than the three-word tweet shared on July 4.

Table 2 contains the same information for the five largest negative tone spikes.

Table 2

5 Most Negative Spikes

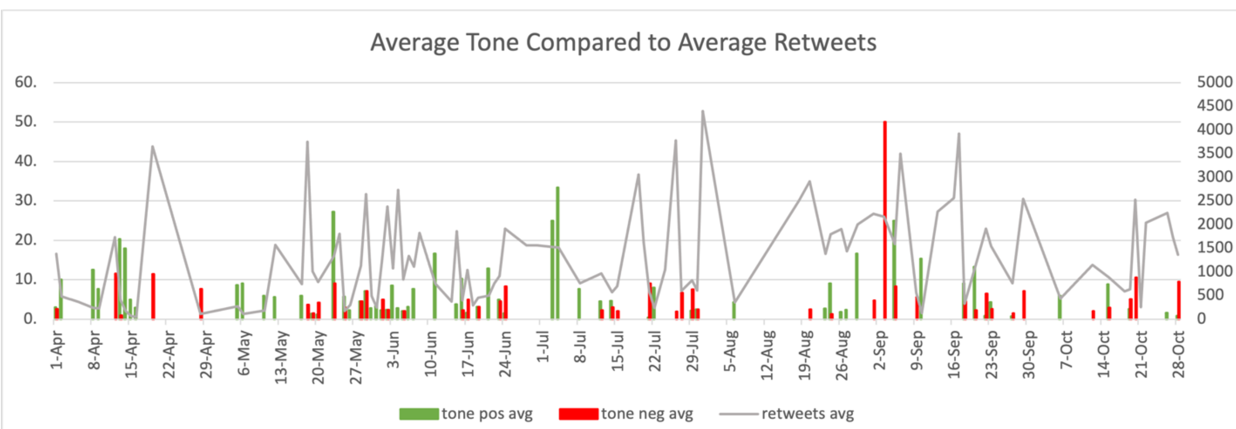
Date	Tweets for the Day	Individual LIWC Score	Average LIWC Score
September 3, 2021	OPPOSE!	100	50
	Impeach. Convict. Remove. #ImpeachBiden	0	
April 12, 2021	The Biden administration's $235,000,000 payout to the Palestinian Authority is outrageous and appalling. Today, I filed the "No Funding for Terrorists Act" to put America First!	11.54	11.54
April 19, 2021	I just went inside the Capitol to file my resolution to #ExpelMaxineWaters for her history of inciting violence and ordering Black Lives Matter terrorism against National Guardsmen in Minnesota.	10.34	11.42
	Today, I filed H. Res. 327 to hold Democrat @RepMaxineWaters accountable for inciting violent riots and Black Lives Matter terrorism. It's time to #ExpelMaxineWaters!	12.5	
October 20, 2021	The solution to the invasion at the Southern border, rapid inflation, empty grocery shelves, and tyrannical COVID mandates: #ImpeachBiden	10.53	10.53
October 28, 2021	Republicans MUST vote AGAINST the Democrat Communist takeover via the so-called infrastructure bill and Biden's budget! #JustVoteNo	5.88	9.53
	#BuildBackBetter = #DestroyDivideDemoralize the American People	20	
	No Republican should hand over their voting card to Nancy Pelosi and help Joe Biden pass his America Last China First agenda. The GOP must stand in lock step and VOTE NO on the so-called infrastructure bill.	2.7	

The most negative day was September 3, 2021. On this day, there was a one-word tweet that received a score of 100 for negative tone. The tweet "OPPOSE!" was tagged as a negative dictionary word, and because it was the only word, the message was completely negative. The second tweet from this day received a score of 0 for negativity; however, the words "impeach," "convict," and "remove" all have a negative connotation. When looking at the other days include in the table, the words "terrorists," "appalling," "violent," "destroy," and "NO" are likely what resulted in a negative tone score.

After looking at the comparison between positive and negative tone scores, a graph was created to compare these tone scores to the retweets each tweet received. This is one way to track Greene's interactions with users and see the potential effect of sentiment on audience engagement. Figure 3 shows the created graph.

Figure 3

Graph – Average Tone of Tweets Compared to Average Number of Retweets



Looking at the connection between tone and audience engagement, the five greatest spikes for retweeted messages were identified for further focus. Because the graph shows the average number of retweets for each day, all the tweets shared on the five days with the largest spikes were included in the table. Table 3 shows the days with the highest average number of retweets, including the content of the tweets and the average LIWC tone variables for each message.

Table 4

5 Most Retweeted Messages

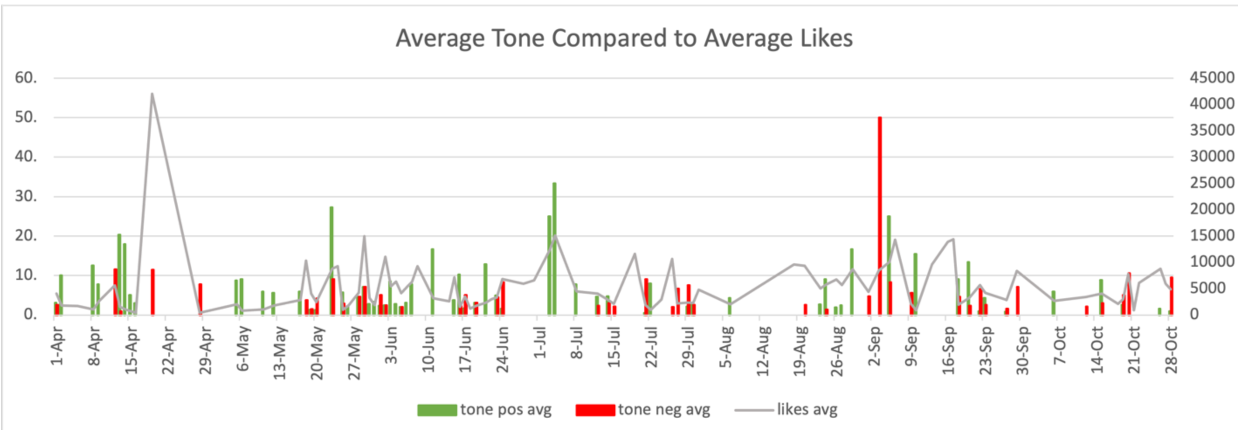
Date	Tweets for the Day	Average Number of Retweets	Average Positive LIWC Score	Average Negative LIWC Score
July 31, 2021	NO LOCKDOWNS NO MANDATORY VACCINES! #RESIST	4,396	0	0
September 17, 2021	It's time.	3,920	0	0
July 26, 2021	There are 435 members of Congress. But in the House, just a few members can pass a bill by voice vote. I spent 2 hours requesting roll call votes. If I wasn't on the floor, these bills would have passed. Americans should be appalled. And Congress should vote on every bill.	3,773	0	1.96
May 18, 2021	Instead of continuing the witch hunt against President Trump and his supporters, we need to investigate BLM/Antifa domestic terrorism! Watch my floor speech from this morning!	3,747	0	3.7
April 19, 2021		3,645.5 (avg)	0	11.42 (avg)
	I just went inside the Capitol to file my resolution to #ExpelMaxineWaters for her history of inciting violence and ordering Black Lives Matter terrorism against National Guardsmen in Minnesota.	*5379**	*0**	*10.34**
	Today, I filed H. Res. 327 to hold Democrat @RepMaxineWaters accountable for inciting violent riots and Black Lives Matter terrorism. It's time to #ExpelMaxineWaters!	*1912**	*0**	*12.5**

**Individual data for each tweet, the total average is included at the top of the cell.*

In addition to comparing tone scores to the retweets each tweet received, the average tone scores were compared to the average number of likes. This is another way to track Greene's interactions with users. Figure 4 shows the created graph.

Figure 4

Graph – Average Tone of Tweets Compared to Average Number of Likes



To focus further on the connection between tone and audience engagement, the five greatest spikes for the number of likes were identified for further focus. Because the graph shows the average number of likes for each day, all the tweets shared on the five days with the largest spikes were included in the table. Table 4 shows the days with the highest average number of likes, including the content of the tweets and the average LIWC tone variables for each message.

Table 4

5 Most Liked Messages

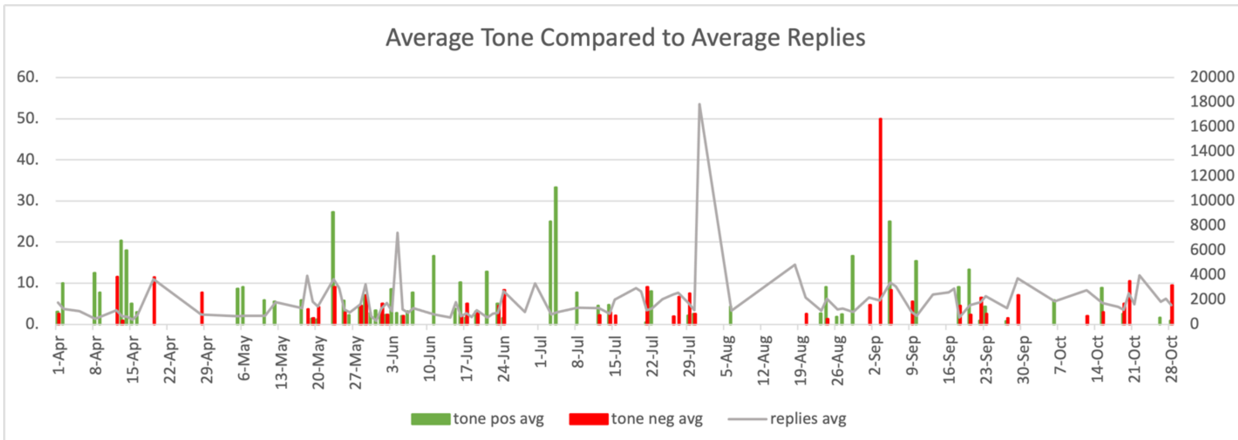
Date	Tweets for the Day	Average Number of Likes	Average Positive LIWC Score	Average Negative LIWC Score
April 19, 2021		42,043 (avg)	0	11.42 (avg)
	I just went inside the Capitol to file my resolution to #ExpelMaxineWaters for her history of inciting violence and ordering Black Lives Matter terrorism against National Guardsmen in Minnesota.	*19,672**	*0**	*10.34**
	Today, I filed H. Res. 327 to hold Democrat @RepMaxineWaters accountable for inciting violent riots and Black Lives Matter terrorism. It's time to #ExpelMaxineWaters!	*64,414**	*0**	*12.5**
July 4, 2021	Happy Independence Day [emoji]!	15,126	33.33	0
May 29, 2021	I fight for the PEOPLE, not the politicians! I need more help in Congress!	14,954	7.14	7.14
September 17, 2021	It’s time.	14,353	0	0
September 6, 2021	#ImpeachBiden	14,265	0	0

**Individual data for each tweet, the total average is included at the top of the cell.*

To fully compare Twitter’s audience engagement features, a graph was created to compare the average tone of tweets to the average number of replies received. This covers the three interactive features – retweets, likes, and replies. The three graphs can then be compared to determine any effect of tone on audience engagement for Greene's Twitter. Figure 5 shows the created graph.

Figure 5

Graph – Average Tone of Tweets Compared to Average Number of Replies



Duplicating the tables made for the previous graphs, the five greatest spikes for the number of replies were identified for further study on the connection between tone and audience engagement. Because the graph shows the average number of replies for each day, all the tweets shared on the five days with the largest spikes were included in the table. Table 5 shows the days with the highest average number of replies, including the content of the tweets and the average LIWC tone variables for each message.

Table 5

5 Most Replied Messages

Date	Tweets for the Day	Average Number of Replies	Average Positive LIWC Score	Average Negative LIWC Score
July 31, 2021	NO LOCKDOWNS NO MANDATORY VACCINES! #RESIST	17,862	0	0
June 4, 2021		≈7,410.67	≈2.78	0
	The Communist Chinese government needs to pay up for the damage they've done to the world!	*1,333**	*0**	*0**
	Thanks to @RepGregSteube for co-sponsoring my "Fire Fauci Act" (HR 2316)! #FireFauci	*899**	*8.33**	*0**
	Today, I sent this letter to Joe Biden to demand an immediate investigation into Anthony Fauci's lies and his potential involvement in the cover up of the origins of the China virus. The American people deserve answers on the Wuhan lab & Fauci deserves to be held accountable!	*20,000**	*0**	*0**
August 18, 2021	Audrey Smith from Chickamauga, GA playing the UGA Battle Hymn Trumpet Solo on the big screen!! Northwest Georgia couldn't be be prouder!	556	9.09	4.55
October 22, 2021	Impeach. Convict. Remove. This is why we must #ImpeachBiden.	3,971	0	0
May 18, 2021	Instead of continuing the witch hunt against President Trump and his supporters, we need to investigate BLM/Antifa domestic terrorism! Watch my floor speech from this morning!	3,925	0	3.7

**Individual data for each tweet, the total average is included at the top of the cell.*

The literature cited previously supports the use of social media to reach a large audience. As stated previously, it has been found that a favorable opinion of one's Twitter usage and amount of activity results in greater credibility among young followers. Knowing this, the graphs raised the question of correlation between tone and tweet engagement in the form of retweets, likes, or replies. The correlation matrix was found for each using SPSS.

Correlations

When looking at the table below, it can be seen that there was a significant negative correlation between the number of retweets and positive tone, $r(197)=-.21$, $p=.002$. Additionally, there was a significant negative correlation between the number of replies and positive tone, $r(197)=-.16$, $p=.027$. While there was no correlation between likes and tone, replies and negative tone, or retweets and negative tone, it does raise the question if the negative correlation would continue for a larger dataset of Greene's tweets. This question could also be applied to other politicians on either a local or national scale.

Table 6

Correlation Between Tone Variables and Retweets, Like, and Replies

		tone_pos	tone_neg	Retweets	Likes	Replies
tone_pos	Pearson Correlation	1	-.125	-.214**	-.104	-.157*
	Sig. (2-tailed)		.079	.002	.143	.027
	N	199	199	199	199	199
tone_neg	Pearson Correlation	-.125	1	.010	.055	-.002
	Sig. (2-tailed)	.079		.884	.442	.982
	N	199	199	199	199	199
Retweets	Pearson Correlation	-.214**	.010	1	.588**	.656**
	Sig. (2-tailed)	.002	.884		<.001	<.001
	N	199	199	199	199	199
Likes	Pearson Correlation	-.104	.055	.588**	1	.269**
	Sig. (2-tailed)	.143	.442	<.001		<.001
	N	199	199	199	199	199
Replies	Pearson Correlation	-.157*	-.002	.656**	.269**	1
	Sig. (2-tailed)	.027	.982	<.001	<.001	
	N	199	199	199	199	199

*** Correlation is significant at the 0.01 level (2-tailed).*
** Correlation is significant at the 0.05 level (2-tailed).*

Discussion

Political Public Relations is growing as the use of social media becomes more common in the political sphere. Campaigns and political messaging have changed throughout time to best fit the current society, with new developments in social media and digital media playing a key role in the way candidates interact with potential voters. Not only have the actual social media platforms available evolved and allowed for new outlets of communication, but it has also opened doors for candidates to interact with their audiences directly, building rapport and creating an online community to share their messages with.

The results described above show the impact of the wording used in Greene's tweets and messages on her audience. Six months' worth of tweets were pulled and coded using the LIWC system, providing a manageable amount of data to focus on. It provided a large enough dataset for a chart and graph to be created that could be trusted and used for further study. Previous data and articles supported what was found, with messages that had a higher tone variable receiving more attention from users.

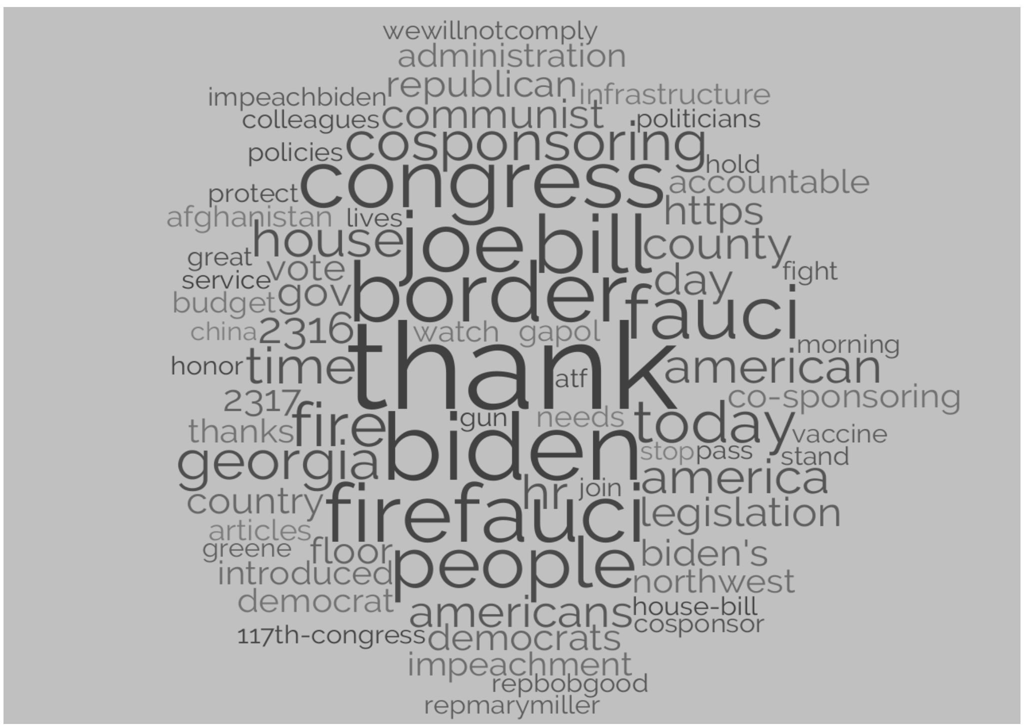
The goal of this research project was to find the potential effect of tweet sentiment on audience engagement when looking specifically at messages from Greene's professional Twitter account. While the results do show a negative correlation between positive tone and the number of likes and retweets, there was not significant correlation in other categories. The expectation when beginning this study was of a significant positive correlation between negative tone and audience interaction. Greene has a strong media presence and often included in controversial conversation, having an active social media presence, and often using divisive wording. This divisive wording is associated with negative tone, which often has a mobilizing effect in politics (Mueller & Saeltzer, 2020). The mobilizing effect causes the messenger to respond quickly in defense, but also engages the audience.

The LIWC analysis of Greene's tweets revealed that there were recognizable spikes in positive and negative tone. The spikes were able to be compared to the average number of retweets, likes, and replies to each message, utilizing these features of Twitter to compare tone to audience engagement. While the results were not what was anticipated, this project was approached broadly with the intention of analyzing the data and understanding the results fully to apply them to future research. Ultimately, these results do not point to an overwhelming correlation between audience engagement and tone.

The following figure shows a word cloud of Greene's tweets. This word cloud contains the common words and phrases used in the messages analyzed. Positive words like "thank" and negative words like "fire" are easily recognized and can better help to understand the overall sentiment of Greene's Twitter. This word cloud can also be developed for a larger period of time in future research.

Figure 6

Marjorie Taylor Greene Word Cloud



CHAPTER V

CONCLUSION

Implications

While sentiment is important to consider when disseminating messages, it is not the only factor that affects engagement. The literature supports the public opinion of politicians as a primary motivator for communicating on social media. Younger generations are more likely to positively support the tweets of politicians that they already have a positive opinion of, attaching a high credibility based on prior knowledge. However, Twitter can be used to reach large audiences and the tone used in message can play a role in developing an opinion of the user.

Limitations

Throughout this study, there were many limitations that were discovered and are worth noting. Many of these limitations dealt with the LIWC analysis. First, the automated content analysis cannot understand sarcasm or satire. The program takes the literal meaning of the messages, which could result in a word being labeled as a positive or negative tone word when it was not intended as such. Additionally, the tweets that were chosen for this study were only messages that included her own wording. Tweets that had no words or were solely a retweet of another user were not included. Those messages also could have a positive or negative tone that would add to Greene's overall sentiment. Another limitation with the LIWC analysis is the use of hashtags, which often are a combination of multiple words into one phrase. This merging of words labels it as one word for analysis, not registering the individual components with the system.

While LIWC was able to provide a base for this research, the system was unable to fully analyze the data for the desired information. Using the dictionary analysis system limited the coding for tone words to only the words included in LIWC's tone dictionary. Upon further study of the content of the messages, words that portrayed a negative sentiment received a zero score for negative tone. Doing a manual content analysis or using a different program could bring better results for future study.

Another limitation of this study is the account chosen. Greene's professional account was selected intentionally, but interactions differ with personal and professional accounts. Because of this, tone and engagement may also differ, preventing a complete analysis of Marjorie Taylor Greene. Additionally, this study focuses solely on Twitter and does not account for other social media platforms and their effect on engagement. Also, doing a one-person case study limits the application of results to other studies. Greene was chosen because of her unique position and social media presence, however that means there are not many accounts like her that the result could be relevant. The timeline chosen for the study is another limitation that should be discussed. The time chosen did not include an election cycle. The election season can result in more social media activity and intentional wording. To further study sentiment, it would be beneficial for future research to include messages shared during an election season.

Majority of the interactions on social media happen with ones' followers. Because of this, it is important to note that Greene's followers may have a preconceived notion of her, thus affecting their engagement. Followers likely have a positive perception of the user and may have a different reaction to messages than others. Also, people tend to resonate with words differently.

The dictionary assignment of negative and positive tone are not representative of what all readers may feel of a word.

Future Research

The findings of this paper have led to the discussion of future research questions. It could be important to further research the timing of the spikes, looking at outside events to determine what could have caused the deliberately positive or negative messaging.

As previously mentioned, it would be beneficial for future research to include messages shared during an election season. Including this could expand the dataset and lead to a greater correlation between sentiment and audience engagement. It also could be beneficial to duplicate this research on different politicians with a larger following, resulting in higher numbers of engagement and interactions for comparison.

To test the effectiveness of Twitter posts, a similar study could be done on the chosen politicians' other platform profiles. This information, along with the data from Twitter, could then be compared to they're polling results or approval ratings for any correlation.

Broader Conclusion

The literature gathered about political public relations and sentiment analyses of Twitter provided the necessary background for this case study of Marjorie Taylor Greene. All of the literature built on the communication methods and materials that I have studied through public relations and political science. The goal of this thesis was to find any potential effect of tweet sentiment on audience engagement when looking specifically at messages from Marjorie Taylor Greene's professional Twitter account. The results supported the importance of wording and tone in online messaging and the sentiment analysis has raised questions for future research.

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