

**Bird is the Word:
An Assessment of Donald Trump's Language Use on Twitter in Relation
to His Public Opinion Ratings in the 2016 Presidential Election**

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Abstract

The upset victory of Donald Trump in the 2016 presidential election caused many political scientists to theorize how and why this occurred. Literature regarding this election is particularly interesting in the political psychology field, which assesses Trump's victory as a result of employing calculated, psychologically-charged language and in his communication style that resonated with voters. Trump's campaign also featured a great use of social media, namely Twitter, in communicating directly with his base. This study analyzes Trump's tweets from his nomination at the Republican National Convention on July 19, 2016 through the day before the 2016 presidential election on November 7, 2016. This study specifically focuses on Trump's uses of psychologically-charged language in his tweets in conjunction with his favorability ratings over this time period. Based on the stored dictionary in the LIWC software, LIWC was utilized to analyze Trump's Twitter text and code for his use of language indicative of clout, anger, anxiety, positive emotion, negative emotion, focus on the past, focus on the present, and focus on the future. After running three time-series regressions using these independent variables and collapsing the data on a daily basis, we are able to better understand the relationship between Trump's use of particular language on Twitter and his favorability ratings among the public. Model 2 yielded statistically significant results for positive emotion language at a p-value of 0.05 and anger was statistically significant at a p-value of 0.1. Although two of the models' variables did not yield any statistically significant results, we are still able to assess slight relationships between the particular language variables and Trump's favorability rating. The lack of many statistically significant results also casts doubt on many theories regarding results of the 2016 presidential election and has implications for the 2020 presidential election.

Keywords: 2016 presidential election, Donald Trump, Twitter, LIWC, psychologically-charged language variables.

Introduction

On the morning of November 9, 2016, Americans awoke to the news that Donald Trump had been elected the 45th president of the United States. This election was both unique and surprising. The 2016 presidential candidates were unprecedented as the Democratic candidate, Hillary Clinton, was the first female presidential candidate of a major political party and the Republican candidate, Donald Trump, was a businessman-turned reality television star. In addition, the candidates were extremely disliked in comparison to other presidential candidates in modern American history (Abe 2018, 71). The result of this election was also shocking because the forecasting and prognosticating had been quite erroneous. Not only was forecasting from the majority of news outlets inconsistent and often incorrect, but Trump also won the nomination and general election without the support of many party elites, which is typically a large predictor of a candidates' success (Abe 2018, 70). This is a relevant consideration with important implications regarding navigating future elections for both the public and for presidential candidates. Donald Trump will likely run for president again in 2020, so superior knowledge of Trump's campaign tactics and the use of particular language in his 2016 campaign will contribute to a better understanding of effective campaign strategies for candidates in 2020 and beyond. In addition, the use of social media in elections is still a relatively new phenomenon and one that is likely to persist in the future, so exploring the best ways for politicians to communicate, especially on social media, is likely only going to become more important and relevant in the future, particularly as demographic changes will yield more voters as heavy social media users.

In the emerging field of political psychology, there are multiple theories and studies that offer explanations for Trump's success in the 2016 presidential election. However, this literature

is often conflicting, as scholars cite different strategies that Trump utilized throughout his campaign and actors that helped Trump secure a strong electorate. Another chronicled aspect of Trump's 2016 campaign was his use of social media, namely Twitter, to communicate with his base on a daily basis throughout the duration of the general election campaign. Despite the vast literature on Trump's use of Twitter in the political psychology field, there is little information on how the specific language used in Trump's Twitter account affected public opinion and Trump favorability ratings. By analyzing his tweets and coding for particular emotional and psychologically-charged language regarding clout, anger, anxiety, positive emotion, negative emotion, focus on the past, focus on the present, and focus on the future, this thesis seeks to provide a clearer understanding of the ways in which Trump utilized emotional and psychological mechanisms regarding language and communication and how these factors affected his favorability ratings.

Overall, this study seeks to answer the following research question: How did the nature of the language that Trump used on Twitter affect his favorability ratings from the RNC (July 19, 2016) to the day before the 2016 Presidential election (November 7, 2016)?

Despite the research that has focused on Trump's success in terms of psychologically connecting to his base and his success by campaigning and communicating via Twitter, there is a gap in the literature. There is a dearth of literature that assesses how the psychologically-charged language that Trump uses via Twitter relates to favorable public opinions among his constituents. Therefore, this study builds on previous literature and focuses on language that Trump uses that many political psychology scholars have cited in their theories regarding his victory. Focusing on these variables regarding his language use on Twitter and analyzing the way that specific language use affected his favorability ratings offers new information and a unique way to assess

Trump's success in the 2016 presidential election and offers information that may be useful in future elections regarding communication between candidates and the public on social media platforms.

Literature Review/ Theory

Political Psychology Theories Regarding Trump's 2016 Presidential Election Victory

Recent literature exploring the 2016 presidential election has attributed the shocking victory of Donald Trump to many theories in the political psychology field. Because 2016 yielded an especially unprecedented result, many political commentators and experts offered an array of postelection theories regarding why Trump was successful (Francia 2017, 440).

Marc Hetherington and Jonathan Weiler's political psychology theory regarding the nature of American politics and Trump's 2016 victory is rooted in the idea that opposing worldviews inform voter preferences and led particular segments of voters to support Trump (Hetherington and Weiler 2018). Hetherington and Weiler divide the American electorate into fixed, fluid, and mixed voters and attribute particular characteristics and worldviews to these groups. According to Hetherington and Weiler, those who are the fixed voters made up the majority of Trump's base and supported Trump mainly due to psychological emotions related to fear (Hetherington and Weiler 2018, 17). The authors also claim that fear is the most primal instinct and impacts how individuals view the world (Hetherington and Weiler 2018, xi). Hetherington and Weiler define the fixed voters as those who are fearful of social and cultural changes and prefer comfort and predictability, the fluid voters as those who are more open to changing social and cultural norms, and the mixed voters as those who fall between the two, but feel pressured to pick a side given the political polarization of the two parties (Hetherington and

Weiler 2018, xii-xiv). In terms of Trump's communication, the fixed voters who are more fearful, were attracted to Trump's clear communication style and the idea that he would be able ameliorate their fears by to solving America's most pressing problems (Hetherington and Weiler 2018, 31). Even Trump's campaign slogan "Make America Great Again" communicated to the public, especially those with a fixed view, that America would revert back to an environment that was comfortable for them (Hetherington and Weiler 2018, 37). Additionally, Trump espoused ideas of strength, force, and order, which resonated with those who held fearful worldviews (Hetherington and Weiler 2018, 160, 163). However, Hetherington and Weiler also note that the intolerant messages that Trump sometimes communicated may not be sustainable for long-term success as a politician (Hetherington and Weiler 2018, 222).

Hetherington and Weiler's theory that worldview impacts political beliefs in addition to other preferences also helps to explain why the political parties have become more polarized and why individuals who belong to one of the parties feel that the other party's agenda is threatening to the nation (Hetherington and Weiler 2018, 120). This has perpetuated an "us vs. them" mentality that is present in other literature regarding greater threats felt between the political parties as a result of partisan polarization. The "us vs. them" mentality as well as the idea of feeling threatened is also discussed by Diana C. Mutz. Mutz discusses these feelings a bit differently than Hetherington and Weiler, and characterizes them as a threat to the status of white Americans rather than focusing solely on the emotion of fear (Mutz 2018, 4330). Mutz casts doubt on the popular "pocketbook theory," which theorizes that those who are disgruntled with their financial situations wanted to punish the party (Democrats) that led them to this economic state (Mutz 2018, 4331). Mutz refutes this theory because past research has shown that individuals' economic hardships rarely cause voters to punish the government and because

Trump was victorious while the American economy was improving (Mutz 2018, 4331). Mutz puts forth a theory of dominant group status threat, which occurs when the dominant group feels threatened and wants to revert to the status quo to increase their status and assuage their fear of a threat (Mutz 2018, 4331). Mutz argues that segments of Americans felt this threat because white Americans are becoming the minority ethnic group in the country, and because the U.S. is not the only global power, but has to compete with other world powers (Mutz 2018, 4331-4332). Mutz's research found that individuals who shifted from voting for a Democratic candidate in the past to voting for Trump in 2016 likely did so because of their views on trade, immigration, and China as a global power (Mutz 2018, 4334-4335). In addition, the overall landscape of American voters shifted towards a more Republican view from 2012 to 2016 and SDO (social dominance orientation) has risen from 2012 to 2016 (Mutz 2018, 4333). This corroborates her theory that individuals who felt greater dominant group threats shifted to voting for Trump. Mutz concludes that many voters in the 2016 presidential election felt anxiety regarding the future status of the group that they belonged to and that group status has a significant impact on political behavior and preferences (Mutz, 4338). Finally, Mutz believes that the status threat theory will continue to be present in American politics because of globalization's continued prevalence and the ways in which the candidates in the 2016 presidential election placed issues related to group threats on the agenda (Mutz 2018, 4338).

Hetherington and Weiler reference certain personality characteristics of voters and Mutz touches on personality characteristics such as SDO (social dominance orientation). Many other political scientists also attribute particular personalities and qualities to liberals and conservatives in addition to Democrats and Republicans. The big five personality traits are typically used in comparing the differing ideological perspectives and parties in the American electorate. A study

done by Jo Ann Abe looked specifically at the 2016 candidate personality differences according to voters supporting Trump vs. Clinton (Abe 2018). Abe notes that there are two specific schools of thought regarding personality traits and political preferences, one of which focuses on the personalities of the voters with respect to the five factor model of personality (Abe 2018, 70). The other school of thought focuses on the personality characteristics of the politicians rather than the voters and claims that voters are drawn to particular candidates based on their personalities (Abe 2018, 71). Abe's study analyzed particular language that the voters used to narrate the 2016 candidates. Abe analyzed participants' writings of candidates using LIWC, a text analysis software, which detects words and helps to avoid biases that are common among self-reported measures (Abe 2018, 72). According to Abe, populist rhetoric consisted of direct language and collectivist pronouns and authenticity is characterized by the use of more "I" words and present-tense verbs (Abe 2018, 77). This is relevant because many theories cite that Trump's authenticity was beneficial for his campaign. The study concluded that participants' ratings of Trump's and Clinton's personality traits aligned with their voting preferences more so than demographic variables, political affiliation, and racial attitudes (Abe 2018, 75-76). Thus, this study highlights the importance of potential voters' conceptions of candidate's traits and personalities. The results also demonstrate that Trump supporters' narratives scored higher on language measures of authenticity, collectivist pronouns, and conservative values and scored lower on moral foundational liberal values than Clinton supporters' narratives (Abe 2018, 78). Positive emotion language was associated with positive evaluations of Trump's personality, while negative emotion language was associated with positive evaluations of Clinton's personality and negative evaluations of Trump's personality (Abe 2018, 78). It is also worth noting that Clinton supporters rated the personalities of the candidates in a way that was more

similar to ratings done by experts and personality psychologists, suggesting that Clinton supporters seemed to have a more accurate interpretation of the candidates' traits (Abe 2018, 79).

Lilliana Mason's theory regarding Trump's 2016 presidential victory explores ingroup behavior as well as emotions such as anxiety and anger that affect voting behaviors and political participation. This is similar to Hetherington and Weiler's characterizations regarding social political groups, but Mason also emphasizes particular emotions that were not addressed as thoroughly in Hetherington and Weiler's analysis. Mason's theory assesses the present social polarization in American politics coupled with intergroup conflict and threats from outgroups (Mason 2018). Mason argues that the greater alignment of political and social identities has led to increased levels of prejudice, anger, enthusiasm, and activism (Mason 2018, 77).

Psychologically, this social and political polarization has increased intergroup competition and fostered an electorate in which individuals are angrier towards party opponents and more favorable towards their own political parties (Mason 2018, 82-83). In addition, the isolation that goes hand in hand with greater social polarization causes individuals to experience negative emotions regarding threats to their groups in an effort to protect their self-esteem (Mason 2018, 85).

Mason's theory emphasizes that the emotions anger, enthusiasm, and anxiety encourage greater political participation in different ways. Group competition fosters feelings of anger and enthusiasm among voters and encourages emotional political action; however, this political participation lacks a thoughtful processing of information (Mason 2018, 83, 86). Conversely, anxiety is a psychological emotion that motivates voters to accumulate greater information and act more thoughtfully, but still in a biased way (Mason 2018, 86). Therefore, anxiety leads to more thoughtful political thought, whereas individuals who feel anger or enthusiasm rely more

on simple heuristics and cues to navigate politics (Mason 2018, 86). Anger and enthusiasm are more likely to cause political action and lead to more optimistic views regarding the future because of their action (Mason 2018, 122). In relation to Trump and the 2016 presidential election, Mason theorizes that Trump supporters were more likely to feel that they had been “left behind,” had a lack of opportunities, and were characterized by fears of cultural changes occurring (Mason 2018, 135). The fears and threats regarding social status felt by Republican supporters is also apparent in Hetherington and Weiler’s as well as Mutz’s theories regarding Trump voters in the 2016 presidential election. Overall, these theories highlight the greater emotions of anger and anxiety among Trump supporters in 2016.

The intergroup biases and threats that Mason chronicles in the 2016 presidential election and the increased social polarization between Democrats and Republicans are unlikely to be reversed anytime soon given the sentiment among both parties and party leaders in this election (Mason 2018, 133). The intergroup biases discussed by Mason are also discussed by Oc, Moore, and Bashshur. Oc et al. (2018) discuss the idea of ingroups vs. outgroups in relation to the political parties and that individuals aim to favor their groups, especially when they feel threatened (Oc et al. 2018, 2). These partisan identities become especially salient during elections as the two groups are competing for political power and feel threatened by the opposing side (Oc et al. 2018, 2). Oc et al.’s research found that Republicans had a greater negative affect towards Democrats before the 2016 presidential election, but after Trump’s shocking victory, Democrats felt greater negative affect towards Republicans (Oc et al. 2018, 6-7). Similar to Mason’s point about the trajectory of social polarization in American politics, Oc et al. also discuss the increased negative affect among Democrats towards Republicans after the election to

suggest that this trend of outgroup hostility and biases will continue for the foreseeable future (Oc et al. 2018, 14).

The negative affect felt by Republicans before the 2016 presidential election is clear from the language that Donald Trump and Trump supporters used at the Republican National Convention. Uncivil language included chants such as “lock her up” regarding Hillary Clinton, and Trump encouraged this opposition and bias against the opposing party in order to focus more attention on himself and garner votes (Mason 2018, 133). The uncouth ways that candidates and supporters of opposing parties communicated to one another throughout the election was not limited to rallies, and was compounded by the use of the internet and social media. Elizabeth Suhay, Emily Bello-Pardo, and Brianna Maurer also research the increased affective and social polarization of American politics and completed two experiments to research how online criticism impacted social polarization (Suhay et al. 2017, 95). Suhay et al. note that the increased use of online communication such as Facebook, Twitter, discussion forums, and news websites allow more people to communicate about politics (Suhay et al. 2017, 96). This type of communication facilitates greater circulation of opinions rather than facts, criticisms of opposing candidates, and uncivil language that perpetuates groupthink, disparaging the opposing party, decreasing tolerance, and encouraging others to communicate in similar disrespectful ways (Suhay et al. 2017, 96, 99). This level of incivility between the political parties is also evident in political elites. The uncivil language that Trump espoused to amass a strong base is also evident in his amateurish, casual, and sometimes uncivil language and communication style he used on Twitter throughout his campaign.

Twitter and Social Media as a Means of Communication in Politics

Trends in political candidates' use of social media, such as Twitter, have demonstrated a significant impact on the scope and importance of candidate communication with the public via these platforms. Existing literature has explored this phenomenon, discussing the evolution of social media's role in political campaigns and the role that social media has played in the 2008, 2012, and 2016 presidential elections. From a historical perspective, the degree to which individuals identify with their political party has been increasing over time and the amount of social contact that individuals have with their political party has been increasing as well (Mason 2018, 104-106). This, coupled with the abundance of social contact via social media, has made social media platforms especially influential in presidential and other political elections.

The rise in particular technologies and media platforms has impacted the nature of politics over time. The first instance in American history of a president consistently utilizing technology to communicate with Americans occurred when FDR gave his fireside chats on the radio. Even though the radio was not fully developed in the 1930s, FDR utilized this form of mass media in order to endorse himself as a president, deliver news, and also to allow the American public to feel as though they personally knew him (Yu 2005, 89). Just as politicians use media today, FDR relied on the radio to deliver "real news," interact directly with voters in a way that was not filtered by the press, and to endorse his programs (Yu 2005, 89-93). FDR was able to make Americans feel like they knew him intimately and his style of communication was also consequential (Yu 2005, 90). FDR's communication style was confident and strong, but also personal as he often addressed Americans as "friends" and used collectivist pronouns such as "we" (Yu 2005, 90). FDR's fireside chats and strategic use of the radio as a tool in his administration was consequential in affecting many future political candidates and presidents to

promote a strong media image for themselves (Yu 2005, 93). The use of mass media platforms for political candidates and presidents to interact with the public is seen throughout history, following FDR's use of the radio and technological advances.

Following World War II, political parties were at the forefront of communication with the public and by the 1960s, television was the principal source of media and disseminating information regarding politics to the public (Enli 2017, 51-52). In addition, there has been a rise in political social contact in personal relationships since the 1970s, which has continued to grow with the advent of "internet activism," which has had an increased mobilization effect on voters (Mason 2018, 105-106). Prior to Americans' and politicians' widespread use of social media, politicians relied on blogs and YouTube to connect with their bases and have favored platforms such as Facebook and Twitter in more recent political campaigns (Enli 2017, 51). The current "digital era" is marked by an increase in personalization, anti-elitism, and populist-rhetoric in social media platforms such as Facebook, Twitter, and Instagram and has led to a shift in the landscape of how politicians interact with the public (Enli 2017, 52).

The consequences of increased use of social media by politicians has affected the way that politicians interact with the public and also how the public evaluates candidates and news sources. Social media allows politicians to directly communicate with voters and puts greater emphasis on campaigning from individual politicians rather than campaigning from political parties as a whole (Enli 2017, 52). In addition to being able to communicate with voters and establish views on policies and other candidates, Twitter allows candidates to receive immediate feedback from their constituents based on mechanisms like "retweets" and "likes," which can help politicians to better strategize their campaigns (Wang, Yuncheng, and Luo 2016, 723). Given the emphasis on the politician's communication on these social media platforms, it is

clearly advantageous for politicians to be adept at connecting with voters in both formal and informal settings (Enli 2017, 52). Evidence of the impact that social media has had on previous presidential elections is clear.

In the 2004 presidential election, blogs were the central technological tool used to reach voters (Enli 2017, 51). Four years later, the 2008 presidential election is considered the first “social media election” and the emphasis on social media in political elections became even more prevalent between the 2008 presidential election and the 2016 presidential election (Enli 2017, 51-52). In 2008, both John McCain and Barack Obama’s campaigns had Facebook, YouTube, Myspace, and Flickr accounts (Enli 2017, 52). However, since 2008, video-oriented social media platforms such as Facebook and Twitter became much more important in the 2012 presidential election and the use of social media platforms by candidates has become more significant than candidate websites (Enli 2017, 52). Obama’s skilled use of social media in the 2008 presidential election is believed to have established both Twitter and other social media platforms as important means for campaigning (Wang et al. 2016, 723). In 2012, Obama won the presidential election and had nine social media platforms that he used compared to Mitt Romney’s use of five social media platforms (Enli 2017, 52). After social media’s prominence in the 2008 presidential election, social media use became more organized and technical and many attribute Obama’s 2012 victory to his thoughtful navigation of social media as a campaign tool (Enli 2017, 55). Interestingly, by 2016, the presidential candidates Donald Trump and Hillary Clinton utilized fewer social media platforms in their campaigns, but used the most wide-spread social media platforms to a greater extent than previous candidates had (Enli 2017, 52). Trump and Clinton both used Twitter, Facebook, YouTube, Instagram, and Clinton’s campaign also used Pinterest (Enli 2017, 52). In tandem with the rise of social media platform use in political

campaigns, the 2016 presidential election also demonstrates that social media often bypassed editorial media as a direct news source for voters (Enli 2017, 52-53).

In addition to social media networks, individuals who discuss politics with those in their social circles are more likely to be socially engaged and are more likely to publicly participate in political elections (Mason 2018, 107). Therefore, the rise of social media and public displays of political participation are likely to have significant results on presidential elections.

Twitter in particular has presented a unique way of communicating for political candidates. However, this platform is still an innovative campaign tool, so there is not a longstanding precedent for the most effective way of utilizing Twitter in political campaigns (Lee and Lim 2018, 851). Twitter is unique because it provides a means of political candidates to quickly respond to events and convey their reactions to the public (Lee and Lim 2018, 851). Unlike some other popular campaign platforms, Twitter provides a platform for candidates to speak in real-time and directly with the public through retweeting messages or mentioning other users in their tweets (Lee and Lim 2018, 851). Therefore, Twitter provides a way for candidates to do more than just educate voters on their policy positions through speeches and websites, but allows the public to actually get a better sense of how the politicians communicate and learn about the politicians' personalities (Lee and Lim 2018, 851). Twitter has also had a great impact on allowing candidates to set the agenda for what they want to focus on and helps candidates to maintain their public image (Enli 2017, 59). Social media and the rise of platforms like Twitter have also allowed non-politicians to be successful in the political realm, even if their campaigns are not as traditional as those of professional politicians (Enli 2017, 59). Non-traditional candidates rarely attain visibility in the more traditional media environment, so social media such as Twitter allows these candidates to gain more visibility through an unfiltered lens (Lee and

Lim 2018, 850). This, in turn, has allowed politically inexperienced candidates such as Donald Trump to enter into and be successful in the political field. The tension between professional vs. amateur communication from politicians to voters was evident in the 2016 election. Unlike Clinton, Trump engaged in casual, uncivil, and often amateur language and communication with the public, which may have contributed to his popularity (Enli 2017, 59). The differing styles of Trump and Clinton's communication skills is further discussed in a later section.

Measuring Public Opinion and the 2016 Presidential Election

Aside from accumulating information about the role of social media, particularly Twitter, in U.S. presidential elections, this study also requires a valid way of measuring public opinion ratings of Trump through polling. Given that the results of the 2016 presidential election were shocking to many, it seemed plausible to blame polling data as an unreliable prediction tool because it seemed to have failed in accurately predicting the winner of the election (Wright and Wright 2018, 81). Some theories suggest that the incorrect polling was due to factors like voters changing their votes at the last minute; however, on November 7, 2016, simulations of electoral college outcomes demonstrate that Trump's probability of winning was about 47% (Wright and Wright 2018, 81, 85). Other political science experts note that as far as national polling goes, in 2016 polling data was for the most part accurate (Kennedy 2018). The national polling was nearly accurate, as many pre-election polls projected that Clinton would win the popular vote by a three-point margin, and Clinton won the popular vote by a two-point margin (Kennedy 2018). In addition, some sources cite the 2016 national polls to be some of the most accurate in estimating the popular vote since 1936 (AAPOR 2016). Comparing the election polls in 2016 to those in 2012 provides further evidence that discrediting national polls is irrational. When comparing the two election years, it is clear that the national polls in 2016 were even more

accurate than those in 2012 (Sides 2016). One such political scientist, Costas Panagopoulos, assessed whether the 2012 polls or the 2016 polls were more accurate during the week leading up to the 2016 presidential election. Panagopoulos found that sources such as McClatchy/Marist and IBD/TIPP were extremely accurate in their predictions (Sides 2016). Additionally, only a couple of the sources in 2016 had a statistically significant partisan bias and only a couple of the 2012 predictions had a very minimal bias (Sides 2016 and Sides 2012).

It is difficult for election polls to accurately forecast the result of an election because election polls are not only predicting who out of the electorate will vote, but also which way individuals will vote (Kennedy 2018). There are a few theories as to why the state polling predictions seem to have gone awry in the 2016 presidential election. The state polls indicated that Clinton had a slight advantage, especially in the final polling of some key battleground states such as Pennsylvania, Michigan, and Wisconsin (AAPOR 2016). However, these battleground states voted for Trump, which was surprising because they had voted for the Democratic candidate in the six previous presidential elections (AAPOR 2016). Some theories as to why state polling data undermined the possibility of a Trump success are the following: voters changed their votes the last week of the election, polling did not adjust for the greater amount of polling participants who were more likely to support Clinton, and that some Trump supporters did not disclose their support for him in polling (Kennedy 2018; AAPOR 2016). The last reason cited is also known as the Shy Trump effect. The Shy Trump effect theorizes that particularly hostile conservative opinion environments cause individuals to resist reporting their opinions on moral issues (AAPOR 2016). However, the Shy Trump effect is unlikely to have occurred given postelection research (AAPOR 2016).

In terms of how specific events affected the polling, it is difficult to decipher a relationship between such an event and polling data alone (AAPOR 2016). In order to try to decipher a relationship between events and polling, experts analyzed five national tracking polls that took place during the three weeks leading up to the 2016 presidential election (AAPOR 2016). Some of the sources show conflicting data. For example, ABC News/Washington Post demonstrate Clinton's favorability decreasing in late October, but then increasing close to election day, whereas the sources IBD/TIPP demonstrate the opposite for Clinton's support and show that Clinton support increased in late October, but then decreased in November (AAPOR 2016). In order to reconcile the different polling predictions from varied sources, the authors computed the average margin to give all of the sources the same influence on projecting the election outcome (AAPOR 2016). The authors found that the average of these sources resulted in a two-point percentage win for Clinton, which was the outcome of the election; therefore, demonstrating that the average of sources is nearly precise in reflecting voter preferences and public opinion ratings in the final weeks before the election (AAPOR 2016). Therefore, this thesis analyzes the relationship between the average of over forty national polling sources and Trump's communication on Twitter in order to determine whether Trump's Twitter communication was as significant as some theories suggest.

Literature Regarding Trump and Twitter in the 2016 Presidential Election

Many political scientists, including those on Trump's campaign team, have attributed much of his success in the 2016 presidential election to his presence and communication on Twitter. As a result, political scientists have researched Trump's communication style, content, and frequency of Twitter use and some research has compared Trump's Twitter use to that of Clinton's.

Jayeon Lee and Young-Shin Lim are among the political scientists who have researched the differences between Trump's and Clinton's Twitter styles and nature of their language. Part of Lee and Lim's research focused on September 12, 2015-September 18, 2015, which was the week of the second Republican primary debate which occurred on September 16, 2015 (Lee and Lim 2018, 851). The second part of Lee and Lim's research focused on October 9, 2015-October 15, 2015 which was the week of the first Democratic primary which took occurred on October 13, 2015 (Lee and Lim 2018, 851). In all, Lee and Lim analyzed 228 of Clinton's tweets and 295 of Trump's tweets (Lee and Lim 2018, 852). The authors focused on notable differences between Trump's and Clinton's Twitter use regarding issues, content, source of retweets, multimedia use, and level of civility (Lee and Lim 2018, 849). Through this research, Lee and Lim note that Twitter use is beneficial for candidates, especially when candidates use Twitter to interact with others (Lee and Lim 2018, 850). Through analyzing Tweet content, Lee and Lim found that Trump incorporated more user-generated content in his tweets, while the vast majority of Clinton's tweets consisted of original content (Lee and Lim 2018, 849). Trump's Twitter style was also more interactive because approximately half of Trump's tweets were "retweets" or replies to other users (Lee and Lim 2018, 849). Clinton's Twitter content included issues, campaign-related activities as well as endorsements and positive evaluations about her as a candidate (Lee and Lim 2018, 853). The majority of Trump's content included supportive words or endorsements about his candidacy, followed by criticisms of others, and lastly information about campaign-related activities (Lee and Lim 2018, 853). Not surprisingly, tweets that criticized other candidates were four times more likely to appear in Trump's tweets compared to Clinton's (Lee and Lim 2018, 853). Trump also utilized a less traditional communication style as 10.5% of Trump's tweets include uncivil language which is indicative of Trump's amateur

campaign style that other researchers discuss as well (Lee and Lim 2018, 849, 851). Enli also notes that unlike the amateur style of communication utilized by Trump, Clinton followed a more traditional way of communicating to her base. While Clinton mirrored the precedent set by Barack Obama's campaign and utilized a more professional style of social media campaigning, Trump demonstrated a proclivity towards amateurism in 2016 (Enli 2017, 55). Enli performed a quantitative comparison of Trump and Clinton's tweets as either traditional, which he defines as professional and reminiscent of established standards of tweeting styles vs. untraditional or amateurish which does not follow the traditional standards of tweeting (Enli 2017, 56). Enli found that 82% of Clinton's tweets were in line with traditional communication styles compared to 38% of Trump's tweets (Enli 2017, 56). In addition, Enli's research finds that about 55% of Trump's tweets were characterized as unconventional compared to 13% of Clinton's tweets (Enli 2017, 56). While it may appear that Trump's informal communication style on Twitter was due to his lack of political experience or an absence of a campaign strategy, his informal communication style was actually beneficial in accumulating media coverage, because the content of his tweets was often discussed in the mainstream media (Enli 2017, 55-56). Trump's ability to garner media attention through his Twitter account is also evaluated in literature regarding the free media hypothesis, which is discussed later in greater depth.

Trump's informal style of communication was perceived as attractive to potential voters because it was deemed authentic compared to Clinton's predictable and refined communication style (Lee and Lim 2018, 854). Lee and Lim note that there were certain limitations in his study because the timeline was not very close to the election day and that the two weeks that Lee and Lim sampled were deliberate because the candidates were more likely to communicate during days when there was a debate (Lee and Lim 2018, 851). Therefore, a longer study would likely

yield more accurate results. However, Enli corroborates Lee and Lim's research that Trump's amateur and nontraditional style was attractive to voters because it made him seem like a real outsider, which in line with his campaign theme (Enli 2017, 56). In Enli's comparison of Trump and Clinton's tweets, Enli notes that Trump wrote or dictated most of his tweets which helped his constituents to get to know him better, whereas Clinton's account was primarily dictated by others which made her seem more distant to the public (Enli 2017, 57). Approximately one third of Trump's tweets demonstrate authenticity markers, meaning that the tweets articulated impoliteness, political incorrectness, and utilized capital letters and punctuation in a particular way that embodied the way Trump would have personally spoken (Enli 2017, 58). Conversely, Clinton only demonstrated authenticity markers in about 5% of her tweets, which perpetuated her professional and detached public image that she had established in television debates and public rallies (Enli 2017, 58). Research since the 1970s has argued that candidates' images as well as voters' evaluations of authenticity and trustworthiness are significant factors in influencing how constituents vote; therefore, a natural conclusion would be that voters were attracted to Trump's amateur and authentic communication style (Enli 2017, 58-59).

Another theory regarding Trump's victory put forth by Peter L. Francia is the Free Media Theory (FMT from hereon). The FMT assesses Trump's ability to garner free media advertising via social media in comparison to other Republican candidates in the nominating process and Hillary Clinton in the general election. This theory focuses on the timeline of the general election, which is the same as the timeline that this thesis focuses on; Francia's work also evaluates public opinion data regarding Trump and Clinton, which is also relevant to this study (Francia 2017, 446, 449). The FMT argues that Trump's social media presence was a significant factor in his victory and that he was able to become highly visible because of his social media

usage without having to spend money (Francia 2017, 444). Specifically, the impact of Trump's Twitter usage was two-fold. Trump's Twitter allowed him to create a base by communicating directly with the public, building a solid following, and reaching millions of people (Francia 2017, 445). Secondly, Trump's controversial statements and language, much of which was on Twitter, were often reported by news media in order to attract viewers (Francia 2017, 445).

While Francia's study did not make causal claims regarding Trump's free social media usage and his victory, this research does demonstrate that the five conditions of FMT were met and potentially significant in the 2016 and future presidential elections (Francia 2017, 440). The first condition that Trump met was that he had more free media coverage than Clinton, and the second condition that he met was that he had more Twitter followers than Clinton, especially during the key final months of the election cycle (Francia 2017, 446). The third condition Trump met was that a higher percentage of people reported seeing more social media posts supporting Trump than Clinton, and the fourth condition he met was that a higher percentage of people reported seeing more news stories about Trump than Clinton (Francia 2017, 446). Finally, the fifth condition that Trump met stipulates that a higher percentage of people reported spending more time talking about Trump in personal conversations than about Clinton (Francia 2017, 447). Francia claims that Trump meeting these five conditions demonstrates that there is empirical weight to the FMT (Francia 2017, 447). Francia also measured Trump's monetary advantage via social media. Utilizing MediaQuant, which measures the monetary value of a media mention, Francia measured the amount of free media value accrued by November 1, 2016 for Donald Trump and Hillary Clinton (Francia 2017, 447). Francia found that Trump had a free media value of \$4.96 billion compared to Clinton's free media value of \$3.24 billion (Francia 2017, 447). Trump's media advantage was unprecedented and exceeded that of Romney and

Obama in 2012. Trump was even able to decrease the advantage that Clinton had in paid advertisements (Francia 2017, 447). By November 8, 2016, Trump had 13 million Twitter followers while Clinton only had 10.3 million followers and Trump's Twitter account alone generated \$402 million in free attention while Clinton's Twitter account only generated \$166 million in free attention (Francia 2017, 448).

In addition to calculations regarding the monetary value of free media attention Trump secured in the 2016 election, Francia's study also focuses on public opinion data from YouGov regarding the 2016 presidential election (Francia 2017, 449). In June 2016, 43% of likely voters and in August 2016, 40% of likely voters reported seeing more news stories of Trump than Clinton. In contrast, in June 2016, only 12% of voters and in August 2016, only 13% of voters reported seeing more news stories of Clinton than Trump (Francia, 450). Trump was also more widely discussed as a topic in personal conversations (Francia 2017, 450). Despite the vast free media attention Trump had throughout the campaign, a lot of coverage about him was negative which may cast doubt on the FMT; however, 77% of his supporters claimed to trust fact-checking journalists and experts "not much or not at all," which may mean that Trump's base was unaffected by negative mainstream news stories about him (Francia 2017, 450-451). Overall, Francia's research demonstrates that future presidential candidates may fare especially well when their campaigns prioritize generating free media rather than utilizing other traditional campaign tactics (Francia 2017, 451).

Despite the seeming consensus that Trump's 2016 victory could be attributed, at least in part, to his use of Twitter and social media, some political scientists disagree with this theory. Levi Boxell, Matthew Gentzkow, and Jesse M. Shapiro argue that the internet did not play a significant role in Trump's victory (Boxell, Gentzkow, and Shapiro 2018, 1). These researchers

examined three measures regarding individuals' use of the internet, including whether the respondent uses the internet, whether the individual has seen or heard any information regarding the election on the internet, and whether the respondent was likely to have had internet access or not in 1996 because the timeline that researchers used ranged from 1996-2016 (Boxell et al., 2). Based on the researchers' data, the majority of Trump supporters were not part of the groups that were the most active internet users and that Trump was more popular among less internet-active groups than Mitt Romney in the 2012 presidential election (Boxell et al., 2-3). The authors note limitations to these findings such as the fact that social media content regarding the election may be broadcasted on traditional media platforms as well, those that are usually inactive online may be even more heavily influenced by the internet when they do have access to it, and that internet users may have been more averse to voting for Trump before viewing the internet, but more pro-Trump after viewing internet content (Boxell et al., 6). While Boxell et al.'s information is revealing about some understudied assumptions about Trump's victory, the limitations mentioned seem to impact the findings given the vast literature that suggests that Trump's social media presence was heavily discussed in more traditional news forums.

The literature discussed regarding political psychology theories about the 2016 presidential election, the increased use of social media and Twitter as tools in political campaigns, public opinion data, and Trump's specific use of social media and Twitter in the 2016 presidential election lead me to explore the following independent language variables: clout, anger, anxiety, positive emotion, negative emotion, a focus on the past, a focus on the present, and a focus on the future. These variables were specifically chosen based on the past research that has touched on these variables in relation to Trump's popularity among voters and the psychology of voters that attracted them to Trump.

Past research theorizes Trump's strong, authoritative demeanor was attractive to particular voters, which is why the variable *clout* is explored. Literature has also focused on the ways in which anger mobilized voters to support Trump and how Trump utilized angry emotions to rile up voters. Anxiety is also referenced as a motivating factor for voters to support Trump and that fear as well as anxiety are significant in impacting political participation and attracting voters to particular candidates. Literature also assesses both positive and negative emotions in relation to both Trump and Clinton. While a past research study notes that positive emotion was more highly aligned with Trump than Clinton, other research notes the strength of Trump's use of anger and fear in motivating voters, so positive and negative emotion variables were explored. Lastly, past research delves into the idea that many of Trump's supporters included voters who were wary and fearful about the future and longing for America to return to the more comfortable past. Other literature notes that that present-tense verbs are indicative of authenticity. Lastly, some literature theorizes that Trump was attractive to voters because of his problem-solving rhetoric and demeanor that made voters feel safe because he was able to solve their problems in the future. Therefore, variables that explore Trump's use of language focused on the past, present, and future were also included as variables in this study.

Data/ Methods

The research for this study began with collecting and analyzing all of Trump's tweets from the 2016 Republican National Convention on July 19, 2016 through the day before 2016 presidential election on November 7, 2016. Trump was the exclusive Republican candidate during this time period, so assessing favorability ratings regarding Trump when there were no other Republican candidates would likely result in a clearer conclusion as to what factors contributed to Trump's success in the presidential election against Hillary Clinton rather than

why he was successful in securing the Republican nomination over the other Republican candidates. Additionally, the general election time period between being officially nominated through the election is a crucial time for candidates to garner positive opinions from the public and when most of the intensive campaigning takes place. Therefore, analyzing Trump's communication and language use via Twitter during the general election time period was the most suitable timeline to analyze in order to try to understand his larger campaign strategy and what Trump wanted to convey to the public to secure a presidential victory.

Trump's public opinion ratings related to his favorability as a candidate are varied depending on the source. The news source, method of polling, and the number of responses gathered has led to slightly different daily public opinion ratings of Donald Trump. Because this study is interested in daily percentages of Trump's favorability ratings, daily polling data would be sensitive to changing based on small factors which would have affected the accuracy of the results from this study. Past literature regarding public opinion polling demonstrates that the average of multiple polling sources typically delivers a more accurate estimate of public opinion and forecasting elections than just relying on one source (AAPOR 2016). As a result, I decided to use the national polls data from FiveThirtyEight because this is not only a reputable source regarding political engagement, but also because this source provided daily Trump favorability ratings from multiple sources for each day from July 19, 2016 through November 7, 2016 (for more information please see the following link: <https://projects.fivethirtyeight.com/2016-election-forecast/national-polls/>). FiveThirtyEight included polling data of candidate favorability percentages from the following sources: ABC News/ Washington Post, American Research Group, Angus Reid Global, CBS News/ New York Times, CCES/YouGov, Centre College, CNBC/Hart/Public Opinion Strategies, CNN/Opinion Research Corp., Consumer Surveys,

CVOTER International, Echelon Insights, Edison Research, Emerson College, Farleigh Dickinson University (Public Mind), Fox News, George Washington University, GfK Group, Google Consumer Surveys, Gravis Marketing, Greenberg Quinlan Rosner, IBD/TIPP, icitizen, Insights West, Ipsos, Kaiser Family Foundation/ PSRAI, Marist College, Monmouth University, Morning Consult, NBC News/ Wall Street Journal, Normington, Petts & Associates, Penn Schoen Berland, Pew Research Center, PSRAI, Public Policy Polling, Public Religion Research Institute, Quinnipiac University, RABA Research, RAND (American Life Panel), Rasmussen/ Pulse Opinion Research, Red Oak/ Google Consumer Surveys, RKM Research and Communications, Inc., Saint Leo University, Selzer & Company, Suffolk University, SurveyMonkey, Survey USA, The Times-Picayune/Lucid, University of Delaware, USC Dornsife/LA Times, YouGov, and Zogby Interactive/JZ Analytics.

Many of the polling sources from FiveThirtyEight have been included in previous literature discussing polling in the 2016 presidential election and are reputable polling sources.

FiveThirtyEight listed the favorability ratings for all three candidates in the 2016 presidential election: Donald Trump, Hillary Clinton, and Gary Johnson. In order to exclusively compare Trump's daily favorability rating compared to that of his greatest competition, Hillary Clinton, I calculated the two-party favorability rating for Donald Trump in terms of percentages. This was done by dividing Trump's daily percentages by the sum of Trump and Clinton's daily percentages. In other words, I used the formula: $\text{Trump's daily percentages} / (\text{Trump's daily percentages} + \text{Clinton's daily percentages})$. After calculating Trump's percentage of the two-party favorability from all of the sources, some days had multiple sources and, therefore, multiple daily polling averages. I then calculated the average of two-party favorability ratings on

a daily basis so that each day from July 19, 2016 through November 7, 2016 only had a single percent favorability rating for Trump.

In order to analyze and code for Trump's language in his tweets, I first copied the text of all Trump's tweets from July 19, 2016 through November 7, 2016 into an Excel sheet. This Excel sheet contained two columns, one of which was the text of Trump's tweets and the other which contained the dates that the tweets were written. I then saved the tweet text data as a CRV file to upload into the linguistic analysis software. The software that I used to code the text of the tweets was Linguistic Inquiry Word Count (LIWC), a program that analyzes language in texts and attributes particular words to "psychologically meaningful categories" (Tausczik and Pennebaker 2009, 24). LIWC has a processing component in order to fully process the text and has stored dictionaries in order to access definitions that correspond with the words in the text (Tausczik and Pennebaker 2009, 27). LIWC is then able to analyze texts and compare the words to definitions in the dictionary (Tausczik and Pennebaker 2009, 27). LIWC is particularly adept at analyzing emotional language including positive and negative emotion words which was useful for this study (Tausczik and Pennebaker 2009, 32).

The independent variables studied and analyzed in the LIWC software included Trump's language in his tweets indicative of: clout, anger, anxiety, positive emotion, negative emotion, focus on the past, focus on the present, and focus on the future. These variables were chosen based on past political psychology theories regarding Trump's victory in the 2016 presidential election. The clout variable was assessed because political scientists such as Hetherington and Weiler describe Trump as an authoritarian-like leader who was elected in order to provide a solution to those with a fearful worldview and partly attribute Trump's victory to his ability to problem-solve and communication style of directness to ease the cognitive anxieties that many

voters felt going into the 2016 election. Researchers also theorize that anger motivates individuals to politically participate in an unthoughtful way and to strategically utilize their votes to punish the government (Mason 2018). Therefore, anger was also a variable that this study assessed. The variable anxiety was assessed because many political scientists reference anxiety of threats from the opposing party or about the direction of American politics as making individuals feel wary about the future. Lilliana Mason also theorizes that anxiety triggers potential voters to politically participate in a thoughtful and biased way. Positive emotion and negative emotion variables were also considered. Given the literature that compares Trump and Clinton's affiliations among voters with these emotions, the idea that inter-political party biases increase negative affect for the opposing side, and the fact that Trump used uncivil and disparaging language throughout his campaign, these two variables were relevant to this study. The past, present, and future tense variables were also evaluated. Some literature focuses on the idea that many voters were longing for the American political and cultural climate to revert to the past and a more traditional order, which may have impacted the consequences that past-focused language had on voters. Given Trump's authentic and personal communication style with his base coupled with linguistic assessments that claim that authenticity markers in language include directness, I-words, present-tense verbs, and relativity words, evaluating Trump's use of present tense would likely be representative of how authentic he was in his communication (Abe 2018, 77). Lastly, the future-tensed language is related to the anxieties felt by many voters as some theories assert that individuals who were overlooked in the past were anxious about the future and were more likely to support Trump (Mutz 2018, Hetherington and Weiler 2018). Linguistically, the future tense is used in more goal-oriented language. Trump's rhetoric seemed to offer solutions to many issues facing America which secured him support from more fearful

voters, so his use of the future tense may have also affected the ways that voters viewed his conceptions of problem-solving and a better future landscape of American politics. Below is a table illustrating the category of words which are the independent language variables, examples of the words according to LIWC software dictionary, the number of words in each category stored in the dictionary in the LIWC software, and the psychological correlates based on LIWC standards.

Category	Examples	Words in Category	Psychological Correlates
Clout	N/A	N/A	Relative social status, confidence, or leadership
Anxiety	Worried, nervous	91	Negative Emotionality
Anger	Hate, kill, annoyed	184	Negative Emotionality
Positive Emotion	Love, nice, sweet	406	Emotionality
Negative Emotion	Hurt, ugly, nasty	499	Emotionality
Past Tense	Went, ran, had	145	Focus on the past
Present tense	Is, does, hear	169	Living in the here and now
Future Tense	Will, gonna	48	Future and goal oriented

After uploading the CSV file containing the texts of Trump’s tweets to LIWC and selecting the variables that were the independent variables in this study, I created a master Excel sheet. This Excel sheet contained columns of LIWC language entries for the particular independent variables that corresponded with each of Trump’s individual tweets. LIWC outputs

variables in terms of the percentage of the total word count for each variable. Therefore, the language variables had to be coded in such a way that a one-unit change for the variables would represent changes on the individual word level. This was done by dividing the LIWC-generated number for each variable for each tweet by 100 in order to obtain a proportion and then multiplying the resulting number by the total word count for that particular tweet. I then summed the values for each variable for all tweets within a given day. As a result, this study obtained the daily total number of words for each language variable. I then merged this file with the daily Trump favorability data in R based on the date that the tweets were written.

Results/Analysis

Using the data previously discussed, I ran three different time series regression models in R to determine how the independent variables, in this case: Trump's Twitter use of language indicative of: clout, anger, anxiety, positive emotion, negative emotion, focus on the past, focus on the present, and focus on the future, affected the dependent variable. The dependent variable in this study was Trump's favorability rating based on public opinion data. The time series regression was done using R software with alpha level = .05. The data was analyzed in R and included three different models which included variables regarding the timing of Trump's tweets and their association with his favorability rating. A table demonstrating the different models is below with the following variables included in the model: T=tweets, t=time, A=approval rating, l=1 day.

Model	<u>Independent Variables</u>	<u>Dependent Variables</u>
Model 1	T_{t-1}, A_{t-1}	A_t
Model 2	$T_t - T_{t-1}$	$A_t - A_{t-1}$
Model 3	$T_{t-1} - T_{t-2}, A_{t-1} - A_{t-2}$	$A_t - A_{t-1}$

The first model utilized in the regression demonstrates how T_{t-1} is associated with the approval A_t . In other words, this model assesses how Trump’s tweets on a particular day are associated with his approval rating on the next day. This model controls for approval at $t-1$, which demonstrates how the lagged value of tweets relates to the contemporary values of approval. There is a lag time of one day on both the independent and the dependent variables in this regression. The one-day lag time was chosen because it is unlikely that the majority of the public represented in polling data read or heard about Trump’s tweets on the news immediately after he posted a tweet. Therefore, it is unlikely that public opinion polling of favorability ratings regarding Trump would change immediately. The one-day lag time allows for more of the public to have learned about his tweets and, therefore, for the tweets to have an effect on how favorably the public viewed him. While a longer lag time of up to three days may have also been appropriate for this study, a lag time of one day would likely provide accurate and statistically sound conclusions because Trump’s tweets are heavily discussed on multiple social media platforms and in more traditional media outlets such as the daily news, so it is likely that those who were reporting their favorability rating of Trump would have heard or seen news about his tweets from the day before. The regression results for this model are below. Only one of the regression models yielded statistically significant results, however the associations between the independent variables and dependent variables for each model are discussed below. This

regression table includes the name of the independent variables, the estimate, the standard error, and the p-value.

Model 1 Regression Results: Lagged Model

Coefficients:

Variables	Estimate	Std. Error	P-value
(Intercept)	69.696	4.244	< 2e-16 ***
Average with 1-day lag	-0.471	0.089	7.32e-07 ***
Clout with 1-day lag	0.005	0.003	0.207
Anger with 1-day lag	0.020	0.098	0.835
Anxiety with 1-day lag	-0.032	0.175	0.853
Pos. Emotion with 1-day lag	-0.002	0.028	0.937
Neg. Emotion with 1-day lag	-0.019	0.050	0.703
Focus Past with 1-day lag	0.019	0.042	0.649
Focus Present with 1-day lag	-0.012	0.027	0.656
Focus future with 1-day lag	-0.036	0.045	0.424

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

When interpreting all three models it is important to take into account what a change in one unit of the estimate measure represents. A one-unit increase in this dataset demonstrates how an additional word that corresponds with one of the independent language variables impacts Trump's public opinion ratings in terms of percentages. In other words, the data demonstrates how for every one-word increase in a certain language variable, the percent of his favorability

rating changes. Additionally, the following analyses of the three models are based on the assumption that all other variables are being held constant.

The Model 1 regression did not yield any statistically significant results. The sample size in this regression is $n=102$ and the adjusted R-squared is 0.1924. In the Model 1 regression, we see a slightly positive relationship between Trump's use of clout language and his favorability ratings. For a one-unit increase in Trump's use of clout language, we should expect to see a 0.005% increase in Trump's favorability ratings. There is also a slightly positive relationship between Trump's use of anger language and his favorability ratings. For a one-unit increase in the use of angry language, we should expect to see a 0.020% increase in Trump's favorability ratings. Trump's use of anxiety language has a slightly negative relationship with his favorability ratings. For every one-unit increase in Trump's use of anxiety language, we should expect to see a 0.032% decrease in his favorability ratings. Both positive emotion and negative emotion language have slightly negative relationships with Trump's favorability ratings. For every one-unit increase in Trump's use of positive emotion language, we should expect to see a 0.002 decrease in his favorability ratings. Additionally, for every one-unit increase in Trump's use of negative emotion language, we should expect to see a 0.019% decrease in Trump's favorability ratings. In terms of time-focused variables, past-focused language has a slightly positive relationship with Trump's favorability ratings, whereas present-focused and future-focused language have slightly negative relationships with Trump's favorability ratings. For every one-unit increase in Trump's use of language focused on the past, we should expect to see a 0.019% increase in Trump's favorability ratings. For every one-unit increase in Trump's use of language focused on the present, we should expect to see a 0.012% decrease in Trump's favorability

ratings. Lastly, for every one-unit increase in Trump’s use of language focused on the future, we should expect to see a 0.036% decrease in Trump’s favorability ratings.

The second model utilized in this study assesses whether the tweets at a time t minus tweets at a time t-1 affected the approval of time minus approval of time minus one. In other words, this model assesses whether the way that Trump’s tweets changed from yesterday to today impacted the approval rating to change from yesterday to today. Model 2, therefore, evaluates the concurrent difference in terms of Trump’s tweets and his approval ratings. The regression results for Model 2 are below. This regression table includes the name of the independent variables, the estimate, the standard error, and the p-value.

Model 2 Regression Results: Differences Model

Coefficients:

Variables	Estimate	Std. Error	P-value
(Intercept)	0.025	0.227	0.912
Clout Concurrent Difference	-0.007	0.005	0.138
Anger Concurrent Difference	0.228	0.130	0.082 .
Anxiety Concurrent Difference	-0.023	0.221	0.914
Pos. Emo. Concurrent Difference	0.078	0.036	0.035 *
Neg. Emo. Concurrent Difference	-0.076	0.067	0.254
Focus Past Concurrent Difference	0.076	0.056	0.174
Focus Present Concurrent Difference	-0.018	0.038	0.629
Focus Future Concurrent Difference	0.045	0.059	0.443

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The Model 2 regression yielded statistically significant variables. The positive emotion variable was statistically significant at a p-value of 0.05 and the anger variable was significant at a p-value of 0.1. The sample size for this model is $n=104$ and the adjusted R-squared is 0.0511. In the Model 2 regression, there is a slightly negative relationship between Trump's use of clout language and his favorability rating. Thus, for every one-unit increase in Trump's use of clout language, we should expect to see a 0.007% decrease in Trump's favorability ratings. There is a slightly positive relationship between Trump's use of anger in his language with his favorability ratings. For every one-unit increase in Trump's use of anger language we should expect to see a 0.228% increase in Trump's favorability ratings. There is a slightly negative relationship between Trump's use of anxiety language and his favorability ratings. For every one-unit increase in Trump's use of anxiety language, we should expect to see a 0.023% decrease in Trump's favorability ratings. In addition, there is a slightly positive relationship between Trump's use of positive emotion language and his favorability ratings. For every one-unit increase in Trump's use of positive emotion language, we should expect to see a 0.078% increase in Trump's favorability ratings. Trump's use of negative emotion language has the opposite effect. Trump's use of negative emotion language has a slightly negative relationship with his favorability ratings. For every one-unit increase in Trump's use of negative emotion language, we should expect to see a 0.076% decrease in Trump's favorability rating. Trump's use of language focused on the past and language focused on the future have slightly positive relationships with his favorability ratings, whereas Trump's use of language focused on the present has a slightly negative relationship with his favorability ratings. For every one-unit increase in Trump's use of language focused on the past, we should expect to see a 0.076% increase in Trump's favorability ratings. For every one-unit increase in Trump's use of language

focused on the present, we should expect to see a 0.018% decrease in Trump's favorability rating. Lastly, for every one-unit increase of Trump's use of language focused on the future, we should expect to see a 0.045% increase in Trump's favorability rating.

The third model utilized in this study assessed whether tweets at time t minus 1 minus tweets at time t minus two affects the approval of time t minus the approval of time t minus one. In other words, this model evaluates whether tweets that change from two days ago to yesterday cause Trump's approval rating to change from yesterday to today. This is a significant model in this study because it is realistic that Trump's tweets, which are written at all times of day, would not immediately reach every potential voter. It is more likely that a potential voter would read the tweet on Twitter or hear about it in the news hours after it has been posted or on the following day. Therefore, it is logical to assess whether the changes that Trump implements in his language impact changes in public opinion favorability ratings of Trump. Additionally, testing the impact of Trump's tweets on public opinion in terms of these changes is a model that would imply a greater level of causation rather than just evaluating the correlational relationship between Trump's tweets and his favorability ratings on the same day. This test is the strongest of the three models, but it is also the most conservative test because in order for the test to yield causal evidence, the differences have to precede the dependent variable. This type of test avoids a Type I error, but is more likely to produce a Type II error. The regression results for this model are below. This regression table includes the name of the independent variables, the estimate, the standard error, and the p-value.

Model 3 Regression Results: Lagged Differences Model

Coefficients:

Variables	Estimate	Std. Error	P-value
(Intercept)	1.301e-02	1.459e-01	0.929
Average Concurrent Difference with 1 day lag	-7.802e-01	6.295e-02	<2e-16 ***
Clout Concurrent Difference with 1 day lag	1.175e-03	3.407e-03	0.731
Anger Concurrent Difference with 1 day lag	-4.089e-03	8.486e-02	0.962
Anxiety Concurrent Difference with 1 day lag	7.473e-04	1.416e-01	0.996
Pos. Emo. Concurrent Difference with 1 day lag	9.372e-05	2.448e-02	0.997
Neg. Emo. Concurrent Difference with 1 day lag	-4.453e-02	4.306e-02	0.304
Past Focus Concurrent Difference with 1 day lag	3.032e-02	3.626e-02	0.405
Present Focus Concurrent Difference with 1 day lag	1.759e-02	2.431e-02	0.471
Future Focus Concurrent Difference with 1 day lag	-3.458e-02	3.840e-02	0.370

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The Model 3 regression did not yield any statistically significant results. The sample size in this model is n=102 and the adjusted R-squared is 0.6123. In Model 3, there is a very slight positive relationship between Trump's use of clout language and his favorability. For every one-unit increase in Trump's use of clout language, we should expect to see a 1.175e-03% increase in

Trump's favorability. There is a slightly negative relationship between Trump's use of anger language and his favorability rating. For every one-unit increase in Trump's use of anger language, we should expect to see a $4.089e-03\%$ decrease in Trump's favorability. Trump's use of anxiety language has a slightly positive relationship with his favorability. For every one-unit increase in Trump's use of anxiety language, we should expect to see a $7.473e-04\%$ increase in Trump's favorability. This model concludes that Trump's use of positive emotion language has a slightly positive relationship with Trump's favorability rating, while Trump's use of negative emotion language has the opposite effect. For every one-unit increase in Trump's use of positive emotion language, we should expect to see a $9.372e-05\%$ increase in Trump's favorability. For every one-unit increase in Trump's use of negative emotion language, we should expect to see a $4.453e-02\%$ decrease in Trump's favorability. Trump's use of language focused on the past and present have slightly positive relationships with Trump's favorability rating, but that Trump's use of language focused on the future has a slightly negative relationship with Trump's favorability rating. For every one-unit increase in Trump's use of language focused on the past, we should expect to see a $3.032e-02\%$ increase in Trump's favorability. Similarly, for every one-unit increase in Trump's use of language focused on the present, we should expect to see a $1.759e-02\%$ increase in Trump's favorability. Lastly, for every one-unit increase in Trump's use of future-focused language, we should expect to see a $3.458e-02\%$ decrease in Trump's favorability.

Limitations

It is important to note some limitations to take into account regarding this study. Firstly, the timeline that this study focuses on includes approximately the last five months of Trump's 2016 presidential campaign and does not account for any of Trump's Twitter correspondence

throughout the Republican primaries or before he was nominated as the Republican candidate. Future studies that focus on a longer timeline of Trump's Twitter correspondence beginning when he announced his presidential bid on June 16, 2015 will likely achieve more accurate results regarding the kinds of language and communication he had with his base via Twitter (DelReal 2015). Running another time series regression with a longer timeline would likely yield more statistically significant results and a clearer pattern in Trump's language use on Twitter in relation to public opinion ratings of Trump.

This study also only evaluated very specific language variables. While the variables selected to research were chosen because they were reminiscent of Trump's major campaign themes, and were derivative of political psychology theories regarding Trump's communication, it would likely provide a more thorough understanding of Trump's communication if future studies focused on more language variables and communication cues. Other language variables such as Trump's use of I-pronouns vs. We-pronouns may yield significant results as previous literature has touched on the psychological consequences of using individualistic vs. collectivist pronouns in communication in appealing to the masses (Abe 2018, 77; Tausczik and Pennebaker 2009, 33).

The LIWC software utilized to code for the independent language variables may have also presented imitations to this study. This particular software was chosen because it offers an objective dictionary assessment of the words and language in Trump's tweets and it is designed from a psychological framework, which is aligned with this study's political psychology focus. While LIWC is a computer software that specializes in coding language and has been constantly updated since 1993, there may have been certain limitations to this software that affected the results of this study (Tausczik and Pennebaker 2009, 28). One of the limitations of the LIWC

software is that it does not code for the context in which the word is in so it would not necessarily detect changes in word meanings based on context or detect irony or sarcasm (Tausczik and Pennebaker 2009, 30). Given the literature regarding Trump's amateurish and casual communication style via Twitter, it is possible that the software may have calculated the frequency of certain language variables that does not accurately depict the way that Trump was conveying particular points or reflect the way that people, rather than a computer, would have understood Trump's messages. Despite these potential limitations, LIWC does provide a strong analysis of language by comparing words to dictionary definitions and is a much more reliable mechanism to use when evaluating language patterns than relying on a subjective way of analyzing Trump's tweets.

Lastly, the time series regressions ran were engineered so that the independent variables were Trump's use of specific types of language and the dependent variable was his public opinion ratings over time. While this test does account for causation rather than just correlation, it would be noteworthy to run future time series regression studies in which Trump's favorability ratings are the independent variables and the language he uses are the dependent variables. With the current models used, we may be missing a key piece regarding the direction of causation regarding the independent and dependent variables in this study. Running the time series regression analysis using the independent and dependent variables in the opposite direction may yield results that are statistically significant and would suggest that the language and communication style that Trump used on Twitter were impacted by public opinion rather than his language use and communication style affecting his public opinion ratings.

Conclusions

This study sought to better understand the relationship between Donald Trump's use of psychologically-charged language in his Twitter account and his favorability ratings during the 2016 presidential election. This issue is pertinent to current discussions and theories regarding Trump's victory in 2016. There is myriad literature discussing political psychology theories that purports to explain Trump's victory, the ways in which Trump appealed to particular psychological motivations among voters, public opinion regarding Trump and Clinton, and how Twitter and social media impacted Trump's victory. However, there is a gap in the literature regarding how Trump employed psychologically-charged language and communication via Twitter to the public to enhance his favorability ratings. Therefore, this study sought to bridge the gap between traditional political psychology theories regarding Trump's 2016 victory and those that looked specifically at Trump's communication on Twitter throughout the 2016 presidential election cycle by evaluating Trump's use of psychologically-charged language in his Twitter account and the public's response to this communication.

Despite the vast literature discussing the psychology of Trump supporters and the merits of utilizing social media in campaigning, only Model 2 concluded that the positive emotion variable was statistically significant at a p-value of 0.05 and the anger variable was statistically significant at a p-value of 0.1. Three different models were utilized in a time series regression in this study and two of the three models confirmed the null hypothesis. While previous political psychology theories have discussed the ways that Trump's style of communication and Twitter use specifically related to Trump's use of language defined as and indicative of clout, anger, anxiety, positive emotion, negative emotion, focus on the past, focus on the present, and focus on the future, impacted his favorability ratings and contributed to his victory in the 2016 presidential election, this study found very little evidence of confirming such theories. As a

result, this study casts doubt on some prior theories and research, and finds that it is unlikely that Trump's use of particular language on Twitter actually affected voters' favorability ratings of Trump. While, Trump's use of positive emotion and anger in his tweets may have positively influenced his public opinion ratings, these results demonstrate a debunking of popular political psychology theories of the 2016 presidential election rather than corroborating many of them.

The failure of many of the independent variables to significantly impact Trump's favorability ratings leaves us with an even more muddled understanding of what actually occurred in the 2016 presidential election. The 2020 presidential election is just over a year away, so tying up the loose ends of the political science theories as they relate to the 2016 presidential election is imperative in order to understand how the campaign strategy of Trump was successful in securing a strong base, swaying many swing states in his favor, and how that strategy may be employed in the 2020 presidential election. While Trump or other potential presidential candidates may look at these results and implement more positive language or language indicative of anger against the government, opposing party, or candidate, the vast non-statistically significant results of this study demonstrate that political scientists may need to think more carefully about the relationship between Trump's and other politicians' use of Twitter and public opinion ratings. These results suggest that no matter what Trump said, his favorability ratings remained unaffected. This may set the stage for the 2020 presidential election to feature political campaigns that are more colloquial and that are imbued with communication that is authentic and even a bit unfiltered. This could ultimately lead to a proclivity for less traditional campaign styles. Given that Twitter is still a relatively new campaign tool, the 2020 presidential election will likely be very telling as to what role social media, especially Twitter, will play in political elections for the foreseeable future and how to best utilize Twitter for political

communication. Because of Twitter's success in helping Trump to secure media attention and visibility among voters, it is likely that in the 2020 presidential election both Democratic and Republican candidates will increase their use of Twitter and other social media platforms to generate more free media for themselves as well as to interact with and understand the demands of the public. The increased use of Twitter coupled with more authentic communication styles may suggest that American politics and presidential campaigning are entering a new phase in which politicians utilize modern technology and social media platforms as important tools in their campaign arsenal.

To conclude, this study presents several significant avenues for future research regarding this topic. Future research that addresses the issues covered in this study over a longer period of time would likely yield clearer and potentially statistically significant results, as each independent variable would have more values. At the same time, because trends are more likely to appear over a longer period of time due to outliers being less consequential, the future research could yield robust results. Another avenue of research could involve studies that assess Clinton's psychologically-charged language use on Twitter throughout the 2016 presidential election and compare the Clinton variables to the Trump variables. This would likely yield more holistic results and demonstrate which communication style or language use was more effective. A statistical comparison of how Twitter language use affects the favorability ratings for the two candidates respectively would include less one-sided data and provide insights about the differences between both the candidates and their constituents. Without being able to assess if there were significant differences between Clinton and Trump's use of psychologically-charged language in their Twitter accounts, we may only be attempting to understand a fragmented depiction of how Trump's Twitter use and language via Twitter related to his favorability ratings

in the 2016 presidential election. Future studies should also investigate other language variables not characterized in this study. While the variables assessed in this study were chosen on the basis of political psychology literature and theories, other language variables may prove to be more effective in swaying voters a certain way and affecting the favorability ratings of Trump. Greater research and studies regarding this topic would help both politicians and constituents to better navigate presidential elections and will likely be consequential for presidential elections in 2020 and beyond.

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