2020 U.S. Presidential Election: Analysis of Female and Male Users on Twitter

Amir Karami  
University of South Carolina, USA  
karami@mailbox.sc.edu

Spring B. Clark  
University of South Carolina, USA  
sbclark@email.sc.edu

Anderson Mackenzie  
University of South Carolina, USA  
ma61@email.sc.edu

Dora Lee  
University of South Carolina, USA  
dorathea@email.sc.edu

Michael Zhu  
University of South Carolina, USA  
mz3@email.sc.edu

Hannah R. Boyajieff  
University of South Carolina, USA  
boyajieh@email.sc.edu

Bailey Goldschmidt  
University of South Carolina, USA  
goldschb@email.sc.edu

The order of authors is not finalized yet, TBD

ABSTRACT

Social media is commonly used by the public during election campaigns to express their opinions regarding different issues. Among various social media channels, Twitter provides an efficient platform for researchers and politicians to explore public opinion regarding a wide range of topics such as economy and foreign policy. Current literature mainly focuses on analyzing the content of tweets without considering the gender of users. This research collects and analyzes a large number of tweets and uses computational, human coding, and statistical analyses to identify topics in more than 300,000 tweets posted during the 2020 U.S. presidential election and to compare female and male users regarding the average weight of the topics. Our findings are based upon a wide range of topics, such as tax, climate change, and the COVID-19 pandemic. Out of the topics, there exists a significant difference between female and male users for more than 70% of topics. Our research approach can inform studies in the areas of informatics, politics, and communication, and it can be used by political campaigns to obtain a gender-based understanding of public opinion.

KEYWORDS

Election; Twitter; Text Mining; Topic Modeling; Gender

INTRODUCTION

There is a positive correlation between public preferences and actions in politics [1]. To inform politicians of public preferences, there is a need to measure public opinion that is “an aggregate of the individual views, attitudes, and beliefs about a particular topic, expressed by a significant proportion of a community” [2]. Traditional methods such as interviews are essential tools for politicians to track public opinion regarding different issues. However, these methods are labor-intensive and time-consuming.

Social media has become a mainstream channel of communication with a growing popularity across all U.S. populations in the last decade [3]. In 2021, seven-in-ten Americans use at least one of social media platforms [4]. Social media has been used by the public during election campaigns to share their opinion regarding different issues [5]. Among social media, Twitter is a popular platform with more than 68 million U.S. adult users [6], including 38.4% female and 61.6% male users [7]. Twitter offers free Application Programming Interface (API) to collect data. Politicians and journalists have analyzed Twitter data to look at Twitter data to understand public opinions [5]. Research using Twitter data is a popular topic and has increased significantly during the last decade [3]. Researchers have utilized Twitter data for different applications, such as examining COVID-19 [8], happiness, diet, and physical activity [9,10], obesity [11], disinformation [12], domestic violence [13], LGBT users [14], sexual harassment [15], and geotagging behaviour [16].
Research on mining the content of tweets has focused on two main directions. The first direction measured the sentiment of tweets regarding candidates [19]. This direction has utilized both supervised [20] and unsupervised [19] methods to identify the sentiments of the tweets for each candidate. The second direction utilized text mining methods to understand the semantic of tweets. For example, one study has combined both sentiment analysis and topic modeling to identify positive and negative topics regarding economic issues in the 2012 U.S presidential elections [21]. A similar study has utilized topic modeling and sentiment analysis to understand public opinion in the 2018 Central Java Gubernatorial Election [22]. Another study proposed a framework based on mining the content of tweets to identify reasons behind the popularity of a politician [23]. Topic modeling and co-occurrence retrieval methods were also used to explore topic trends in the 2012 Korean presidential election [24]. Sentiment and semantic analyses were utilized to investigate the predictability of U.S presidential elections [25] and analyze the behavior of users [26].

To understand the direction of public opinion in a political event, it is important to obtain a gender-based understanding of public discussions. There exists studies examining the differences between female and male users regarding the content of tweets, such as comparing the social media communication of male and female politicians [27–29], female and male reporters [30], and normal male and female users [31–34]. While these studies offer valuable gender-based perspective to politics and media, there is no research on comparing normal female and male users regarding the topics of tweets during an election.

To address the limitation, this paper uses both quantitative and human coding methods to collect and analyze a large number of tweets posted by female and male Twitter users during the 2020 U.S presidential election, which is an important political event for U.S. and the rest of world. The election was held on November 3, 2020 with the highest voter turnout by percentage since 1900. In this election, Joe Biden defeated Donald Trump with more than 81 million votes, the most votes ever cast for a candidate in a U.S. presidential election [35]. This election faced issues such as the COVID-19 pandemic, racial unrest, and climate change [35]. Both candidates were very active on Twitter and had millions of followers [36]. For example, Donald Trump posted thousands of tweets during his presidency, had over 88 million followers, and received more than 389 million retweets and 1.6 billion likes by Jan 8, 2021 [37].

Considering tweet analysis through a gender lens, this research identifies the topics of tweets and compares female and male users based on the average weight of the topics. This study sought to answer the following research questions:

RQ1: What are the topics of tweets posted by U.S. female and male users during the 2020 U.S. presidential election?

RQ2: Was there a significant difference between the female and male users regarding the average weight of each topic identified in RQ1?

To address RQ1 and RQ2, we use topic modeling to identify themes of tweets, human coding to analyze the topics, and statistical analysis to compare female and male users. The paper proceeds as follows. Next, we explain our research methodology, which provides more details on our data collection and analysis. Then, we follow with an explanation of our findings. Finally, we review the study’s limitations and discuss future directions.

METHODOLOGY

This section provides more details on data collection and analysis. We developed a research framework that consists of three phases: data collection and pre-processing, topic modeling and analysis, and statistical comparison (Figure 1). We applied our framework on tweets posted by female and male users during the 2020 U.S. presidential election.
**Data Collection and Pre-processing**

We collected data using a data service provider called BrandWatch. We used queries including “trump” OR “biden” to collect 10,000 tweets per month from June 1, 2020, until the election date, November 3, 2020 for each of the 12 swing states defined by the election analytics website FiveThirtyEight [38]. We focused on swing states (e.g., Florida and Michigan) because these states decide the winner of an election in U.S. [39].

BrandWatch let us collect tweets posted in the swing states and written in English by female and male individual users (vs. other accounts such as organizations) and exclude retweets. While there are more than two gender identities such as transgender and non-binary, BrandWatch platform categorizes the gender of users as female, male, and NA (not available). The last category means that the platform could not identify the gender. In total, we have collected 1,440,000 tweets. We have removed verified accounts, URLs, and account names starting with @. Then, we filtered out short tweets containing less than five terms and duplicate tweets based on username, date, and state. This process has provided 306,142 tweets, posted by 117,203 (38.3%) female and 188,939 (61.7%) male uses.

**Topic Modeling and Analysis**

To address RQ1, we used both text mining and human coding in this phase. We utilized topic modeling to identify topics discussed in the tweets. Among different models, Latent Dirichlet Allocation (LDA) is an unsupervised text mining method to identify themes in a corpus [40]. This popular and valid method has been applied on different corpora in different domains such as health and politics [41]. LDA assumes that each document has a mixture of topics and each topic includes a distribution of words in a corpus and represents a theme [40]. The outputs of LDA for n documents (tweets), m words, and t topics provided two matrices, including probability of each of the words for each topic or $P(W_i|T_k)$ and the probability of each of the topics for each document or $P(T_k|D_j)$ [42]. $P(W_i|T_k)$ recognizes semantically related words representing a theme and $P(T_k|D_j)$ shows the weight of each topic per document.
To estimate the number of topics, we used the C_V method [43] to measure the coherence for the number of topics from 2 to 100 topics. Developed in the gensim Python package [43], the C_V method is highly correlated with human ratings [44]. We found the optimum number of topics at 34. Then, we applied the Mallet implementation of LDA [45] on our corpus. We set the Mallet at 34 topics and 4000 iterations. We also used the list of stop words in Mallet to remove most common words such as “the” and “a.” We compared five sets of 4000 iterations to validate the robustness of LDA. This experiment showed that there was no significant difference between the mean and standard deviation of the log-likelihood of the five sets.

To understand the overall theme of topics, two coders qualitatively investigate each topic following two steps. First, the coders analyzed the top words of each topic using P(Wi|Tk) and the top tweets of each topic using P(Tk|Dj). The coders answered two questions: (Q1) “Does the topic have a meaningful and relevant theme?” and (Q2) “What is the overall theme of each meaningful and relevant topics?” Q1 helped remove the meaningless and irrelevant topics. In Q2, the coders used consensus coding [46] to identify a theme and create a label for each topic. For example, “trump,” “people,” “covid,” “mask,” “care,” “wear,” “virus,” “die,” “rally,” and “americans” appeared in a topic which coders assigned the label “Trump Administration Response to COVID-19 Pandemic.”

**Statistical Comparison**

To address RQ2, we developed statistical tests to compare female and male users regarding the average weight of topics. We applied the two-sample t-test developed in the R mosaic package [47]. We defined the significance level based on sample size [48] using $\frac{0.05}{\sqrt{N}}$ [49], where N is the number of tweets. As we had 306,142 tweets, the passing p-value was set at 0.0009. We adjusted p-values using the False Discovery Rate (FDR) method to minimize both false positives and false negatives [50].

To identify the magnitude of the difference between female and male users regarding the average weight of topics, we used the absolute effect size using Cohen’s d calculated by dividing the mean difference by the pooled standard deviation [51]. The original Cohen’s d index has been classified as small (d=0.2), medium (d=0.5), and large (0.8) effect sizes [52]. The Cohen’s d index classification has been extended to very small (d=0.01), small (d=0.2), medium (d=0.5), large (d=0.8), very large (d=1.2), and huge (d=2.0) effect sizes [53].

The Cohen’s d classification has two limitations. First, the classification is based on small sample sizes [52]. Second, the average effect size in large samples is less than the one in small samples [54]. For example, most effect size values in a study with a large number of documents found to be in or below the small threshold [55]. To address the limitations of applying Cohen’s d on large datasets, we measured the mean of effect sizes of sample sizes used in developing the initial Cohen’s d classification [52], including 8, 40, 60, 100, 200, 500, and 1000 random tweets, instead of all tweets analyzed in this study.

**RESULTS**

We present our results based on analyzing the 306,142 tweets in two parts. The first part illustrates the topics of tweets. After identifying and analyzing the 34 topics, we found 29 meaningful and related topics. Table 1 shows the topics and their label. The topics cover a wide range of topics from climate change to covid-19 pandemic. We observed that “trump” appeared in all topics, but “joe” (biden) only appeared in one topic (debate). This indicates that the center of discussions was Donald Trump.
Most topics were related to U.S. internal issues, including the Trump administration response to the COVID-19 pandemic, tax, vote by mail, BLM (Black Lives Matter) movement, police violence, and protesters, supreme court, white supremacy, vaccine and public trust, left democrats, and senate election. For instance, the third topic focused on Trump administration response to the COVID-19 pandemic. A relevant tweet claimed the administration “ignored early coronavirus warning signs, dismissed the seriousness of the threat, attacked the advice of doctors and scientists, failed to institute an adequate national plan for testing and contact tracing. now 150,000 americans have died. this is on trump.”

Some topics were related directly to Donald Trump and his behavior, family, campaign, supporters, and rallies. For example, the second topic was about wearing mask policy in place for Trump rallies. Regarding this topic, one user said, “trump rally will use buses. confined spaces and trump rally attendees will be encouraged to wear a mask but not mandated. rally attendees will be temp scanned but before the buses or after the busses? and buses start at 8:00 am but the rally isn’t until 4 pm.”

Some other topics were about the election, including comparing presidents, election analysis, supporting and opposing a candidate or vote for/against the candidate, polls, and the debate of candidates. For example, the first topic was a discussion on comparing U.S. presidents (e.g., Trump vs. Obama), their performance, and. Regarding this topic, the following tweets compares Obama and Trump: “a lot of that is obama leftovers. your president made it a point to begin taking credit for obama's accomplishments before he was even in office for 1 year. obama inherited a lousy economy and turned it around. trump inherited a good one, and immediately claimed it as his own.”

The rest of the topics covered international issues, including climate change, foreign policy, and Russian bounty program. For example, the author of a tweet related to foreign policy said, “iran would've had nuke weapons for 5yrs by now if not for nuke deal. iran had uranium for 10 nukes. deal removed nuke mtls, decreased ability to get uranium. had inspections. trump abandoned our allies & ended deal w/ iran. iran now headed toward nuke weapons. world more dangerous.” This tweet discussed the nuclear deal with Iran that U.S. was withdrawing from the deal in 2018.

Table 1: Topics of tweets posted in U.S. during the 2020 presidential election.

| Label                                                                 | Top-10 Words of Each Topic                                                                 |
|----------------------------------------------------------------------|-------------------------------------------------------------------------------------------|
| Comparing Presidents                                                 | trump president obama years history made bush bad job worst remember                        |
| Wearing Mask in Trump Rally                                          | trump people covid mask care wear virus die rally americans                                 |
| Trump Administration Response to COVID-19 Pandemic                   | covid trump pandemic virus coronavirus deaths americans response cdc administration         |
| Media and Fake News                                                  | trump news media lies fake fox truth fact false cnn                                        |
| Trump Campaign, Russia, and FBI Investigation                        | trump campaign barr crimes fbi russia administration report investigation prison            |
| Trump Family                                                         | trump donald family wife child father daughter melania son ivanka                           |
| Vote by Mail                                                         | election trump vote mail usps ballot voter office service post                              |
| Vote for Trump                                                       | trump america country president donald american people vote great states                    |
| Election Analysis                                                    | trump election win office lose house republicans senate hold democrats                      |
| BLM (Black Lives Matter) Movement, Police Violence, and Protesters  | trump police violence supporters people cities blm protesters portland riots                |
| Trump Foreign Policy                                                 | trump war peace deal world middle china iran east israel                                   |
| Trump Supporters                                                     | trump supporters signs flags today train front maga car put                                |
| Supreme Court                                                       | trump law court administration supreme rights federal plan judge rules                     |
| White Supremacy                                                     | white trump house racist black proud stand people boys support supremacists                 |
| Pro-Trump                                                            | trump president god love donald family happy bless birthday america                         |
| Trump Rally                                                          | trump rally president campaign live watch great donald make governor                        |
| Russian Bounty Program                                               | trump putin russian russia troops american military bounties soldiers knew                  |
We measured the average weight of topics per tweet. In doing this, we found that polls and foreign policy were the most and the least popular topics, respectively (Figure 2). The top-3 most popular topics indicate that users were very interested to follow polls, promote their candidate, and talk about how Trump administration responded to COVID-19. For example, one user compared 2016 poll results and the 2016 elections results in some swing states, “cnn lv polls nov. 7, 2016 pennsylvania: 47-42 - clinton north carolina: 45-43 - clinton new hampshire: 49-38 - clinton florida 45-45 trump won all of these with the exception of nh, which he lost by less than .5 percent (not 11 points). just sayin.”

The three least popular topics were Trump foreign policy, vaccine and public trust, and Mary Trump’s book that provided an insider view of the Trump family dynamics [56]. For instance, one user said, “this pisses me off! i want to read this book like, now! judge temporarily blocks publication of tell-all book by president trump’s niece.” This tweet referred to temporary stay of the release of the book ordered on June 30, 2020. However, the order was reversed on July 1, 2020, and the book was published on July 14, 2020 [56].
Figure 2: The overall weight of topic per tweet.

The second part of our findings shows the comparison of female and male users regarding the average weight of the 29 topics discussed in the tweets. Table 2 indicates that there was a significant difference (adjusted p-value <0.0009) between female and male users regarding 21 (73%) topics. Out of the 21 significant differences between female and male users, there were 14 small and 7 very small effect sizes, indicating that the differences were not trivial.
| Topics                                      | Adjusted p-value | Results | Cohen’s d of Sample Sizes | Effect Size |
|---------------------------------------------|-------------------|---------|---------------------------|-------------|
| Comparing Presidents                        | 0.000             | *F<M   | 0.1                       | Very Small  |
| Wearing Mask in Trump Rally                 | 0.000             | *F>M   | 0.2                       | Small       |
| Trump Administration Response to COVID-19 Pandemic | 0.274             | NS     | NS                        | NS          |
| Media and Fake News                         | 0.000             | *F<M   | 0.3                       | Small       |
| Trump Campaign, Russia, and FBI Investigation | 0.000             | *F<M   | 0.2                       | Small       |
| Trump Family                                | 0.000             | *F>M   | 0.1                       | Very Small  |
| Vote by Mail                                | 0.873             | NS     | NS                        | NS          |
| Vote for Trump                              | 0.000             | *F>M   | 0.1                       | Very Small  |
| Election Analysis                           | 0.000             | *F<M   | 0.1                       | Very Small  |
| Blm (Black Lives Matter) Movement, Police Violence, and Protesters | 0.783             | NS     | NS                        | NS          |
| Trump Foreign Policy                        | 0.000             | *F<M   | 0.1                       | Very Small  |
| Trump Supporters                            | 0.000             | *F>M   | 0.2                       | Small       |
| Supreme Court                               | 0.891             | NS     | NS                        | NS          |
| White Supremacy                             | 0.000             | *F<M   | 0.2                       | Small       |
| Pro-Trump                                   | 0.000             | *F>M   | 0.2                       | Small       |
| Trump Rally                                 | 0.000             | *F>M   | 0.2                       | Small       |
| Russian Bounty Program                      | 0.000             | *F>M   | 0.1                       | Very Small  |
| Climate Change                              | 0.000             | *F<M   | 0.2                       | Small       |
| Anti-Trump                                  | 0.030             | NS     | NS                        | NS          |
| Vaccine and Public Trust                    | 0.474             | NS     | NS                        | NS          |
| Mary Trump's Book                           | 0.001             | NS     | NS                        | NS          |
| Senate Election                             | 0.000             | *F<M   | 0.2                       | Small       |
| Trump Behavior                              | 0.000             | *F<M   | 0.2                       | Small       |
| Left Democrats                              | 0.469             | NS     | NS                        | NS          |
| Voting for/against Trump                    | 0.000             | *F>M   | 0.2                       | Small       |
| Tax                                         | 0.000             | *F<M   | 0.1                       | Very Small  |
| Trump Town Hall                             | 0.000             | *F>M   | 0.2                       | Small       |
| Polls                                       | 0.000             | *F<M   | 0.2                       | Small       |
| Debate                                      | 0.000             | *F>M   | 0.2                       | Small       |

Out of the 21 topics, the weight of 11 topics were higher for male users than female users. These 11 topics include (1) comparing presidents, (2) media and fake news, (3) Trump campaign, Russia, and FBI investigation, (4) election analysis, (5) Trump foreign policy, (6) white supremacy, (7) climate change, (8) senate election, (9) Trump behavior, (10) tax, and (11) polls. The weight of the following 10 topics were higher for female users than male users: (1) wearing mask in Trump rally, (2) Trump family, (3) vote for Trump, (4) Trump supporters, (5) pro-Trump, (6) Trump rally, (7) Russian bounty program, (8) voting for/against Trump, (9) Trump town hall, and (10) debate.

There was not a significant difference between female and male users on eight topics: (1) Trump administration response to COVID-19 pandemic, (2) vote by mail, (3) BLM movement, police violence, and protesters, (4) supreme
court, (5) anti-Trump, (6) vaccine and public trust, (7) Mary Trump's book, and (8) left democrats. Out of the top-10 topics in Figure 3, seven topics had a different weight for male and female users (Table 2), including four topics were discussed more by male users than female users and three topics that were discussed more by female users than male users.

We also identified the top-10 topics based on the average weight of each topic per tweet for female and male users (Table 3). Out of the top-10 topics, there were five common topics between female and male users, including voting for/against Trump, anti-Trump, vote for Trump, Trump administration response to COVID-19 pandemic, and Trump behavior. Pro-Trump, debate, wearing mask in Trump rally, vote by mail, and left democrats were among the top-10 topics of female users, but not male users. On the other side, polls, senate election, election analysis, tax, and comparing presidents were among the top-10 topics of male users, but not female users.

| Top-10 Topics of Female Users | Top-10 Topics of Male Users |
|------------------------------|-----------------------------|
| Pro-Trump                    | Polls                       |
| Voting for/against Trump     | Trump Behavior              |
| Anti-Trump                   | Trump Administration Response to COVID-19 Pandemic |
| Vote for Trump               | Voting for/against Trump    |
| Trump Administration Response to COVID-19 Pandemic | Anti-Trump |
| Debate                       | Senate Election             |
| Wearing Mask in Trump Rally  | Election Analysis           |
| Trump Behavior               | Tax                         |
| Vote by Mail                 | Vote for Trump              |
| Left Democrats               | Comparing Presidents        |

**DISCUSSION**

Social media analysis has fewer limitations than traditional methods such as face-to-face interviews. Researchers and politicians commonly use social media data to understand public opinion during elections. It is also important to find differences between the opinion of female and male users. This paper set out to study topics of tweets posted by female and male users during the 2020 U.S. presidential election. Our results show that female and male users have discussed a wide range of topics in their tweets, and Donald Trump was at the center of many Twitter conversations, which could help to reduce promotion costs of Trump’s campaign. However, the election result shows that being at the center of Twitter conversations may not always be beneficial as seen from the election results. We also found that there was a significant difference between female and male users regarding the average weight of most topics.

Two surveys developed by the Pew Research Center and Gallup [57,58] have identified 17 important issues for voters, including economy, terrorism and national security, the response to the coronavirus, healthcare, education, race relations, gun policy, violent crime, abortion, immigration, climate change, foreign affairs, taxes, the federal budget deficit, relations with China, relations with Russia, and supreme court. Our analysis shows that Twitter users have discussed about eight out of the 17 issues, including race relations, violent crime, tax, supreme court, response to COVID-19 pandemic, foreign policy, climate change, and relations with Russia. Our results do not show that Twitter users did not discuss other issues because LDA identifies major topics, not all topics. Out of the eight issues, response to the COVID-19 pandemic was among top-10 topics of both female and male users and tax was among the top-10 topics of male users.

On a theoretical level, our results increase our understanding of social media communications and how female and male users viewed and engaged with the 2020 U.S. presidential election. Our findings can be used for developing social media communication strategies for political campaigns, such as customizing messages for reaching and engaging female and male audiences on Twitter in general.
Methodologically, this study presents a new way in which female and male users can be analyzed and compared using text mining, human coding, and statistical analysis. Our approach shows how big data analytics can be applied to social media data to provide a gender-based insight into political events. Our findings contribute to the literature surrounding topics that are discussed during an election, differences between female and male users, and most popular topics of female and male users. The proposed approach can be utilized for not only political events but also other non-political events such as health issues (e.g., vaccines). This research also provides some benefits, including offering a cost-effective and time-saving approach to obtain public opinion and evaluate plans and policies, augmenting traditional opinion polls, disclosing the difference between female and male discussions, and illustrating topic priorities in female and male discussions.

While this research offers a new perspective into understanding the content of social media comments posted by female and male users, there exists some notable limitations. First, this paper has considered a binary classification (female or male) of users. However, there are non-binary users outside the binary classification, such as transgender users [59]. Second, the age of Twitter users is mostly between 18 and 49 years old. The characteristics of this demographic is more likely democrat-aligned, educated, and have high income [60]. Third, the queries are limited to two terms (“trump” or “biden”), which may cause us to miss other relevant tweets. Fourth, our findings should not be generalized to all U.S. female and male users because this study is limited to one social media platform. Despite these limitations, this study provides novel insights into the topic priorities of female and male Twitter users during the 2020 U.S. election.

CONCLUSION

This study presented a novel approach of identifying the difference between female and male Twitter users regarding the weight of topics in tweets posted during the 2020 U.S. presidential election. We found topics representing a wide range of themes and disclosed that female and male users on Twitter had different priorities of discussions during the 2020 U.S. presidential election. This research highlights that social media can provide gender-based insights during political events. Our work can be used to further understand differences between social commentary of female and male users on social media. Researchers in information and social sciences could utilize our approach and findings to develop new hypotheses.

There are several future directions for future work to address the limitations of this study, such as including non-binary users, inferring the demographic information of users, and extending the queries. It would also be interesting to analyze non-English tweets, identify and compare social bots, and explore the change of topics across different locations and regions.

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