Do Female politicians receive more negative responses on social media?

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Abstract

Gender bias has created tremendous obstacles for females in their career development, including those in power. Previous research dived into traditional political campaigns to reveal the impact gender bias had on females running for office. This paper builds on these studies and examines if and how the impact exists in the era of social media. We performed sentiment analysis on 30,137 tweets from 10 politicians as well as 34,301 replies directed at them. Results showed that female politicians did receive more negative replies online and that their language style was significantly different from that of males. However, there was no causal relationship discovered. In studying gender bias on social media, we hoped to provide insights and directions for female politicians as they navigate the road to higher office.

Keywords: Gender Bias; Social Media; Politics; Sentiment Analysis

Word count: 4667

Do Female politicians receive more negative responses on social media?

After the 2020 vice presidential debate, Democratic nominee Kamala Harris was criticized of being “abrasive, condescending, and not likeable” (Fox News, 2020), although she has been careful enough to keep smiling and remain silent while her counterpart Mike Pence repeatedly interrupted her. This has again drawn attention to the heated topic of gender stereotypes in the political world. Numerous past research argued that gender stereotypes clearly affect female politicians running for office. Survey results suggested that the general belief in potential gender favorism among female politicians negatively impacted voters’ support for Hillary Clinton during the 2008 Presidential Primaries (Goldman, 2018) and that hostile sexism was a strong indicator of voting behavior against Clinton in the 2016 Presidential Election (Ratliff, Redford, Conway & Smith, 2019). In this digital era, the battlefield for political events have immensely shifted online. Common social platforms such as Twitter, Facebook, Instagram and YouTube were utilized by both the Clinton and Trump campaigns in 2016 (Enli, 2017). Therefore, it is becoming increasingly important to understand whether gender bias towards female political candidates also exists on social media. The goal of this study is to extend research on gender bias into the realm of social media and use statistical methods to detect and quantify this type of bias.

Looking in the long course of history, women were faced with tremendous obstacles in their pursuit of equal political representation. The first woman to run for the U.S. House of Representatives didn’t appear until 1866. Elizabeth Cady Stanton ran as an Independent although back then she didn’t even have the right to vote (Ginzberg, 2009). In fact, women were not granted full voting rights until 1920 (Darcy, Welch & Clark, 1994). A Congressional seat was finally taken by a woman in 1916. From there, more women joined the fight and increased their share of voice in the political world. However, until November 2020, women only make up of 24% of the U.S. Senate and 27% of the U.S. House of Representatives (Represent Women, 2020).

The entrance of women into the political realm brought with it new types of gender bias. Newspaper articles covering political races showed bias in two aspects: the amount of media coverage and the substance of media coverage (Kahn & Goldenburg, 1991). Newspaper coverage of 26 U.S. Senate races in 1984 and 1986 devoted an average of 12.9 paragraphs to male candidates each day while females got 10.5 (Kahn & Goldenburg, 1991). Similar pattern was observed during the 2004 Democratic presidential primaries when Bob Graham received 22 articles per newspaper per month on average while the number was only 8 for Carol Moseley Braun despite the fact that they had nearly the same advantage based on polling results (Falk, 2010). Besides underrepresentation in media, the substance of media coverage featuring female candidates was more focused on their viability and less on their issue positions (Kahn & Goldenburg, 1991). From Victoria Woodhull to Sarah Palin, pioneering female politicians had to endure greater degree of scrutiny for their eligibility to run as candidates (Finneman, 2015). Woodhull was portrayed as a laughingstock and lunatics. Patin was criticized of lacking political experience (Finneman, 2015). Other major focuses in the portrayals of women politicians from the 1870s to the 2000s were appearance, personal lives and personal traits while political actions were emphasized more often in those of their male opponents (Finneman, 2015).

Women's opportunity to run for office continues to be unquestionably limited. Sanbonmatsu in 2006 interviewed party leaders regarding the impact of candidate gender on their recruitment strategies. Many party leaders expressed concerns about female candidates' electability as they believe voters still evaluate candidates based on gender stereotypes to some extent. As a result, though party leaders will be open to female candidates who are well qualified, they wouldn't put more effort into recruiting them either (Sanbonmatsu, 2006). In other words, females need to prove themselves more eligible than males in order to be accepted.

This study built on research in traditional political campaigns and examined the topic under the influence of social media campaigning. Over the past few years, focus of political campaigns has shifted drastically from traditional media such as TV and Radio to social media. From 2012 to 2016 in the U.S., combining local, state, and nationwide election, campaign spending on digital media increased from 1.7% to 14.4% (Borrell Associates Inc., 2017). Today, many political candidates purchase banner ads on Twitter and Facebook during election. Video features are also largely utilized for promoting political campaigns with hyperlinks to drive traffic to website and collect audience emails (Bossetta, 2018). Public accounts of the political candidates are easily accessible by simply searching for their names (Bossetta, 2018). Candidates post about their political opinions, react to comments, share stories of personal lives, and even make policy announcements as was often done by former President Donald Trump. Social media campaigning enables larger scale of connectivity and interactivity between political candidates and audiences, thus shifting the way of political communication away from the old top-down model to a new horizontal model (Johansson, 2019).

An increasing number of young female activists have started using social media to connect with and support each other, to have political discussions and to organize events in the “real world” (Schuster, 2013). For instance, in 2015, a Twitter hashtag campaign “SayHerName” was launched in support of Black women victims of violence (Brown, et al, 2017). Activists shared names of victims as well as links to news articles and images on Twitter to appeal for public attention and action (Brown, et al, 2017). Approximately 2,090 tweets were posted on a daily basis under the hashtag between January and September 2016, with the highest record of 30,716 tweets on one single day (Brown, et al, 2017). Female activists highly valued the flexibility, accessibility and ability to reach large groups of people through social media (Schuster, 2013).

If traditional media coverage shows bias against female candidates, will the trend continue on social media? Some would argue that the bias is by all means reproduced on social media since we’ve seen various cases of sexualized female figures becoming a means of driving traffic among male users (Davis, 2018). The way social media uses images of women in advertising also cultivated an air of body shaming especially among young girls (Klein, 2013). The #A4waist challenge that went viral on social media was an example for body shaming and self-objectification. Women were encouraged to share pictures of them holding a piece of A4 paper to prove that the paper obscures their waists (BBC Trending, 2016). Although social media opened up space for women to share beautiful things in life, it also put them at risk of falling victim to male gaze (Davis, 2018).

Gender bias no social media serves as roadblocks for professional women as well. One study showed that female athletes are carefully balancing the traits of "athlete" and "feminine" in their self-representation on social media in fear of appearing too strong and challenging for the "maleness of sport" or too sexy and disqualifying as an athlete (Toffoletti & Thorpe, 2018). What's more, female game developer Zoe Quinn receiving death threats and sexual harassment on Twitter marked the start of the harassment campaign Gamergate against women in gaming (The New York Times, 2014). Multiple female game developers were then attacked on social media for being feminists and showing support for those victims (Business Insider, 2014). Male Internet users tend to form an alliance to chase women out of the areas which were traditionally dominated by men. They stigmatize women by attacking them based on gender-related factors, and thus discrediting their professional achievements.

Some researchers suggested that in the face of online malice, women tend to strategically engage in political behaviors that are less offensive and less visible (Bode, 2017). Women also see less strategic benefits from personalizing through social media while their male counterparts put more weight on showcasing their personal lives (McGregor, Laurence & Cardona, 2017) as typical masculine traits proved more beneficial to the hypothetical candidate than typical feminine traits (Huddy and Terkildsen, 1993).

With the increasing reliance on social media in political campaigns, it is essential to understand whether there is a difference in people's reaction towards political candidates of different gender in the digital world, and whether that difference is influencing the way the candidates choose their topics and tones.

One method commonly adopted by researchers to quantify gender bias is text analysis. In a study by Parkin and Mackenzie, they used a content analysis tool called Gender Bias 14 which is comprised of descriptors that reflect different aspects of genderness. The tool was then applied to the content of Key Stage 3 textbooks, revealing that 16 out of 18 chapters were highly male biases with more male images, male role-models, male pronouns and male-gendered words presented (Parkin & Mackenzie, 2017).

Text analysis can also facilitate the evaluation of audience sentiment or opinions towards an event, a person or a group. This type of opinion mining across social media is referred to as social media sentiment analysis. A basic form uses natural language processing techniques to extract binary sentiments on particular issues (Prichard, et el, 2015). Bae and Lee used sentiment analysis to identify positive and negative audiences of popular users on Twitter. They collected replies and retweets of 13 popular users in various societal areas, and classified sentiment based on a list of words that are pre-coded for polarity. A sentiment score of each tweet (the number of positive words divided by the number of negative words occurring in the text of a tweet) was then calculated to determine the overall sentiment (Bae & Lee, 2012).

This study sought to apply sentiment analysis to Twitter posts of political candidates and the replies directed at them. By doing so, we looked to explore how gender of political candidates impacted their interactions on social media, and addressed the below three research questions in particular:

RQ1. Do Female political candidates receive more negative responses on social media?

RQ2. Do Female political candidates tend to be less aggressive than Males when posting on social media?

RQ3. Does the negative responses Female political candidates receive on social media affect the tone/aggressiveness shown in their own posts?

Methods

With a quantitative methodology, the study included sentiment analysis and statistical testing. Sentiment analysis was used to quantify the reactions to politicians, as well as classifying the overall tone of tweets from the politicians. T-tests were used to compare linguistic variables from and about male versus female politicians.

Data

To control for the influence of political party, we only focused on the Democratic Party for this analysis. We selected top 5 politicians within each gender based on a Stacker article popularity ranking (Stacker, 2020), and excluded those who does not have a public Twitter account. The final list consisted of Elizabeth Warren, Nancy Pelosi, Hillary Clinton, Alexandria Ocasio-Cortez, Kamala Harris, Pete Buttigieg, Barack Obama, Bernie Sanders, Joe Biden and Bill Clinton.

Through Twitter API (Twitter Developer v2, 2020) and the Tweepy library in Python, we obtained two datasets. The first dataset contained tweets posted by the politicians, including their original tweets and retweets of other people's content. Due to Twitter api limitation, we could only get the most recent 3,200 tweets per politician. Dates for the tweets ranged from April 6, 2013 to February 22, 2021. Variables included user handle, text of the tweets, number of retweets received and number of likes. The second dataset included 3,200 replies to each of the politicians acquired through Twitter Search api. Only direct replies were kept for the analysis, replies to the replies were removed from the dataset. Variables included user handle of the politicians and text of the replies.

Feature

Since gender of the politician who posted the tweet was an important feature of this study, we introduced the Gender variable to both the tweets and replies dataset. The 5 female politicians posted 16,136 tweets and received 16,945 replies. Male politicians had 14,001 tweets with 17,356 replies.

Outcome

We used Python pre-defined classifier VADER to calculate sentiment for each of the replies. VADER assigned 3 separate scores for "Negative", "Postive" and "Neutral" sentiments based on all the words and symbols within each tweet. The scores added up to 1. Then it returned a "Compound" score that takes values from -1 to 1 after normalizing and summing the three scores (Pipis, 2020). The threshold we used for this analysis came from the developer notes: if compound score >= 0.05, sentiment is positive, if compound score <= -0.05, sentiment is negative, else neutral (vader-sentiment 3.2.1.1, 2019). Initial Statistics showed that Female had a mean of 0.06 (SD = 0.41) in terms of compound score, while male group had a higher mean of 0.08 (SD = 0.40).

Tone and language style of the politicians were also introduced to the tweets dataset using a text analysis application called Linguistic Inquiry and Word Count (LIWC). LIWC analyzes each word, punctuation, phrases and emoticons within a text file, compares them against its dictionary developed by a group of researchers and assigns them to pre-defined linguistic categories and dimensions (Pennebaker, Boyd, Jordan and Blackburn, 2015). Four summary variables (Analytical Thinking, Clout, Emotional Tone and Authenticity) were returned with standardized scores ranging from 0-100. The higher the score, the closer the language style is to the linguistic dimensions. Among the four, Analytical Thinking represents logical, formal and hierarchical thinking patterns; Clout indicates social status and confidence; Emotional Tone suggests positive tone with a score higher than 50 and a negative one with a score below 50; Authenticity reveals the degree to which people are honest or deceptive in words. (https://liwc.wpengine.com/interpreting-liwc-output/).

Data Analytic Plan

Before the analysis, we pre-processed the tweets dataset by removing html links and politician user screen names after the mention sign. We kept emoji symbols since they will also have an impact on the sentiment score. After deleting the records with empty text, 30,137 tweets from politicians and 34,301 replies remained.

To answer RQ1, an independent t test was conducted on the replies dataset. The difference in the means of the compound score between male and female politicians was tested for statistical significance in order to determine whether female politicians received more negative sentiment on social media. For RQ2, we examined mean and standard deviation for each LIWC summary variable. We then conducted t tests on the mean differences in scores between female and male politicians. Last but not least, for RQ3, we used correlation matrix to uncover the relationship between responses and politicians' tone and language style.

Results

Research Question 1

From basic stats, we learnt that both female and male politicians received mean compound scores greater than 0.05, which overall indicated positive sentiment. However, males' mean compound score did come in 0.02 higher than females'. Statistical significance was found in this difference, $t\ (34193) = -4.66$, $p < 0.001$. That said, replies to female politicians were less positive than that to their male counterparts.

We then grouped the replies into their corresponding sentiment groups. A reply with a compound score $>= 0.05$ was considered positive while a reply with a $<= -0.05$ score was

Table 1

Summary Statistics of Compound Score by Gender

Gender	Number of Replies	Compound Score Mean	Compound Score SD
Female	16,945	0.06	0.41
Male	17,356	0.08	0.40

negative. Anything in between was labeled neutral. The female group had 6% more negative replies, 7% less neutral replies and 2% less positive replies than the male group. Although the difference in the percentage of positive replies was similar between the two groups, females had notably more negative replies and less neutral replies, contributing to a lower mean compound score. Four female politicians, Hillary Clinton, Kamala Harris, Elizabeth Warren and Nancy Pelosi, all had a neutral mean sentiment. Only Alexandria Ocasio-Cortez received a positive sentiment with a mean compound score of 0.23. On the other hand, three out of five of the male politicians had positive sentiment, including Barack Obama, Bill Clinton and Pete Buttigieg. Bernie Sanders and Joe Biden each had a neutral sentiment.

Research Question 2

To answer RQ2, we performed sentiment analysis on the tweets dataset using LIWC. Four summary variables (Analytical Thinking, Clout, Emotional Tone and Authenticity) were examined for both genders.

A significant difference was found between male and female politicians for Analytical Thinking, $t\ (29313) = 8.60$, $p < 0.001$. Tweets from female politicians contained more formal, logical and hierarchical words than that from males. Female politicians tended to be less narrative in their language with a lighter focus on personal experiences.

Additionally, female politicians were generally less confident with a mean Clout score

Table 2

Compound Score and Sentiment by Politician

	Compound Score Mean	Sentiment
Female		
Alexandria Ocasio-Cortez	0.23	Positive
Kamala Harris	0.04	Neutral
Elizabeth Warren	0.02	Neutral
Hillary Clinton	0.00	Neutral
Nancy Pelosi	-0.02	Neutral
Male		
Pete Buttigieg	0.32	Positive
Barack Obama	0.17	Positive
Bill Clinton	0.06	Positive
Bernie Sanders	0.02	Neutral
Joe Biden	-0.01	Neutral

of 75.15. Although the mean Clout score for Males was only 1.55 higher, the difference was statistically significant, $t\ (29578) = -5.52$, $p < 0.001$. Results suggested that female politicians demonstrated less leadership and lower social status with their choice of words on social media. Sample low Clout score tweets included: “It’s okay I would’ve done the same”, and ’I’m so bummed about it… virtual hearings aren’t the same, I’m sorry." by Alexandria Ocasio-Cortez, as well as “Thanks, I’m fine. But everyone better vote.” by Hillary Clinton. Female politicians used words and phrases that are humbler and revealed less about their social status when expressing political opinions online.

Interestingly, when it came to Emotional Tone, female politicians went below the 50 threshold, suggesting a more negative emotional tone. Male politicians’ tone was more positive with a score of 54.89. A significant difference was also discovered here, t (29494) = -16.91, $p < 0.001$. Females used stronger and angrier words towards political issues. For example, Elizabeth Warren tweeted: "This makes me sick. Every eviction of struggling families is a failure by our government & the new CDC order isn't enough.". Another example by Kamala Harris went: "There are two systems of justice when stealing hedge clippers gets a Black man life in prison but the officers who murdered Breonna Taylor are still free."

Lastly, both female and male politicians scored low in Authenticity (31.25 for females and 36.79 for males). The difference was significant again, t (28827) = -14.14, $p < 0.001$. More words or phrases in the tweets from female politicians were considered "dishonest" and "deceptive" by the LIWC system.

In conclusion, female politicians did not necessarily show less aggressiveness in their political expression. They used words with more negative emotions but in a humbler and less condescending way.

Table 3

LIWC Summary Variable Statistics by Gender

	Analytical Thinking		Clout		Emotional Tone		Authenticity	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Female	75.48	28.15	75.15	24.41	47.30	38.74	31.25	32.65
Male	72.64	28.88	76.70	24.29	54.89	38.95	36.79	35.07

Research Question 3

Finally, we checked correlation between the compound score of replies and scores for the four summary variables on the tweets dataset. The mean of compound score received showed negative correlation with Analytical Thinking and Clout scores and positive correlation with Emotional Tone, Authenticity and gender. Tweets from male politicians that appeared more personal, humble, positive and authentic would likely gain higher sentiment score in replies, and vice versa. Nevertheless, none of the correlation between the compound score and the LIWC summary variables was significant ($p > 0.05$). We could not come to any conclusion that the negative responses female political candidates received on social media affected their tone or language style. Further analyses would be needed in order to drive more insights.

Table 4

Correlation Matrix

	1	2	3	4	5	6
1. Compound Score	-	-0.34	-0.14	0.17	0.34	0.27
2. Analytical Thinking	-0.34	-	-0.09	-0.07	-0.59	-0.19
3. Clout	-0.14	-0.09	-	0.59	0.60	0.33
4. Emotional Tone	0.17	-0.07	0.59	-	0.70*	0.57
5. Authenticity	0.34	-0.59	0.60	0.70*	-	0.65*
6. Gender	0.27	-0.19	0.33	0.57	0.65*	-

* Correlation is significant at the 0.05 level

Discussion

Summary of Results

The results suggested that gender bias does exist in the social media realm for female politicians. Females did, to some extent, experience gender discrimination when expressing feelings and leaving political remarks online. The analysis around RQ1 revealed that the average sentiment in replies the female politicians got were more negative than males. The number of negative replies females received outnumbered what males received while the number of neutral and positive replies were lower.

In terms of politicians' own sentiment and language style, female politicians were more analytical with a focus on political opinions instead of personal life. This finding was in line with the previous research done by McGrefor, Laurence & Cardona (2017) that women see less value in personalizing through social media than males. They also held more negative feelings when commenting on political issues but tended to express it in a less confident and condescending way. They did not show off or were less conscious about their social status during these social media communications.

However, there was no definite relation found between replies sentiment and politicians' tone and style. The negative replies female politicians received did not demonstrate importance in shaping or changing their communication style. This could imply that politicians developed their own language style due to gender and some other factors, and it remained rigid no matter how Twitter users responded to it.

Limitations

For this analysis, we were only taking into account 5 female and 5 male politicians, who also enjoy the greatest popularity and publicity in the Democratic Party. Focusing on those top political leaders could on one hand allow for a clearer and more obvious view on the impact of gender in politics. On the other hand, it could lead to less representative results of all politicians given that those 10 politicians all have their own strong personalities, unique experience and political views. Other factors such as age and race could also impact the sentiment of replies they received. We recommend expanding the analysis to include more target politicians and features.

Additionally, replies might not be representative of general population since we were only utilizing Twitter data within a short timeframe. There could be a certain pattern of sentiment in replies specific to this social platform that we haven't examined. Also, due to limitations on the Twitter API, we were only able to capture at most 3,200 latest tweets and replies respectively for each candidate. The replies dataset especially only contained posts during about a week, ranging from February 14, 2021 to February 22, 2021. This means that the replies were directed to only a few most recent posts in the tweets dataset, largely skewing the results. A potential improvement in future studies would be to include more social media platforms and posts generated during a wider range of time.

Future Directions

One important extension to the analysis would be to further dive into RQ3 and uncover the relationship between politicians' tone and the sentiment of the replies they receive. To collect sufficient data, we would first randomly select 100 tweets from each politician during the full range of the tweets dataset (2013 - 2021). Then we get 3,200 replies per tweet via the Twitter Search API by tweet id. Next, we need to compute mean compound score per day on the new replies dataset and mean scores per day for the four LIWC summary variables on the tweets dataset. Following that, we would be able to get five time-series for the trend of mean compound score, mean Analytical Thinking, Clout, Emotional Tone and Authenticity scores over time. We could run regression models on the time series to estimate if there's a linear relation between replies sentiment (compound score) and politicians' tone and language style. This method could provide more accurate results to RQ3, enabling us to better understand the impact of gender bias expressed through negative sentiment online.

Implications and Importance

The analysis on social media sentiment towards female politicians shed light on the current situation for women in politics. It provided support that gender bias was held against female politicians. We believed that it could help raise public awareness and caution of this issue, and inspire additional work to be done to fight against this type of discrimination.

Contradictory to what previous research showed, females did not necessarily show less aggressiveness upon political matters. Instead, they expressed stronger level of negative emotion than their male counterparts. It challenged our perception that females are generally more tender, mild and held back due to certain disciplinary power in the society and led to the display of prominent female voices in the political realm. Although we did observe a positive correlation between emotional tone and sentiment in replies, we did not see that significantly impact the way female politicians express their attitude. We hoped that findings in the correlation between style and sentiment could provide guidance for female politicians when balancing the need for self-expression and effective communication.

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