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A Leader and a Lady? A Computational Approach to Detection of Political Gender Stereotypes in Facebook User Comments

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Voters tend to perceive female and male politicians differently, viewing women in politics through the prism of existing gender stereotypes. Although social media have become one of the key platforms for political communication, little is known about stereotypes that social media users communicate about political candidates. This study investigates how gender influences citizens' evaluations of more than 500 U.S. politicians on social media. Drawing on a large sample of Facebook user comments (n = 13,866,507), we find that female politicians are discussed using traits describing women's personality and appearance. We also show that users associate female politicians with leadership, competence, and empathy. However, the results are different for highly prominent politicians. Specifically, our findings support the idea of leadership roles being more strongly linked to the masculine stereotype, as we observe that Donald Trump is more strongly associated with masculinity and traits relevant for a political career than Hillary Clinton.

Keywords: gender stereotypes, politicians, social media, Facebook, computational methods, word embeddings

Although the number of women participating in U.S. politics has been continuously growing over the past years, women remain largely underrepresented in all levels of elected office (Center for American Women and Politics [CAWP], 2021). Previous research suggests that progress on gender parity is often hindered by gender stereotypes. Namely, female candidates, unlike their male counterparts, are seen as lacking traits that are advantageous for a politician (e.g., aggressive, strong leader; Huddy & Terkildsen, 1993). As voters typically use stereotypes as shortcuts to form an impression about a candidate, their electability, political leanings, and leadership style (Hardy, 2017), stereotyping political actors based on their gender may significantly hinder electoral success of both female and male candidates (Sanbonmatsu & Dolan, 2009).

While experimental and survey research studying voters' candidate perceptions is vast, there is no clear agreement on whether female politicians are attributed stereotypical traits of women (e.g., Lawless, 2004), men (e.g., Dolan, 2010), successful political leaders (e.g., Fridkin & Kenney, 2009), or none of the above (Schneider & Bos, 2014). As social media platforms such as Facebook have recently emerged as an important

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and impactful source of political communication (Kosinski, Matz, Gosling, Popov, & Stillwell, 2015), scholars have begun using social media data to measure public opinion. Despite the increasing importance of social media for modern politics, only a handful of studies have investigated traits that citizens associate with female and male politicians (Hale & Grabe, 2018; Nee & De Maio, 2019; Oates, Gurevich, Walker, & Di Meco, 2019). Previous work on social media has mostly focused on analyzing images that typically exhibit explicit gender bias (Hale & Grabe, 2018; Nee & De Maio, 2019). However, implicit biases that users express in their comments through small differences in language often spread through social networking sites unnoticed, contributing to the perpetuation of discriminatory attitudes (Voigt, Jurgens, Prabhakaran, Jurafsky, & Tsvetkov, 2018). Furthermore, these studies typically analyze highly prominent politicians (e.g., Oates et al., 2019). Since higher leadership positions are more strongly associated with masculinity (Koenig, Eagly, Mitchell, & Ristikari, 2011), voters may be more biased against women in elite positions than against less prominent female politicians. Additionally, as some studies examine stereotypes against a limited set of politicians (e.g., Nee & De Maio, 2019), women, especially female Republicans, may be underrepresented in such samples. Most studies employing experiments and surveys may as well have a limited generalizability, as they often use fictional or hypothetic candidates (e.g., Banwart, 2010), providing little evidence of how citizens use gender stereotyping in evaluation of real-world politicians outside the highly controlled research settings (Hayes, 2011).

In the present study, we conduct a secondary analysis of an existing data set of Facebook user comments (Voigt et al., 2018) to examine which traits potential voters ascribe to politicians. To address the shortcomings of previous work, we create a large sample of more than 500 U.S. politicians serving on different levels of government. We use a novel computational approach (i.e., neural word embeddings) to accurately capture gender stereotypes in texts (Bolukbasi, Chang, Zou, Saligrama, & Kalai, 2016; Garg, Schiebinger, Jurafsky, & Zou, 2018). We connect the computational approach to previous experimental research on trait stereotypes (Schneider & Bos, 2014) by developing and validating a comprehensive list of words representing stereotypical traits. These materials, scripts, as well as an extensive online appendix are made available to foster future studies and ensure reproducibility of our work.[1]

Literature Review

Gender Stereotypes and Candidate Evaluations

Gender stereotypes may stem from conventional social roles and subsequent power inequalities between women and men (Eagly, 1987). Women are typically stereotyped as sensitive, warm, and caring, whereas men are expected to be strong, assertive, and self-reliant (Prentice & Carranza, 2002). Stereotypical masculine traits are thought to be more beneficial than feminine traits for holding national, state, as well as local offices (Rosenwasser & Dean, 1989). Citizens tend to believe that candidates who appear masculine are more competent politicians (Huddy & Terkildsen, 1993) and more effective at handling influential policy issues (e.g., economy and defense) than candidates possessing feminine qualities (Rosenwasser & Dean, 1989). As voters may perceive female candidates as possessing exclusively feminine traits (Bauer, 2015a), feminine stereotypes may fuel the assumption that women are not well suited for leadership positions.

[1] The online appendix can be found at https://osf.io/bhx8y/?view_only=a11c5551c3e142d3a26439f7cf9543fd.

Earlier research on whether female and male politicians are attributed different traits is inconclusive. On the one hand, several studies illustrate that voters are more likely to ascribe masculine traits to male politicians and feminine traits to female politicians (e.g., Lawless, 2004). Specifically, women in politics are seen as *warm*, *gentle*, *feminine*, *sensitive*, *emotional*, *talkative*, and *cautious*, whereas men are viewed as *assertive*, *coarse*, *tough*, *aggressive*, *stern*, *masculine*, *active*, *rational*, and *self-confident* (Banwart, 2010). On the other hand, more recent evidence suggests that gender stereotypes have little effect on candidate evaluations. Several studies illustrate that voters do not attribute female candidates' feminine qualities (Bauer, 2015b; Brooks, 2013; Dolan, 2014). It appears that individuals may not have a clear idea of what female politicians are or should be like, since some literature shows that political women are ascribed neither feminine nor masculine stereotypical traits (Schneider & Bos, 2014).

Female political figures may not be attributed traditional gender-linked traits, but they may still be seen as lacking qualities relevant to the job of a politician. These political traits are often studied as a four-dimensional concept that includes qualities of competence, leadership, integrity, and empathy (Kinder, 1986). Many traits describing political leadership and competence also occur in masculine stereotypes, whereas traits of empathy are present in feminine stereotypes. Some research suggests that citizens do not attribute female candidates positive political traits (e.g., *intelligent*, *strong leader*), but instead describe them negatively (e.g., *dictatorial*, *uptight*; Schneider & Bos, 2014). In contrast, Dolan (2010) finds that political women and men are equally likely to be seen by citizens as *assertive*, *consensus-building*, and *ambitious* (the traits of both leadership and masculine personality), but female candidates are assumed to be more *compassionate* (the trait of both empathy and feminine personality) than their male counterparts. Fridkin and Kenney (2009) even show that voters rate female politicians higher than male politicians on the traits *honest* (integrity), *caring* (empathy), *leadership*, and *experience* (competence).

Several studies indicate that similar trait stereotypes exist in evaluations of Democratic and Republican politicians. Citizens tend to perceive Republican candidates as *stronger leaders* (stereotypically masculine trait) and view their Democratic counterparts as being more *compassionate*, *caring* (traditional feminine traits), and *honest* (Fridkin & Kenney, 2009; Hayes, 2005). Some researchers suggest that gender stereotypes have a greater impact on voter attitudes than party (Sanbonmatsu & Dolan, 2009), while others find that party stereotypes are more influential than candidate gender (Hayes, 2011). However, politicians' gender is found to play the dominant role in candidate evaluation in the absence of party information (Hayes, 2011).

Gender Bias on Social Media

Much of the above-reviewed literature on voters' perception of female and male politicians relies on evaluations of hypothetical or fictional candidates in laboratory experiments (e.g., Huddy & Terkildsen, 1993) and surveys (e.g., Dolan, 2014). These highly controlled environments lack crucial cues of real-life political campaigns that may influence voters' evaluation of candidate traits (Hayes, 2011). Furthermore, participants in these conditions may produce socially desirable answers when reporting gender stereotypes (Schneider & Bos, 2014). Finally, these methods typically rely on relatively small samples, often consisting of students, that fail to represent the larger population (Kosinski et al., 2015). Recently, social media data have emerged as an alternative to the established methods offering an enormous potential for measuring social phenomena (Schober, Pasek, Guggenheim, Lampe, & Conrad, 2016). For studying the role of gender in voters' candidate

perceptions, social media data can, to some extent, address the above-mentioned limitations by examining citizens' opinions about real-world politicians expressed in casual political discussions on social media.

Social media have become crucial sources of political information, including political news and discussions. For instance, Facebook has been a platform for political communication since as early as the 2008 U.S. presidential election (Woolley, Limperos, & Oliver, 2010). During the 2016 U.S. presidential election, Facebook was used by about 70% of Americans (Pew Research Center, 2016) and may have played a decisive role in the outcome of the election (U.S. Senate Select Committee on Intelligence, 2019). Facebook and platforms alike enable direct communication between politicians and citizens, bypassing the traditional media (Douglas, Raine, Maruyama, Semaan, & Robertson, 2015). This interaction has a great potential to influence citizens' perception of politicians (Douglas et al., 2015). For instance, politicians actively engaging in discussions with social media users are perceived as more favorable by citizens (Utz, 2009). Since social media content may strongly influence beliefs of users presented with this content (Walther et al., 2010), social media users' opinions containing biased information about candidates can increase the bias of other online users (Hsueh, Yogeeswaran, & Malinen, 2015) changing their implicitly and explicitly expressed evaluations of politicians. For example, Lee and Lim (2014) show that citizens perceive a candidate more trustworthy if they are exposed to other users' positive comments about the candidate.

With regard to gender bias in social media, existing evidence indicates that users perceive political women and men differently. Facebook user comments addressed to female politicians often include traditionally domestic words (e.g., *husband*, *family*) but also terms related to strength (e.g., *force*; Field & Tsvektov, 2020). Wikipedia users tend to include more content on sex and marriage in their biographies of female public figures, including female politicians (Graells-Garrido, Lalmas, & Menczer, 2015). Reddit users are likely to describe female politicians in relation to their appearance or family and male politicians in terms of their profession and politics in general (Marjanovic, Stańczak, & Augenstein, 2022). Furthermore, Twitter users tend to use more personal than professional language when addressing female political figures in their tweets (Mertens, Pradel, Rozyjumayeva, & Wäckerle, 2019).

To our knowledge, only a handful of studies examined which stereotypical traits social media users ascribe to political actors. This research typically focuses on citizens' evaluations of presidential candidates, with a particular interest for the 2016 and 2020 U.S. presidential elections. The historic battle for presidency between the 2016 election's frontrunners, Hillary Clinton and Donald Trump, and the record number of women running for president in the 2020 election, make these races particularly suitable for studying gender dynamics in large-scale political campaigns. Exiting studies on this topic tend to agree that users of various social media platforms employ stereotypical traits when talking about politicians. During the 2016 election, Twitter users portrayed Hillary Clinton as lacking integrity (*dishonest*, *untrustworthy*) and possessing negative political traits (*dictatorial*, *unqualified*) and feminine physical (*unattractive*, *ill*) and personality traits (*weak*; Nee & De Maio, 2019). Hale and Grabe (2018) illustrate that Reddit users in the Trump subreddit (i.e., Trump supporters) perceived Clinton as lacking integrity (less *moral* and *honest*). They ascribed Trump positive traits of a political leader (more *competent*, *moral*, *honest*, *intelligent*, and *charismatic*), masculine personality (*strong*, *courageous*), and feminine qualities (*creative*). In contrast, users in the Clinton subreddit (i.e., Clinton supporters) perceived her as more *competent* than her opponent, whereas Trump was seen as more *courageous*, *strong*, and *charismatic* (Hale & Grabe, 2018). During the 2020 election, Twitter users were more likely to perceive female Democratic candidates as lacking integrity

(*dishonest*) and leadership traits (*weak leader*), whereas their male counterparts were seen as more electable politicians (*competent*, *strong leader*; Oates et al., 2019).

Present Study

Previous studies using traditional research designs are divided on whether citizens stereotype women as unlikely leaders (e.g., Banwart, 2010) or see them as capable politicians (e.g., Fridkin & Kenney, 2009). In contrast, studies using social media data provide more consistent findings indicating that users employ gender stereotypes when evaluating political candidates and perceive women as weak and untrustworthy leaders (e.g., Nee & De Maio, 2019; Oates et al., 2019). Although these two fields offer much valuable research into the role of gender stereotypes in citizens' candidate evaluations, they have a number of limitations.

First, studied samples of politicians are often limited in their generalizability and size. In studies based on traditional methods such as experiments and surveys, citizens are typically asked to ascribe traits to fictional or hypothetical candidates (e.g., Lawless, 2004) that may create an environment far from "the cacophony of real-world campaigns" (Hayes, 2011, p. 134). Studies on candidate trait evaluation by social media users typically focus on the analysis of high-profile politicians, such as presidential candidates (e.g., Oates et al., 2019). Since higher leadership positions are more strongly associated with the masculine stereotype (Koenig et al., 2011), women in elite positions may be subject to stronger stereotyping than less prominent female politicians. Furthermore, earlier studies often examine stereotypes against a limited set of politicians (e.g., Nee & De Maio, 2019) resulting in underrepresentation of women, especially Republicans. To address these issues, we create a large sample of real-world U.S. political figures that includes more than 500 politicians serving on different levels of U.S. government.

Second, studies using traditional methods are typically time-consuming, costly, and labor-intensive (Schober et al., 2016) and may introduce social desirability bias (Schneider & Bos, 2014). In contrast, social media data may provide more reliable candidate evaluations, as citizens are likely to express their opinions about politicians more freely in casual discussions on social media platforms than in highly controlled settings of experiments and surveys.

Third, the above-reviewed social media studies often focus on analyzing images (e.g., memes) that contain overt instances of gender bias (Nee & De Maio, 2019). However, biases exhibited implicitly through small and hardly noticeable differences in language may be passing through algorithmic filters of social media platforms and spreading to millions of online users (Voigt et al., 2018). Additionally, we find that, despite being one of the most influential social media platforms for political communication (e.g., U.S. Senate Select Committee on Intelligence, 2019), Facebook is rarely used to study political gender stereotypes. Therefore, in the present study, we conduct a secondary analysis of an open-access data set of Facebook user comments called RtGender (Voigt et al., 2018) using context-aware computational methods to identify gender stereotypes that potential voters on this platform hold against politicians. To examine the following research question (RQ), we differentiate between stereotypical gender-linked traits (feminine and masculine *personality*, *cognitive*, and *physical*; Huddy & Terkildsen, 1993) and political traits (*leadership*, *integrity*, *competence*, and *empathy*; Kinder, 1986):

RQ1: What kind of gender-linked and political traits do Facebook users associate with female and male politicians?

As similar trait stereotypes exist in evaluations of Democratic and Republican politicians (e.g., Hayes, 2011; Sanbonmatsu & Dolan, 2009), it is important to consider the role of both gender and party affiliation in trait ascription. Thus, in this study, we ask:

RQ2: Do gender and political affiliation of a politician predict her or his association with stereotypical gender-linked and political traits?

To ensure comparability of our findings with the exiting studies on online users' perceptions of political candidates (e.g., Hale & Grabe, 2018; Nee & De Maio, 2019), we investigate gender stereotypes against Hillary Clinton and Donald Trump. The selected politicians are particularly noteworthy given the timing of the RtGender data set (Voigt et al., 2018) used in this study. In addition, traits ascribed to political leaders may differ from those attributed to ordinary politicians (Koenig et al., 2011). Thus, we provide an additional analysis of stereotypes against prominent politicians:

RQ3: What gender-linked and political traits do Facebook users associate with the most prominent U.S. politicians?

Method

To answer the research questions, we obtained semantic information on relationships between words employing a computational text analysis method, namely neural word embeddings, on a large sample of Facebook user comments. We constructed word groups containing gender-linked traits (stereotypical feminine and masculine attributes) and political traits (qualities relevant to politicians' careers). Further, to investigate politicians' associations with the trait groups, cosine similarity was calculated between the vector of these trait groups and the vector representing a politician's name. Subsequently, we review these steps in more detail.

Sample

Social Media Data

In this study, we conducted a secondary analysis of an open-access data set from a large corpus called RtGender that was collected previously by Voigt et al. (2018). The data set contained 13,866,507 user responses to Facebook posts from 402 members of the 115th U.S. Congress who had a public Facebook page at the time of data collection. The employed data set consisted of user replies; the posts from the politicians were not included. The gender of each politician, their first and last names, and political affiliations were supplied. With respect to the users, no identifying information apart from their first names was provided in the data set.

Politicians

Since the social media data set focused on the replies to Facebook posts of 402 members of the 115th U.S. Congress, we added these political actors to our sample of politicians. As users may engage in political conversations on social media by discussing a broad range of political figures (e.g., a reply to a post from Rep. Roger Williams: "Go Trump/Pence! Keep up your great job!"), we extended the sample by adding politicians who were an essential part of the U.S. political debate at the time of data collection, namely the remaining Congressmembers (n = 154), members of the U.S. Cabinet (n = 30) who served between 2017

and 2018,[2] 2016 U.S. presidential election candidates (Donald Trump, Mike Pence, Hillary Clinton), and former U.S. president and vice president (Barack Obama and Joe Biden). Politicians who had less than 10 mentions in the corpus (n = 70) as well as nonpartisan politicians (n = 4) were removed from the sample. This resulted in the total of 516 politicians (103 women; 226 Democrats).

Text Preprocessing

We converted each word in the Facebook data set to lowercase letters and removed punctuations, numbers, hyperlinks, emojis, and special characters. We replaced various mentions of politicians in the texts (e.g., *Donald Trump*, *Donald J. Trump*, or *President Trump*) with the person's unique identifier (e.g., *donald_trump*; see Section Data Pre-Processing in the online Appendix B for more details).

Word Embeddings

Word embeddings, also referred to as context-predicting models, are unsupervised machine-learning techniques that represent a large amount of data as k-dimensional vectors of real numbers that capture semantic relationships or meanings of words (Jurafsky & Martin, 2009). The foundation of word embeddings is based on the distributional hypothesis (Firth, 1957) positing that words appearing in similar contexts tend to have semantic similarity. In this study, word2vec (Mikolov, Chen, Corrado, & Dean, 2013; Mikolov, Sutskever, Chen, Corrado, & Dean, 2013), specifically skip-gram model with negative sampling (SGNS), was used to calculate word embeddings because of its proven effectiveness in discovering gender stereotypes in textual data (Bolukbasi et al., 2016; Garg et al., 2018). The model predicts the context from the target word training a logistic regression classifier on a binary task (Jurafsky & Martin, 2009). For instance, the technique can accurately predict whether the probability of certain words (e.g., *competent*) appearing nearby the target word is higher for a male (e.g., *Donald Trump*) or a female (e.g., *Hillary Clinton*) politician. By looking at words that often appear in the same context as the target word, one can infer how similar two words, sentences, or documents are in a corpus. Word similarity is a concept in linguistics that emphasizes relations between words (Jurafsky & Martin, 2009) and is typically computed using the cosine similarity between two word embeddings. Similar words are mapped by word embeddings to nearby points in the vector space. Their vectors result in higher cosine similarity values than vectors of less similar words. Bias (in this example, gender bias) can be detected if similarity values between gender-neutral words (e.g., *competent*, *pretty*) and gender-specific words (e.g., *John*, *Mary*) are disproportionately higher for one gender than the other (e.g., *John* is closer to *competent*, while *Mary* is closer to *pretty*). In the present study, for a list of words representing different stereotypical gender-linked traits and political traits, we calculated how similar certain traits were with male and female politicians to detect stereotypes.

We used the Python implementation of the SGNS by Gensim (Řehůřek & Sojka, 2010). To yield meaningful results, the models' parameters were set to standard values recommended by earlier research (Levy, Goldberg, & Dagan, 2015; Mikolov, Chen et al., 2013; Mikolov, Sutskever et al., 2013). Three validated tests from previous studies, namely Word-Similarity 353 (Finkelstein et al., 2002), SimLex-999 (Hill, Reichart, &

[2] The dates are only approximations; Voigt and colleagues (2018) do not provide information on when the comments were published and collected.

Korhonen, 2015), and the analogy test from Mikolov, Chen et al. (2013), were employed for evaluation of our word vectors. In all three tests, human judgements on word relations are used to compare semantic similarity or analogical reasoning with word embeddings. Our word embeddings model performed relatively well on the similarity tasks (Word-Similarity 353 and SimLex-999) but demonstrated a less optimal performance on the analogy test. Rogers, Drozd, and Li (2017) note that many word vector models score under 30% on analogy tests, suggesting that this type of evaluation may not capture all relations between words. In general, results of such mainstream intrinsic evaluations should be interpreted with caution, since the performance of an unsupervised classifier is largely dependent on a specific goal (for more detailed overview of problems associated with word similarity evaluations, see Faruqui, Tsvetkov, Rastogi, & Dyer, 2016). We included the exact values and the discussion of the performance results in the online Appendix B, subsection Training and Evaluation.

Measures

To investigate gender stereotypes in the data set, the association strength between vectors representing each politician and various groups of gender-linked traits and political traits was calculated. These trait groups were developed and validated based on seed words derived from previous experimental research on the perception of politicians (Schneider & Bos, 2014). The categories of the gender-linked traits were comprised of adjectives describing personality, cognitive, and physical qualities of women and men. Political traits consisted of adjectives and a noun (*leader*) describing leadership, integrity, competence, and empathy attributes of a politician. To expand these lists, words with synonymous, near-synonymous, and similar adjectives were derived from the pretrained GloVe Twitter-200 (Pennington, Socher, & Manning, 2014) word vectors. As they were calculated using a large Twitter social media corpus, we assumed that language use in the Twitter data set and in the RtGender Facebook data set was similar. Top 10 words from the Twitter word vectors that were most similar to the character traits were then manually reviewed for each word in a group. To ensure that these words were indeed similar to our adjectives, a qualitative evaluation of the selected words was performed using an online data collection platform Prolific. The previously identified adjectives were presented to 20 native English speakers. They were asked to select words that are used interchangeably with the target adjective in informal communication. Only words chosen by 65% or more respondents were included for further analysis (see the complete list of traits in Table 1A of the online Appendix A).

Finally, the association strength between each politician and each trait group was computed using cosine similarity. To this aim, for each trait group, a mean vector was created by averaging all vectors that represented the respective attributes. Subsequently, the cosine similarity between the mean vector of a trait group and each politician was measured (see more details in the online Appendix B, subsection Association Strength). The resulting values were between –1 and 1, where higher scores indicated stronger associations. Further, when no means (*M*) and standard deviations (*SD*) are reported, the association strength is referred to as bias indicator, or *BI*.

Results

First, we report gender-linked traits and political traits that users associate with male and female political figures. For this purpose, we provide descriptive findings summarizing differences in trait associations between those groups. Second, to explore the relationship between politicians' gender and

political affiliation and traits, regression analyses were performed. Finally, we describe the associations of the selected prominent politicians with various traits.

RQ1: Gender-Linked and Political Traits Associated With Female and Male Politicians

For gender-linked traits (Figure 1), we observed that female politicians were associated more strongly with the typical masculine cognitive and personality traits (M = .118, SD = .05; M = .147, SD = .03, respectively) than with the same groups of feminine traits (M = .109, SD = .03; M = .14, SD = .02). They were more strongly associated with the stereotypical feminine physical traits than with the same group of masculine traits (M = .185, SD = .05; M = .129, SD = .03). Male politicians were more strongly associated with masculine cognitive and personality attributes (M = .129, SD = .05; M = .147, SD = .03) than with the same groups of feminine traits (M = .106, SD = .03; M = .137, SD = .02). However, male politicians were associated more strongly with physical attributes of women than men (M = .161, SD = .04; M = .129, SD = .03).

With respect to between-group differences in associations with gender-linked traits, we observed that female politicians were more strongly associated with feminine personality, cognitive, and physical traits (M = .14, SD = .02; M = .109, SD = .03; M = .185, SD = .05, respectively) than men (M = .134, SD = .02; M = .106, SD = .03; M = .161, SD = .04). Male politicians were more strongly associated with masculine cognitive traits (M = .129, SD = .05) than female politicians (M = .118, SD = .03). There was no difference in the association of women and men with masculine personality and physical traits (M = .147, SD = .03; M = .129, SD = .03, respectively for both women and men).

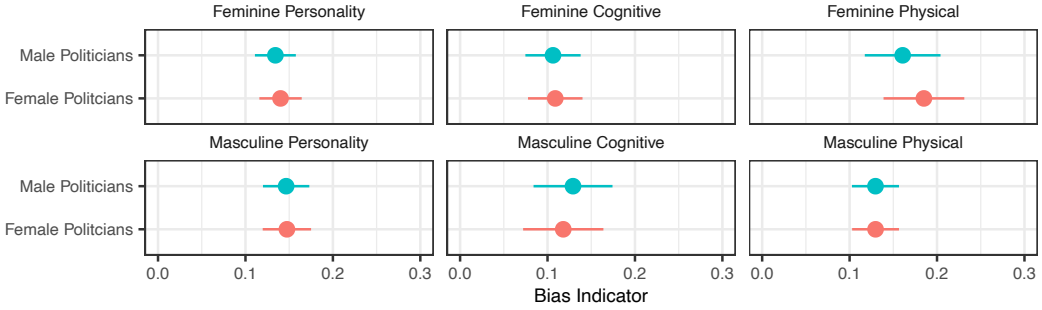

Figure 1. Differences between female and male politicians in their associations with gender-linked traits.

Note. Points represent the mean values of the bias indicator in the groups of female and male politicians for each group of gender-linked traits. Error bars around points represent standard errors.

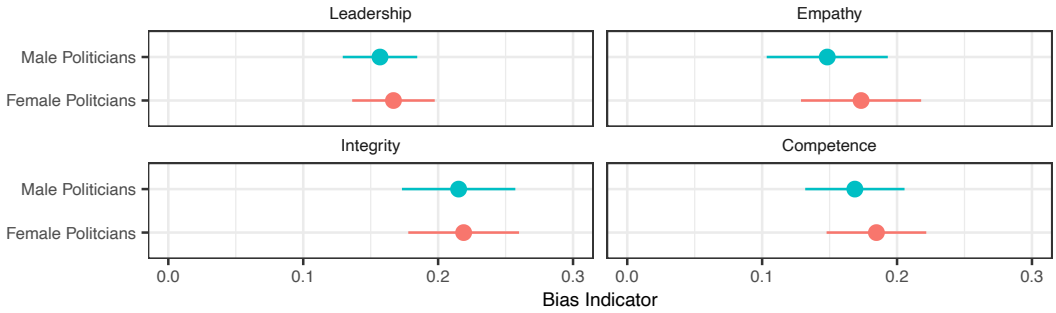

Figure 2. Differences between female and male politicians in their associations with political traits.

Note. Points represent the mean values of the bias indicator in the groups of female and male politicians for each group of political traits. Error bars around points represent standard errors.

For political traits, we found that female politicians were more strongly associated with leadership (women: M = .167, SD = .03, men: M = .157, SD = .03), competence (women: M = .185, SD = .04, men: M = .169, SD = .04), empathy (women: M = .173, SD = .05, men: M = .148, SD = .05), and integrity (women: M = .219, SD = .04 , men: M = .215, SD = .04) than men. Both female and male politicians were more strongly associated with integrity than with other political traits (Figure 2).

RQ2: Relationship Between Gender, Party, and Traits

Multivariate regression analyses were performed between the association strength scores for each trait group as the dependent variables and gender and party of politicians as independent variables. There was no significant interaction between the independent variables in the models, therefore, further we describe the models without interaction effects.

Examining the influence of gender and party on the strength of association of politicians with gender-linked traits, the models with the feminine physical and personality qualities as dependent variables were significant, with $F(2, 513) = 14.16$, $p < .001$ and $F(2, 513) = 3.41$, $p < .05$, respectively (see Table 1). Only gender added significantly to the models. The size and direction of the relationship between the variables indicate that female politicians are more likely to be associated with stereotypical traits describing women's appearance and personality.

With respect to the masculine traits, the models with the dependent variables represented by male-linked physical and personality attributes were statistically significant, with $F(2,513) = 16.68$, $p < .001$ and $F(2, 513) = 3.76$, $p < .05$, respectively. The effect of party, not gender, was significant. Democrats were less likely to be mentioned in the context of masculine personality and physical traits than Republicans (see regression coefficients in Table 2).

Table 1. Results of Multivariate Regression for Feminine Traits.

Variable	Feminine Personality		Feminine Cognitive		Feminine Physical	
	B	*SE*	*B*	*SE*	*B*	*SE*
Constant	.135***	.002	.105***	.002	.158***	.003
Gender (female)	.007*	.003	.002	.004	.022***	.005
Party (Democratic)	−.003	.002	.003	.003	.007	.004
R^2	.013		.003		.052	
Adjusted R^2	.009		−.001		.049	

Note. This table contains unstandardized beta coefficients (*B*) and standard errors (*SE*) for the presented unstandardized beta coefficients. *N* = 516.
*$p < .05$. **$p < .01$. ***$p < .001$.

For political traits, the models with the leadership, competence, and empathy traits as dependent variables were significant, with $F(2, 513) = 7.75$, $p < .001$, $F(2, 513) = 14.14$, $p < .001$, and $F(2, 513) = 38.9$, $p < .001$, respectively. Women politicians were slightly more likely to be described in terms of leadership attributes, empathy, and competence than male politicians. The direction and size of the relationship suggested that Democrats were more likely to be associated with these traits than Republicans. Finally, neither gender nor party had significantly contributed to the association of politicians with integrity traits (see more details in Table 3).

RQ3: Gender-Linked and Political Traits Associated With Prominent Politicians

To review stereotypes about prominent politicians (i.e., Hillary Clinton and Donald Trump), we provide a brief overview of their associations with gender-linked and political traits. The selected presidential candidates were also the most mentioned politicians in the comments.

Hillary Clinton was more strongly associated with cognitive and personality traits of men (*BI* = .117; *BI* = .187, respectively) than with same groups of feminine traits (*BI* = .068; *BI* = .135). She was more strongly linked to feminine appearance (*BI* = .151) than to male (*BI* = .113). With respect to the political traits, she scored higher on integrity (*BI* = .234) and leadership (*BI* = .195) and lower on competence (*BI* = .158) and empathy (*BI* = .129). Among the individual traits, *honest* (*BI* = .343), *honorable* (*BI* = .295), and *stunning* (*BI* = .317) had the strongest association with Clinton. Donald Trump was more strongly associated with masculine cognitive, personality, and physical traits (*BI* = .115; *BI* = .231; *BI* = .153, respectively) than with the same groups of feminine attributes (*BI* = .075; *BI* = .177; *BI* = .134). With political traits, Trump scored higher on integrity (*BI* = .266) and leadership (*BI* = .215) and lower on competence (*BI* = .18) and empathy (*BI* = .145). He was strongly associated with qualities *narcissistic* (*BI* = .437) and *egotistical* (*BI* = .374) but also *honest* (*BI* = .338). Comparing the bias scores provided above, we observed that, in general, Donald Trump appeared more masculine than Hillary Clinton (e.g., masculine personality: $BI_{\text{Trump}} = .231$; $BI_{\text{Clinton}} = .187$). He was also more strongly linked to the political traits than Clinton (e.g., integrity: $BI_{\text{Trump}} = .266$; $BI_{\text{Clinton}} = .234$).

Table 2. Results of Multivariate Regression for Masculine Traits.

Variable	Masculine Personality		Masculine Cognitive		Masculine Physical	
	B	*SE*	*B*	*SE*	*B*	*SE*
Constant	.149***	.002	.131***	.003	.135***	.002
Gender (female)	.003	.003	−.009	.005	.005	.003
Party (Democratic)	−.007**	.003	−.006	.004	−.014***	.002
R^2	.015		.013		.061	
Adjusted R^2	.011		.009		.057	

Note. This table contains unstandardized beta coefficients (*B*) and standard errors (*SE*) for the presented unstandardized beta coefficients. $N = 516$.
*$p < .05$. **$p < .01$. ***$p < .001$.

Discussion

In this exploratory study, we examined gender stereotypes against politicians in Facebook user comments. To answer our research questions, we used a large, open-access data set (Voigt et al., 2018) containing user responses to more than 500 U.S. politicians. We employed a novel computational technique, that is, neural word embeddings, to identify subtle instances of gender bias in the large data set. Based on our findings from more than 13 million Facebook comments, we conclude that citizens may still ascribe female politicians stereotypical traits. Nevertheless, users also associate women more strongly than men with competence, empathy, and leadership. Subsequently, we discuss our major findings.

Associations of Politicians With Gender-Linked Traits

Our descriptive analysis of gender-linked traits that Facebook users ascribe to politicians (RQ1) shows that women in politics are described in terms of feminine stereotypical traits slightly more than their male counterparts. Although these differences are small, we find that women are significantly more strongly associated with feminine personality and physical qualities than men (RQ2). This is consistent with studies using traditional research methods showing that voters rate female politicians as possessing feminine traits and male politicians as possessing masculine traits (Banwart, 2010; Lawless, 2004). Our findings are also in line with studies using social media data suggesting that users focus on the appearance and personal life of female politicians (Graells-Garrido et al., 2015; Marjanovic et al., 2022; Mertens et al., 2019). As politics are strongly linked to masculinity (e.g., Rosenwasser & Dean, 1989), the association with feminine qualities can be detrimental to a politician. More specifically, attention to physical appearance and personal qualities may harm women in politics, since it diminishes their professional achievements and credentials. For instance, Twitter users dubbed Wendy Davis, a Texas Democratic gubernatorial candidate and a proponent of legal abortion, "Abortion Barbie" turning the conversation about the important and sensitive issue of abortion rights into the discussion of the politician's appearance (McGregor & Mourão, 2016). Gender stereotyping is not exclusive to social media platforms, it also occurs in traditional media. Previous research shows that the traditional media pay considerable attention to women's appearance and personal traits irrelevant to the job. This coverage may reinforce existing gender stereotypes about female leaders as unlikely and less capable politicians (e.g., Heldman, Carroll, & Olson, 2005). How exactly such coverage affects social media discourse is an important question to resolve for future studies.

Table 3. Results of Multivariate Regression for Political Traits.

Variable	Leadership		Competence		Integrity		Empathy	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Constant	.165***	.002	.164***	.002	.214***	.003	.138***	.003
Gender (female)	.008**	.003	.012**	.004	.002	.005	.015**	.005
Party (Democratic)	.006*	.003	.012***	.003	.004	.004	.028***	.004
R^2	.029		.052		.003		.132	
Adjusted R^2	.026		.049		−.001		.128	

Note. This table contains unstandardized beta coefficients (*B*) and standard errors (*SE*) for the presented unstandardized beta coefficients.
N = 516. *p < .05. **p < .01. ***p < .001.

Our descriptive analysis detects no difference in the way Facebook users view female and male politicians in terms of masculine personality and physical traits. However, when within-group differences are analyzed (RQ1), women are more strongly associated with masculine than feminine personality and cognitive traits. These findings are confirmed by the regression analyses (RQ2) and are in line with some of the recent studies (e.g., Bauer, 2015b; Brooks, 2013; Dolan, 2014). The fact that women are as likely as men to be associated with masculine traits can be advantageous for their political career, since political leadership is closely aligned with masculinity (Koenig et al., 2011). Candidates who appear more masculine are perceived as more competent leaders (Huddy & Terkildsen, 1993) and more suited to handle influential policy issues (Rosenwasser & Dean, 1989). The fact that Facebook users view women and men in politics as somewhat equally masculine can be explained in part by the way politicians portray themselves in campaign messages. Female politicians stress masculine traits in their campaign communications (Schneider & Bos, 2014) knowing that voters favor female candidates who emphasize masculinity (Bauer, 2017). However, more work needs to be performed to establish whether and to which extent social media users rely on campaign messages in their evaluations of politicians.

As expected, male politicians are more strongly related to the typical cognitive and personality traits attributed to men than to the same groups of feminine traits (RQ1). Contrary to what one might expect, male politicians were associated more strongly with feminine, not masculine, physical traits. These findings are consistent with Schneider and Bos (2014), who find that male politicians lack physical masculine traits. Additionally, the group of feminine physical traits in our study includes adjectives, such as *beautiful* and *adorable*, commonly used in a wide range of contexts. Therefore, these adjectives may appear near the names of politicians, but they might not necessarily refer to politicians' appearance. This occurs because distributional semantic models use a context window to determine which neighboring words will be considered to learn relationships between words.

Associations of Politicians With Political Traits

Female politicians are also more strongly associated with leadership, competence, and empathy than their male counterparts (RQ1 and RQ2). Our results support the findings of Field and Tsvektov (2020), who conclude that social media users discuss female politicians in terms of their personal lives as well as their strengths and competences. As female candidates accentuate both feminine and masculine traits in

their communication with the electorate (Bauer, 2015a) and as masculine qualities overlap with political traits (Koenig et al., 2011), citizens exposed to women's balanced campaign messages may perceive female politicians as both leaders and ladies (Bauer, 2017). Our findings are also partly consistent with survey studies showing that voters evaluate female politicians higher than male politicians on leadership, competence (Fridkin & Kenney, 2009), and empathy (Dolan, 2010; Fridkin & Kenney, 2009). In contrast to Fridkin and Kenney (2009), we find no difference between political women and men in their association with integrity. We presume that the growing number of women in U.S. government (CAWP, 2021) might have sparked conversations about the role of women in modern politics. Additionally, the analyzed time period is linked to multiple scandals involving U.S. Congress and Cabinet members of that time. For instance, accusations of sexual misconduct against dozens of Congressmen between 2017 and 2018 (e.g., Brufke, 2018) might have given citizens a reason to question male leaders, whereas a long series of scandals during and after the 2016 U.S. presidential election (e.g., Donald Trump and Russia's meddling and Podesta e-mails revealing controversial information about Hillary Clinton) might have resulted in voters casting doubt on the integrity of female and male politicians.

Effect of Party on Trait Associations

We show that party plays an important role in trait attribution (RQ2). Republican politicians in our data set are viewed as more masculine that partially confirms the existing party stereotypes (Fridkin & Kenney, 2009; Hayes, 2005). Similar to Dolan (2014) and Hayes (2005), we find that Democrats are associated with empathy. However, in contrast to previous studies (Hayes, 2005), Democrats in our data set are also linked to stereotypical Republican traits of leadership and competence. This can be explained by the differences in partisanship of social media users, since studies show that Republican voters perceive Republican politicians as stronger and more competent leaders, while the same is true for Democratic voters and Democratic candidates (Fridkin & Kenney, 2009).

Associations of Prominent Politicians With Gender-Linked and Political Traits

To make our study more comparable with existing literature on trait attribution on social media, we analyze qualities ascribed to the 2016 U.S. presidential election's frontrunners (RQ3). We observe that Facebook users associate Donald Trump more strongly than Hillary Clinton with masculine and political qualities. This confirms previous findings in the literature (Hale & Grabe, 2018; Nee & De Maio, 2019; Oates et al., 2019) and supports the idea that leadership roles are tightly linked to the masculine stereotype (Koenig et al., 2011; Rosenwasser & Dean, 1989). These results are also consistent with the way candidates portrayed themselves in campaign messages (e.g., Clinton's attempt to maintain the image of a strong and experienced leader who focuses on feminine issues and Trump's display of hypermasculinity; Lee & Lim, 2016).

Limitations

Our research may have several limitations. First, our study does not consider whether discussions of politicians' traits are positive or negative. Knowing sentiment of online conversations can reveal how favorably social media users perceive candidates and their character. Thus, future studies should include sentiment analysis in their examination of gender stereotypes. Second, the data set employed in our study

lacks information on Facebook users' age, gender, and political leaning, one of the major determinants of stereotypes (Dolan, 2010). These factors may help to explain whether, for instance, Republican and Democratic social media users differ in their ascription of traits to politicians. This information is not available to us because of privacy concerns; however, future studies can build a machine-learning classifier that uses linguistic features to differentiate between conservative and liberal leaning users by following techniques of, for instance, Conover, Goncalves, Ratkiewicz, Flammini, and Menczer (2011). Next, the choice of hyperparameters used to control the learning process of neural word embeddings may greatly influence the resulting word vectors (Levy et al., 2015). Here, we followed previous literature using a default set of hyperparameters (e.g., Mikolov, Chen et al., 2013) when deriving word vectors. Future studies should experiment with various coefficients to determine optimal values for parameters to capture gender stereotypes in the political context. Finally, although the differences discovered here are rather small and the associations between politicians and traits are relatively weak, our method and values are comparable with previous research (e.g., see Garg et al., 2018). As an alternative method, future studies can first derive traits that have the strongest association with politicians and then cluster them into respective trait groups (e.g., see Kroon, Trilling, & Raats, 2020).

Conclusion

Our large-scale analysis of social media data provides a glimpse of how political candidates are characterized by potential voters on Facebook. The results are encouraging and add to a growing body of literature that demonstrates a positive trend in the perception of women in politics. Despite the limitations, the applied computational method is efficient and promising in identifying stereotypes in large and unstructured social media texts. Our findings suggest that social media data can serve as an additional source of information for journalists and researchers to capture the current state of public opinion and to better understand the political environment of the country under investigation. Moreover, social media data are especially relevant in the context of personalization and algorithmic curation, as they may contribute to the perpetuation of biases that already exist in our society.

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