Politeness and Posts: a Party and Gender-based analysis of Post Engagements Across a Dataset of US Legislator Tweets and Facebook Posts

Abstract

While there has been considerable sociological and linguistic investigation into the tone of posts on Online Social Networks (OSNs) such as Twitter or Facebook, the corpus has largely lacked scholarly insight into how politicians, particularly those in the United States, grapple with tone (civil and uncivil) in their own OSN posts. This study examines gender-based and party-based relationships between warmth, receptiveness, and polite/impolite language using the 3200 most recent tweets (N = 405,961 observations) — extracted using the Twitter API (Application Programming Interface) — and Facebook posts (N = 1,386,100 observations) — scraped using CrowdTangle — between 2018 and 2020 from official accounts of current US Congressional Legislators. The data suggests that while warm language helps favorites for male-identifying politicians garner more favorites, female-identifying politicians do not experience the same effect. Regarding party, the data suggest that Democrats receive more OSN engagement for 'warm' posts and Republicans receive more engagement from posts with negative emotion and disagreement. These findings and the data do indicate that US Politicians may garner more OSN engagement-metric (favorites, likes) success by doubling down on gender or party-related conventions and this study adds to the growing sociological field investigating OSNs, negativity bias, and politics.

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I. Introduction

American political dynamics have little escaped the influences of caustic language, vitriol, and incivility. In fact, previous research has suggested that candidate-organized political incivility — especially 'attack advertisements' — might even aid with popular appeal (Sonner, 1998). Certainly, much of the incivility pedagogy in the political arena has explored a decline in institutional trust from incivility in traditional settings such as congressional proceedings or televised debates (Mutz and Reeves, 2005; Antoci et al., 2016). In the digital age, though, candidate engagements with voters have donned a different hat: rather than the old-guard model of politician-to-citizen engagement, modern engagement on social media platforms and online social networks (OSNs) operates under a direct communication peer-to-peer model. As American institutions ebb and flow to adjust to the demands of the digital age, the incivility that marrs American politics has seemingly adjusted to the new medium(s). In fact, Kosmidis and Theocaris (2020) find how incivility on social media platforms can actually induce higher levels of positive emotion among exposed audiences. Considering the incorporation of OSNs like Twitter and Facebook in contemporary models of political engagement with audiences, actual analysis of civil/uncivil messaging from politicians is of particular interest to sociological study. More specifically, studying whether messaging among political figures yields different engagement results based on identity markers such as gender and party affiliation, would substantively add to the literature that exists in the confluence of OSNs, United States politics, and civility.

Nonetheless, systemic natural-language processing analysis of US politician social media posts, tweets, accounts, and messaging efforts has been limited. In fact, existing research has either investigated differences in messaging tactics based on gender and party affiliation or has considered how tonality might alter behavior when studying misinformation spread. Recent research from Bode et al. (2020) examines different behavioral outcomes in the uptake of misinformation correction but does not investigate differences in behavior based on the tone of the post, tweet, or message itself. Party and gender-based research on incivility has found differential instances in civility with certain ideological or gendered differences but has refrained from methodologically studying whether US politicians receive more engagement from amicable, warm language or uncivil language There is a critical gap in the literature surrounding the tone of OSN posts, US politics, and performance metrics such as likes and favorites in the context of Twitter and Facebook. This study will examine the relationships between engagements and the language used by US Politicians in a sampling of their most recent tweets and Facebook posts between 2018 - 2020, while specifically considering differences in results for politicians based on gender or party affiliation.

II. Definitions, Theoretical Motivations, and Literature Review

II. I Utilization of ‘Politeness’, ‘Warmth’, and ‘Receptiveness’ Definitions

There is understandably ambiguity surrounding the operating definitions of words such as ‘incivility’. While Pappacharissi (2004) and Gervais (2014) propose working conceptualizations of incivility as that which “threaten[s] a collective founded on democratic norms” or demonstrates a lack of respect respectively, neither study purely determines what ought to be the purest linguistic measure of civil/uncivil tone. Therefore, in an attempt to methodologically strengthen this analysis, I broaden the scope of language and use existing ‘R’ packaging on ‘politeness’, ‘warmth’, and ‘receptiveness’. To determine politeness, I turn to Yeomans et al. (2018) who base the ‘politeness’ R package off methods from computational linguistics that employ algorithms to determine politeness from a machine-learning model that weights the context and valence of the text itself. Although no ‘politeness dictionary’ exists in the package, *Fig. 1* illustrates an example feature_table from the package that highlights linguistic markers that said package would track.

Feature Name	POS Tags	Description	Example
Hello	No	"hi", "hello", "hey"	"Hi, how are you today?"
Goodbye	No	"goodbye", "bye", "see you later"	"That’s my best offer. Bye!"
Please Start	Yes	Please to start sentence	"Please let me know if that works"
Please	Both	Please mid-sentence	"Let me know if that works, please"
Gratitude	Both	"thank you", "i appreciate", etc.	"Thanks for your interest"
Apologies	Both	"sorry", "oops", "excuse me", etc.	"I’m sorry for being so blunt"
Formal Title	No	"sir", "madam", "mister", etc.	"Sir, that is quite an offer."
Informal Title	No	"buddy", "chief", "boss", etc.	"Dude, that is quite an offer."
Swearing	No	Vulgarity of all sorts	"The dang price is too high"
Subjunctive	No	Indirect request	"Could you lower the price?"
Indicative	No	Direct request	"Can you lower the price?"
Bare Command	Yes	Unconjugated verb to start sentence	"Lower the price for me"
Let Me Know	No	"let me know"	"Let me know if that works"
Affirmation	Yes	Direct agreement at start of sentence	"Cool, that works for me"
Conjunction Start	Yes	Begin sentence with conjunction	"And if that works for you"
Reasoning	No	Explicit reference to reasons	"I want to explain my offer price"
Reassurance	No	Minimizing other’s problems	"Don’t worry, we’re still on track"
Ask Agency	No	Request an action for self	"Let me step back for a minute"
Give Agency	No	Suggest an action for other	"I want to let you come out ahead"
Hedges	No	Indicators of uncertainty	"I might take the deal"
Actually	Both	Indicators of certainty	"This is definitely a good idea."
Positive	No	Positive emotion words	"that is a great deal"
Negative	No	Negative emotion words	"that is a bad deal"
Negation	No	Contradiction words	"This cannot be your best offer"
Questions	No	Question words to start sentence	"Why did you settle on that value?"
By The Way	No	"by the way"	"By the way, my old offer stands"
Adverbial Just	Yes	modifying a quantity with "just"	"It is just enough to be worth it"
Filler Pause	No	Filler words and verbal pauses	"That would be, um, fine"
For Me	No	"for me"	"It would be great for me"
For You	No	"for you"	"It would be great for you"
First Person Plural	No	First-person plural pronouns	"it’s a good deal for both of us"
First Person Single	Both	First-person singular mid-sentence	"It would benefit me, as well"
Second Person	Both	Second person mid-sentence	"It would benefit you, as well"
First Person Start	Yes	First-person singular to start sentence	"I would take that deal"
Second Person Start	Yes	Second-person to start sentence	"You should take that deal"
Impersonal Pronoun	No	Non-person referents	"That is a deal"

Fig. 1: *Sample of linguistic markers that the ‘politeness’ package in R tracks.*

Beyond ‘politeness’ itself, our analysis also integrated definitions of warmth and receptiveness to build in. Yeomans et al. (2020) discusses an interpretable machine learning algorithm designed to measure *conversational receptiveness* which they define as language that communicates "one's willingness to thoughtfully engage with opposing views." I base warmth off of Jeong et al. (2019) which created a natural language processing algorithm to metricize warm communication in text based upon existing computational mechanisms of looking at 'polite' and 'warm' text from Danescu-Niculescu-Mizil et al. (2013) and Voigt et al. (2017).

II. II Sociological Basis

A negativity bias or positive-negative asymmetry model is especially relevant for conducting this study. Rozin and Royzman (2001) and Baumeister et al. (2001) are credited for theorizing negativity bias as the psychological principle where bad instances are more causally efficacious than positive instances. Baumeister and Vohs (2007) further frame this idea by describing how in impression formation, people often place more weight on negative aspects than positive aspects. Essentially, some research indicates that negative behavior might stir more than well-intentioned positive behavior.

Placing this research in conversation with social media, tone, and politics, Bellovary et al. (2021) performed a sentiment analysis of 44 news-organization Twitter accounts (N = 140,358) and discerned that negativity was not only more present in the dataset, but also that negativity received more engagements overall. Critically, negativity, impolite language, and perhaps, incivility seemingly receive more engagement on an OSN like Twitter. Nevertheless, the domain literature of social media, language, and politics lacks an overarching study that:

1. Tracks engagement results utilizing natural-language processing R packaging with markers for polite/impolite language, warmth, and receptiveness
2. Measures said metrics with United States Congresspeople and their OSN posting(s) along with gender and party variance
3. Analyzes Twitter and Facebook data.

II. III Literature Consideration and Identified Gap

Regarding relevant literature in which to situate this analysis, I posit that there are a few important theoretical domains to consider before hypothesis construction. While I have discussed the relationship between performance and uncivil/impolite language in politics, both on OSNs and in other political contexts, I ought to discuss party and gender differences.

There is a rather robust body of literature that suggests that Republicans or conservatives are more predisposed to experiencing certain emotions compared to Democrats or liberals. Jost et al. (2003) proffer that conservatives are more fear-prone and disgust-sensitive than liberals. Brandt et al. (2014) and Chambers et al. (2013) both suggest that intolerance and prejudice are both closely related to modern conservative values; Jost et al. (2012) and Huber et al. (2015) go so far as to say that conservative/Republican ideology is associated with heightened defensiveness and threat sensitivity. However, a number of recent findings including Wang et. al (2021) have found that anger and fear-signaling tweets were likely to diffuse in Republican *and* Democratic networks. The conflict between literature suggesting that negative emotions are likely to amplify messaging in conservative/Republican networks and literature finding no distinct difference between negative emotion among liberal/Democratic and conservative/Republican networks suggests the need for further methodological study of engagements based on tweet content.

Beyond party, literature also confirms bias against female candidates in US political systems. Lombard et al. (2021) argue that the United States political ecosystem is rooted in masculine defaults, where hyper-competitive behavior, combative interactions, and an air of 'toughness' are the norm — traits that systematically disenfranchise female candidates. Perreta (2019) discusses a 'double bind' where female candidates in political systems often are expected to conform to their femininity while still displaying what is deemed masculine competence. Jones (2016) posits that female politicians sometimes behave as Hillary Clinton did between 1992 - 2013 where she imbued her political lexicon with more conventionally masculine words and structure; Huddy and Terkildsen (1993) found a preference among voters for male characteristics in higher office, where women were sometimes deemed less competent or not aggressive enough.

From this, a few theoretical foundations become clear. First of all, incivility and impolite language tend to outperform tame and polite language on OSNs. Second, there is conflicting literature surrounding whether impolite language amplifies engagements (in terms of quantifiable OSN post metrics like likes and favorites) for Republican candidates or whether Democratic candidates experience the same or different behavior. Third, a vast swath of literature contends that female politicians and candidates traditionally lean on masculine linguistic markers, which often are deemed less polite. Cumulatively, such a study that measures engagements in these contexts — and one that measures differences across Facebook and Twitter — is needed, where this study can be well situated.

II. IV Hypotheses

Concerning the analysis, I have several *a priori* hypotheses that necessitate experimental evaluation.

General

Hypothesis 1: I predict that generally, and without any subsetting or filtering, negative linguistic markers will result in more favorites/likes.

Party

Hypothesis 2: I predict that, when filtering by party, US Politicians in Congress who identify as Republicans will experience more favorites/likes when using impolite or negative linguistic markers.

Hypothesis 3: I predict that, when filtering by party, US Politicians in Congress who identify as Democrats will experience more favorites/likes when using warm, receptive, and polite linguistic markers.

Gender

Hypothesis 4: I predict that, when filtering by gender, US Politicians in Congress who are female-identifying will receive fewer engagements from warm, receptive, or polite language.

III. Methodology and Research Design

Here I describe the approach that I have followed to scrape data from Twitter and Facebook in order to perform our analysis in *Fig. 2*. The method is described more concretely in the data collection section of the methodology, but essentially, I perform merges of the dataset with US politicians and datasets of the scraped Twitter and Facebook data extracted using a Twitter API (Application Programming Interface) and CrowdTangle — both tools used for data scraping on their respective OSNs. These were merged in R, and then R packaging for 'politeness' with added variables for warmth and receptiveness facilitated the sentiment/regression analysis for the dataset(s).

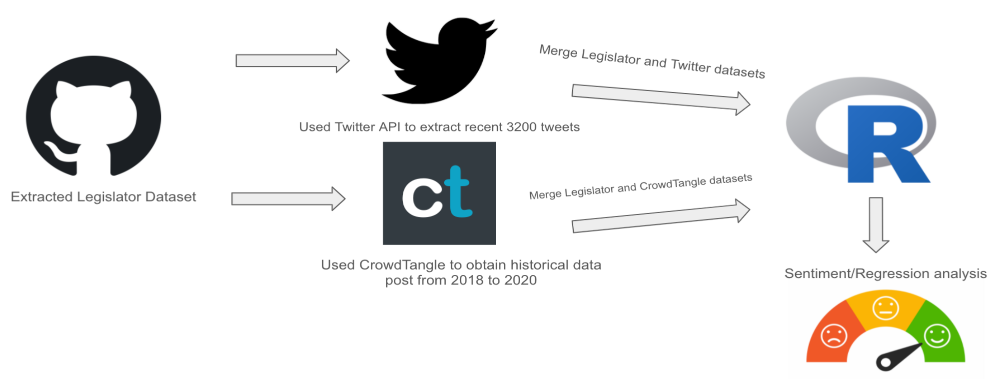

Fig. 2: *Methodological process of our analysis. Begins with finding the US Legislators dataset, using the Twitter API and CrowdTangle to pull recent tweets and historical posts, merging and preprocessing said data, and then piping this into RStudio for sentiment analysis via 'politeness' packaging and multiple linear regression models.*

III. I R Packaging

In order to discern relationships between engagements and natural language processed (NLP) linguistic markers of politeness, warmth, and receptiveness, I chose to analyze a selection of the most recent tweets by US Congressional Legislators and obtain a sample of posts from a relatively recent timeframe using CrowdTangle. Beyond this, to perform our politeness and sentiment analysis, I used a Twitter API and the ‘rtweet’ package, along with the CRAN ‘politeness’ package.

The warmth variable was added to the ‘politeness’ package and was created using the code from the CRAN documentation where a classifier was trained to identify differences between “warm and friendly” or “tough and firm” communication styles based on experimental differences. The trained classifier’s understanding of the linguistic differences between the two communication styles helped us create the warmth variable which I added to the ‘politeness’ package.

The receptiveness variable is based on the linguistic model created by Yeomans et al. (2020) that employed the ‘politeness’ package due to overlap between the existing NLP models built into the package.

Such ‘R’ packaging is of common practice in sentiment analysis NLP investigations such as the one completed in this study. Li et al. (2021) used the 36 linguistic markers built into the ‘politeness’ package to analyze instances of politeness in a dataset of 3.5 million tweets from the Sleeping Giants movement, for example. While some computational social science research uses the ‘sentimentR’ to work through sentiment NLP, so long as other studies have effectively used the ‘politeness’ package, it makes little difference for methodological purposes.

III. II Data Collection

Congress
In this observational research study, the initial data of the US Legislators from obtained from a Github repository that keeps an up-to-date YAML of US Congressional Legislators from 1789 - Present. This repository contains a .csv called legislators-current that features updated documentation of the currently serving members of the US Congress as updated by manual edits from volunteers and automated edits from GovTrack. This dataset was critical towards the conduct of this observational study as it featured the Twitter username/handle and Facebook Account username/handle of US Congressional Legislators. In order to verify the veracity of includes handles in legislators-current, I manually checked the official Twitter accounts and official Facebook accounts with the entries in legislators-current; if there appeared to be a lapse

in the data or the inability to verify with the official account, the campaign account was utilized in its place.

Twitter

The Twitter data was obtained via a Twitter API. Once the legislators-current dataset was adequately mapped out and inserted into RStudio, I used the ‘rtweet’ package and the get_timeline function to obtain the last 3,200 tweets from each legislator and their associated Twitter handle.

Facebook

The Facebook data was scraped via CrowdTangle, a media monitoring tool owned by Facebook/Meta that helps measure engagements and overperformance. With this tool, I tracked historical data from 2018 - 2020 of posts and measured engagement metrics such as likes, shares, reactions (angry, love, etc.) for US Legislator accounts.

Merge Operations

With all this data extracted, I opted to merge the datasets in order to perform OSN analysis with the US Legislator accounts and other details about the Legislator in one combined dataset. Prior to joining/merging datasets, I preprocessed the usernames in the Twitter and Facebook datasets to make sure all the usernames and account names were lowercase to avoid any joining errors. I opted to merge with a left_join function for Twitter and Facebook respectively. For our Twitter dataset, in which I combined the most recent 3,200 scraped tweets and identifying information about the Legislator, I obtained 405,961 observations. The Facebook dataset merge was slightly more intensive. While CrowdTangle had a built-in dataset of US Politicians that I used to obtain historical data, I created a facebook_correct column that inserted the manually verified official Facebook Page usernames and then used a left_join function to merge the datasets. This completed dataset featured 1,386,100 observations.

The only other operations conducted were filters where I subsetted the merged Twitter dataset and the merged Facebook datasets by party and by gender. This allowed for the unique analysis of regression results for Republican US Legislators, Democratic US Legislators, female-identifying US Legislators, and male-identifying US Legislators.

This is standard practice for sentiment analysis as most studies in the practice either have unstructured data that requires analysis or data that requires cleaning and processing before it can be inputted into machine-learning, NLP, or sentiment analysis models. For basis in literature, Sharma and Ghose (2020) discuss issues with data acquisition from online sources and the need to clean for their analysis of sentiment surrounding Indian general elections while Flores-Ruiz and Elizondo-Salto (2021) discuss data preprocessing and processing in their tourist sentiment analysis of Andalusian visitors during the COVID-19 pandemic. Sentiment analysis, whether conducted on tweets or raw text data, often requires merges and processing to ensure that the data can be appropriately analyzed.

III. III Modeling

The quantitative analysis that I employ features a variety of multiple linear regression models for the general Twitter and Facebook merged datasets, along with smaller subsetted datasets of female/male-identifying legislators, and Republican/Democratic legislators. The advantage of using ordinary least squares (OLS) models such as those I employ in this study are interpretable results. For the sake of this analysis, the relationships between certain linguistic markers of politeness/impoliteness and OSN post engagements are to be measured. The goal of the analysis is to determine which linguistic markers are likely to lead to positive and negative engagements such as likes or favorites, and utilizing OLS multiple linear regression models are effective ways of determining what linguistic markers lead to high/low performance. Attention will be devoted towards statistically significant results along with positive/negative estimation(s) for designated linguistic markers.

Example model formulation appears as follows:

$$E_f = \beta_0 \; + \; \beta_1 * warmth \; + \; \beta_2 * receptiveness \; + \; \beta_3 * numberofhashtags$$
$$+ \; \beta_4 * gender \; + \; \beta_5 * followercount \; + \; \beta_6 * friendscount \; + \; \beta_7 * verified$$

For the above model, E_f represents total engagements specifically tracking favorites. The β_0 represents the intercept of the model or how many favorites a post is predicted to receive when all other tracked input variables are zero. The other β values are representative of what a traditional x-value would be in a linear model multiplied by a relevant input variable.

While the above model highlights what an example would look like if measuring the favorites on Twitter with ‘politeness’ package variables, the following models are what I considered in our analysis generally, in regards to party affiliation, and in regards to gender.

Fig. 3: *Mathematical models to be used generally, by party, and by gender.*

Template Twitter Favorites Model

$$E_f = \beta_0 + \beta_1 {*} warmth + \beta_2 {*} receptiveness + \beta_3 {*} positiveEmotion + \beta_4 {*} disagreement$$

$$+\ \beta_5 * agreement\ +\ \beta_6 * negativeEmotion\ +\ \beta_7 * followerCount\ +\ \beta_8 * verified$$

Template Facebook Likes Model

$$E_l = \beta_0 + \beta_1 {*} warmth + \beta_2 {*} receptiveness + \beta_3 {*} positiveEmotion + \beta_4 {*} negativeEmotion$$

$$+\ \beta_5 * likesAtPosting\ +\ \beta_6 * followersAtPosting$$

While these models might seem complex, in reality, our analysis simply tracks a few key factors. First and foremost, differences in favorites and likes are tracked with the Twitter dataset and the Facebook dataset. Secondarily, differences in favorites for Republicans and Democratic US Politicians are tracked on Twitter and Facebook. Lastly, differences in favorites and likes are tracked for female-identifying and male-identifying politicians are tracked across Twitter and Facebook.

I used statistical methods in order to guarantee valid results in the model. These include the exclusion of certain variables if those same variables are being used to subset data frames. This might include the exclusion of a gender variable in the regression (the final model did not end up using gender as one of the input variables) if that same variable was being used to filter the original data frame in some way. I also kept track of r-squared values and residual standard errors in order to measure results.

IV. Results

There are several different results that I obtained from our sentiment/regression analysis, so I will discuss these based upon the overarching theme (general results, party results, or gender results.

General

Fig. 4: *Twitter (Favorites) Model*

```
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)     -9.571e+01  1.997e+02  -0.479  0.63173    
warmth           3.497e+02  1.114e+02   3.138  0.00170 ** 
receptiveness   -2.009e+02  7.247e+01  -2.772  0.00558 ** 
Positive.Emotion -2.701e+01  9.894e+00  -2.730  0.00633 ** 
Disagreement     4.163e+02  1.474e+02   2.825  0.00473 ** 
Agreement        9.628e+00  1.343e+02   0.072  0.94286    
Negative.Emotion  8.244e+01  9.678e+00   8.519  < 2e-16 ***
followers_count  1.335e-03  1.276e-05 104.651  < 2e-16 ***
verifiedTRUE     1.050e+02  1.985e+02   0.529  0.59670    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The data suggest some key important takeaways. First and foremost, given that asterisks are indicative of significance level, it seems as if the most statistically significant relationships in this regression table are the predictions for Negative.Emotion and followers_count. Considering that both of their estimates are positive, the data suggest that the aforementioned two variables are the two variables that our multiple linear regression suggest most significantly improve predicted favorites on Twitter. Beyond this, Positive.Emotion, receptiveness, Disagreement, and warmth all retain some statistical significance in their prediction models, with warmth and Disagreement increasing the amount of predicted favorites on Twitter for US Politicians and receptiveness and Positive.Emotion decreasing them. Without a grand overstatement of what these results might indicate, there are clear takeaways that certain ‘polite’ attributes like warmth increase Twitter favorite predictions while other ‘polite’ indicators like receptiveness, Agreement, and Positive.Emotion either increase favorites by statistically insignificant amounts or cause a decrease, while Negative.Emotion and how many followers a Twitter account has are the main drivers of favorite engagements.

Fig. 5: *Facebook (Likes) Model*

```
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)          9.548e+01  4.052e+01   2.356   0.0185 *  
warmth              -1.528e+02  8.970e+01  -1.703   0.0885 .  
receptiveness       -3.074e+00  9.417e+01  -0.033   0.9740    
genderM              3.957e+01  3.088e+01   1.281   0.2000    
Positive.Emotion    -3.218e+00  7.443e+00  -0.432   0.6655    
Negative.Emotion     1.199e+01  7.075e+00   1.694   0.0902 .  
Likes.at.Posting    -8.890e-03  2.789e-04 -31.872   <2e-16 ***
Followers.at.Posting 9.905e-03  2.749e-04  36.030   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The data suggest a different outcome here; while in the Twitter model for favorites, it seemed as if there were some ‘impolite’ linguistic markers that led to increased favorites. In this model, it appears as if while warmth may increase likes, its statistical significance is marginal compared to the relationships between Likes.at.Posting and Followers.at.Posting which are variables that represent how many Likes that corresponding Facebook page associated with a Legislator the page has at Posting and how many Followers that Page has at posting respectively. Seemingly, the strongest (most statistically significant indicator of more Likes is Followers.at.Posting. We can consider Hypothesis 1 here; the outcome is mixed. Although the inclusion of Negative Emotion and Disagreement are likely to increase engagements, warmth in tweets and followers/followers at posting tend to have positive relationships with engagements. The data do suggest that negative emotion, disagreement, and warmth ought to spur engagement on Twitter — perhaps due to Twitter’s overall negative ecosystem, negative posts work and warm posts, which seem as refreshing, also work — in Facebook, the strength of one’s page is still paramount.

Party

Fig. 6: *Twitter (Favorites) Republican Model*

```
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)     -1.568e+01  1.283e+02  -0.122 0.902724    
warmth          -7.518e+01  1.047e+02  -0.718 0.472777    
receptiveness   -2.734e+01  6.710e+01  -0.407 0.683686    
Positive.Emotion -1.272e+01  9.289e+00  -1.369 0.171051    
Disagreement     4.878e+02  1.367e+02   3.569 0.000358 ***
Agreement        2.627e+01  1.159e+02   0.227 0.820680    
Negative.Emotion  5.195e+01  9.334e+00   5.565 2.63e-08 ***
followers_count   2.265e-03  2.532e-05  89.429  < 2e-16 ***
verifiedTRUE      3.064e+00  1.266e+02   0.024 0.980699    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Fig. 7: *Twitter (Favorites) Democratic Model*

```
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)     -1.194e+02  7.274e+02  -0.164 0.869649    
warmth           6.402e+02  1.735e+02   3.691 0.000224 ***
receptiveness   -1.567e+02  1.136e+02  -1.380 0.167585    
Positive.Emotion -3.737e+01  1.548e+01  -2.414 0.015791 *  
Disagreement     4.298e+02  2.328e+02   1.846 0.064870 .  
Agreement       -9.766e+00  2.248e+02  -0.043 0.965352    
Negative.Emotion  1.003e+02  1.482e+01   6.763 1.36e-11 ***
followers_count   1.593e-03  2.287e-05  69.640  < 2e-16 ***
verifiedTRUE      7.112e+01  7.267e+02   0.098 0.922043    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The Twitter data suggests fascinating findings. Based on this regression, it appears as if there are statistically significant relationships between favorites on Twitter for US Politicians that identify as Republican when they have Disagreement, Negative.Emotion, or have significant followers. Democrats appear to be able to gain Favorites when they have Negative.Emotion as well or when the Legislators have a high followers_count; however, contrary to the Republican regression, Democrats appear to receive more Favorites at the highest level of statistical significance when they include warmth in their Tweets.

Fig. 8: *Facebook (Likes) Republican Model*

```
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)          2.611e+02  5.799e+01   4.502 6.77e-06 ***
warmth              -1.987e+02  1.497e+02  -1.327    0.184    
receptiveness       -2.243e+00  1.583e+02  -0.014    0.989    
Positive.Emotion    -9.065e+00  1.203e+01  -0.754    0.451    
Negative.Emotion     1.087e+01  1.203e+01   0.903    0.366    
Likes.at.Posting     1.537e-02  7.431e-04  20.682  < 2e-16 ***
Followers.at.Posting -7.766e-03  6.065e-04 -12.806  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Fig. 9: *Facebook (Likes) Democratic Model*

```
Coefficients:
                       Estimate Std. Error t value Pr(>|t|)    
(Intercept)           1.009e+02  2.649e+01   3.809  0.00014 ***
warmth               -1.545e+02  7.084e+01  -2.181  0.02916 *  
receptiveness         1.514e+02  7.347e+01   2.060  0.03940 *  
Positive.Emotion      1.031e+01  6.051e+00   1.704  0.08834 .  
Negative.Emotion      1.036e+01  5.477e+00   1.891  0.05862 .  
Likes.at.Posting     -2.528e-03  3.086e-04  -8.191 2.73e-16 ***
Followers.at.Posting  4.323e-03  2.894e-04  14.935  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The data is less telling with the Facebook models. Similar to the general results, it appears as if there are statistically significant relationships between Followers.at.Posting and Likes.at.Posting for both. However, while the initial Likes.at.Posting of the page indicates that an increase is likely to lead to fewer Likes for Democrats, an increase of Likes.at.Posting leads to more likes for Republicans. Similarly, while Followers.at.Posting is statistically significant, it leads to more Likes for Democratic account pages and fewer likes for Republican account Pages. Besides that, there are minimal statistically significant relationships for warmth and receptiveness in the Democratic model, which suggests that receptiveness could lead to more likes.

With this data, I can explore Hypothesis 2 and Hypothesis 3; the data do suggest that Republicans receive more engagements (particularly Favorites) when they use negative emotion and disagreement while Democrats — despite also receiving more favorites from negative emotion, which could speak to the nature of Twitter as a platform — tend to receive positive engagement predictions from the inclusion of warmth in Twitter and, albeit minimally significant, receptiveness in Facebook.

Gender

Fig. 10: *Twitter (Favorites) Female Model*

```
Coefficients: (1 not defined because of singularities)
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      2.016e+02  7.995e+01   2.521   0.0117 *
warmth           1.320e+02  2.927e+02   0.451   0.6521
receptiveness    1.485e+02  1.881e+02   0.789   0.4298
Positive.Emotion -5.094e+01  2.590e+01  -1.967   0.0492 *
Disagreement     4.455e+02  4.285e+02   1.040   0.2986
Agreement       -2.105e+02  3.786e+02  -0.556   0.5782
Negative.Emotion  1.075e+02  2.513e+01   4.277  1.9e-05 ***
followers_count   1.145e-03  2.947e-05  38.865  < 2e-16 ***
friends_count    -5.431e-03  4.297e-03  -1.264   0.2063
verifiedTRUE            NA         NA      NA       NA
---
```

Fig. 11: *Twitter (Favorites) Male Model*

```
Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     -1.455e+02  1.622e+02  -0.897  0.36963
warmth           4.217e+02  1.061e+02   3.973 7.11e-05 ***
receptiveness   -3.342e+02  6.932e+01  -4.822 1.43e-06 ***
Positive.Emotion -1.643e+01  9.444e+00  -1.740  0.08185 .
Disagreement     4.062e+02  1.356e+02   2.995  0.00275 **
Agreement        8.248e+01  1.248e+02   0.661  0.50878
Negative.Emotion  7.218e+01  9.260e+00   7.795 6.51e-15 ***
followers_count   1.440e-03  1.311e-05 109.848  < 2e-16 ***
friends_count     6.888e-04  3.650e-03   0.189  0.85034
verifiedTRUE      8.684e+01  1.609e+02   0.540  0.58942
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

This Twitter data highlights that while female-identifying and male-identifying US Legislators experience statistically significant engagement bumps from instances of negative emotion and higher follower counts, male candidates are heavily rewarded for warmth and heavily hurt for receptiveness in terms of engagements. Importantly, this Twitter data highlights how male-identifying candidates have a far stronger relationship between favorites and warmth than female candidates.

Fig. 12: *Facebook (Likes) Female Model*

```
Coefficients:
                       Estimate Std. Error t value Pr(>|t|)    
(Intercept)           1.541e+02  5.417e+01   2.845  0.00444 ** 
warmth               -1.878e+02  1.433e+02  -1.310  0.19018    
receptiveness         2.098e+02  1.544e+02   1.359  0.17406    
Positive.Emotion      6.213e+00  1.194e+01   0.520  0.60292    
Negative.Emotion     -5.147e-01  1.154e+01  -0.045  0.96444    
Likes.at.Posting     -3.458e-03  6.685e-04  -5.172 2.35e-07 ***
Followers.at.Posting  5.182e-03  6.348e-04   8.162 3.67e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Fig. 13: *Facebook (Likes) Male Model*

```
Coefficients:
                       Estimate Std. Error t value Pr(>|t|)    
(Intercept)           1.284e+02  4.176e+01   3.074  0.00211 ** 
warmth               -1.501e+02  1.094e+02  -1.372  0.17005    
receptiveness        -7.519e+01  1.139e+02  -0.660  0.50921    
Positive.Emotion     -4.825e+00  9.064e+00  -0.532  0.59452    
Negative.Emotion      1.365e+01  8.575e+00   1.592  0.11144    
Likes.at.Posting     -8.960e-03  3.219e-04 -27.832  < 2e-16 ***
Followers.at.Posting  9.940e-03  3.182e-04  31.237  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The overall Facebook data is not particularly revealing. While the statistically significant relationships between Likes.at.Posting (-) and Followers.at.Posting remain (+), no other variables appear to have statistically significant outcomes. With this, I can evaluate Hypothesis 4: based on the Twitter data, it appears as if there is a less strong relationship between Favorites and warmth for female-identifying candidates than for male-identifying candidates. This might speak to the previously mentioned research of female-identifying candidates facing pressure to conform to masculine standards in US Politicians.

Twitter (General)	Favorites (Est)	Significance
Negative.Emotion	8.244 * 10^01	***
followers_count	1.335*10^03	***
Twitter (Republican)		
Disagreemeent	4.878*10^02	***
Negative.Emotion	5.195*10^01	***
followers_count	2.265*10^-3	***
Twitter (Democrat)		
Warmth	6.402*10^02	***
Negative.Emotion	1.003*10^02	***
followers_count	1.593*10^-03	***
Twitter (Female)		
Negative.Emotion	1.075*10^02	***
followers_count	-5.431*10^-03	***
Twitter (Male)		
Warmth	4.217*10^02	***
Receptiveness	-3.342*10^02	***
Negative.Emotion	7.218*10^01	***
followers_count	1.440*10^-03	***

Fig. 14: *Since Facebook produced less variance in statistical significance, the chart on the left compiles the most significant results from the Twitter studies.*

<u>IV. Discussion</u>

Research Question Takeaways

The research question of this analysis hoped to examine relationships, perhaps differential, between 'polite', 'warm' and 'receptive' linguistic markers and engagements. I explored various hypotheses that examined whether or not 'impolite' or negative aspects of speech would lead to engagements. I hoped to evaluate whether Republicans received more engagements from 'impolite' or negative posts and whether Democrats received engagements from 'warm' posts; furthermore, whether female-identifying Legislators experienced more post engagements from 'warm' language, especially in regard to their male-identifying counterparts.

The data I evaluated through the 'politeness' package through the multiple linear regression modeling is immensely important towards addressing these hypotheses. Our findings suggest that the biggest indicators of whether a certain tweet or post will receive engagements (favorites and likes) are follower count/likes of the page at posting and, if on Twitter, negative emotion. More than that, regarding Party, *Fig. 6* emphasizes that Republicans receive favorites on Twitter for negative emotion and disagreement. While *Fig. 7* shows that Democrats receive a statistically significant bump in favorites when their tweets have 'warmth'. On gender, there seems to be no clear takeaway besides the fact that male-identifying candidates receive a significantly positive favorite prediction compared to female-identifying candidates.

For the sake of sociological research, what do these findings mean? Regarding the governing understanding of social media toxicity and negativity bias, it seems as if the results sit quite nicely in that domain — negative emotion trumps all on Twitter as can be seen in Fig. *4*, *6*, *7*, *10*, and *11*. Beyond this, it appears as if these findings interact quite well with literature on party and gender. While Jost et al. (2012) and Huber et al. (2015) suggest that Republicans are threat-sensitive and less tolerant, on Twitter, it appears as if disagreement helps them out significantly. Meanwhile, Democrats, who literature has mixed opinions of regarding civility, definitely do better with warm speech than Republicans do. For sociological inquiry, it appears as if our perceived notions of how the parties might operate, Republicans more combative and Democrats more accepting, quite literally feedback into their own engagements. Surrounding gender, while the literature suggests that female-identifying candidates tend to asymptotically approach male behavior to 'fit in', our findings play into that. Leaper and Robnett (2011) analyze Robin Lakoff's theory that women are more likely than men to use tentative language (hedges, qualifiers) and find that, on average, women do use tentative language — which is often deemed more polite — than men. Our findings fit into this analysis by highlighting that male-identifying politicians receive more engagements from warm language than female-identifying politicians do.

Limitations

Our findings have several limitations. First and foremost, R-squared, adjusted R-squared, and residual standard error values all seemed rather low for the purpose of our analysis. While I did retain some statistically significant findings, r-squared values below 0.2, of which every Figure in the Results section had, are of concern in evaluating findings. Second of all, while the 'warmth' and 'receptiveness' variables seemingly should have been coded to pick up the same linguistic markers, they often conflicted in the regression models; this speaks to something that requires further investigation. Since our analysis relies on observation, the data preprocessing and utilization should be fine. Regarding results, while overall regression results were interesting for Twitter, they were almost effectively useless in Facebook analysis. While negative emotion is all throughout Twitter, Facebook engagements are so overshadowed by the significance of Likes and Followers of the Page at posting, that almost no discernable and meaningful results were able to be obtained. Whether or not said findings are replicated across OSNs or are only true on Twitter is instrumental to sociological understanding, and is critically not present in our findings.

Future Research

If future research can further analyze the difference between OSNs in terms of engagements and politeness, I think it could meaningfully contribute to the corpus. More than this, I think there need to be reproducible efforts at replicating results among other datasets of politicians because the most fascinating results are those that are statistically significant and align with the predictions. While this analysis mostly confirmed our suspicions, there is a long way to go in further investigating gender and party differences in tone and linguistics in social media posts. Further research ought to determine whether such obtained results are generalizable.

IV. Conclusion

Given our original research question, it appears as if in some contexts, such as if someone is a male-identifying or Democratic Legislator, politeness and warm language across their OSNs might enable them to reach a wider audience. However, if someone is Republican and/or female, perhaps Disagreement might help boost their engagement. While these are definite conclusions that come from this analysis, there still is much analysis that needs to be conducted on why such differences exist, how this data fits into the context of the larger field, and whether or not sociologists in the practice can discern generalizable conclusions from this. Although the findings require further investigation, this study provides strong evidence that the old model of politics is changing, and language, however it chooses to evolve, will remain tethered to OSNs and the Internet.

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