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Angry Tweets and Interest Groups

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Abstract

Social media have become a primary vehicle through which interest groups have sought influence on the U.S. political system. While the relationship between social media and politics has been studied, little research has been conducted into which posts, specifically from interest groups, receive the most public feedback. Through a content analysis, I coded more than 2,000 tweets from two pairs of diametrically opposed interest groups according to the type of language that was employed in the tweet (argumentative, agreeable, action-oriented) and the multimedia that was utilized (plain, photo, link, video). Tweets with argumentative language tended to receive more likes, retweets, and replies than tweets without argumentative language. Additionally, linear regression analysis showed there were statistically significant positive relationships between retweets and argumentative language and replies and argumentative language. The positive statistically significant relationship between retweets and argumentative language persisted when the data was disaggregated by organization. Tweets with video tended to receive more public feedback than tweets without video. Multivariable linear regression analysis showed that a tweet's inclusion of video had a larger impact on its likelihood of receiving more public feedback than its inclusion of argumentative language. The implication of this is that future research should consider the related influences that multiple variables have on a tweet's success in receiving public feedback.

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History of Social Media in Politics

The relationship between politics and social media is typically thought of in connection with presidential elections. It makes sense, then, that 2004 Democratic presidential candidate Howard Dean is credited with being the first political actor to take full advantage of the offerings of the internet. While 2000 Republican presidential candidate John McCain and Minnesota Gov. Jesse Ventura are considered to be the firsts to create campaign websites, Dean's campaign employed an interactive site that encouraged users to create their own content, join online discussions, and organize their own events (Hindman 2005). For these reasons, Dean's site acted as a precursor to social media, which are intended to be user-generated and non-hierarchical. Considering Dean was supposed to be a failed candidate, Hindman (2005) attributes Dean's successes to his campaign's use of the internet. The candidate broke fundraising records through small donations and created a grassroots network of supporters, which enabled him to win MoveOn.org's digital primary if not the actual Democratic presidential nomination.

If Dean was the first politician to utilize the full capabilities of the Internet, Barack Obama was the first one to do it successfully. After the 2008 presidential election, *Wired*, a media outlet that covers technology, reported that myBarackObama.com, a social networking site made for the campaign by Facebook co-founder Chris Hughes, had 1.5 million accounts. Volunteers used the website to organize 150,000 campaign-related events. Additionally, 35,000 groups in support of Obama's candidacy were created based on geographical location and interest (Stirland 2008). Since these activities were not directly supervised by the campaign, it further shows the bottom-up nature of digital political activism. Joe Trippi, who ran Dean's presidential campaign and worked on

Obama's successful one, also praised YouTube, which enabled the campaign to post videos for free that were collectively watched for 14.5 million hours. To compare, that would cost $47 million in television advertisements (Miller 2008).

The Obama campaign continued using social media more adeptly than his competitors, at least when it came to elections. In 2012, he had more than 20 million Twitter followers and nearly 30 million likes on his Facebook page compared to Republican presidential candidate Mitt Romney's less than two million followers and less than eight million likes. Even on Spotify, a music streaming service, Obama gained about 15,000 followers compared to Romney who amassed less than 1,000 (Wortham 2012). Of course, Donald Trump became widely known for his use of Twitter during the 2016 election, and he continues to use it to communicate with his 63.7 million followers (@realDonaldTrump). A less reported statistic, however, is that the Trump campaign ran 5.9 million Facebook ads from June to November 2016 while Hillary Clinton's campaign ran only 66,000 (Coppins 2020). According to the Congressional Research Service, 87%-100% of representatives and 94%-100% of senators used Facebook, Twitter, and YouTube during the 114th Congress (2015-16) and 115th Congress (2017-18) (Straus 2018). Clearly, political candidates and leaders use social media to cultivate followers. But political leaders are only one slice of the political pie.

Interest Groups and Social Media

While social media are inextricably linked to contemporary politics and elections, their use by advocacy groups is less understood. Obar, Zube, and Lampe (2012) define advocacy groups as a "systematic effort by specific actors who aim to further or achieve specific policy goals." The term is synonymous with interest group, pressure group, and special interest. The existence of advocacy groups in the U.S. derives from the First Amendment limitation on the government from suppressing citizens' right to petition the government. Historian Alexander de Tocqueville wrote that the freedom to form organizations of citizens to address issues through persuasion and advocacy was an enduring feature of U.S. democracy (Auger 2013). James Madison acknowledged the problems with factions but defended, what essentially are, advocacy groups in Federalist Paper No. 10 by claiming they are inseparable from republican government. He writes, "Liberty is to faction what air is to fire, an ailment without which it instantly expires" (*The Federalist Papers*). In choosing to study advocacy groups, researchers Hong and Nadler (2016) write, "…they play a vital role as liaisons between citizens and politicians, mobilizing people with shared ideas and attitudes and attempting to influence the legislative process and policy outcomes."

Considering the Constitutional right of U.S. citizens to form advocacy groups paired with the possibilities enabled by a generally open Internet that transcends geographic boundaries, it is logical that such groups would take advantage of digital offerings to expand and strengthen their influence. Advocacy group use of social media rests on the idea of connective action. The theory of connective action was developed by sociologists W. Lance Bennett and Alexandra Segerberg in 2013. Their basic argument is that digital media, rather than replicating traditional forms of advocacy, is reforming the ways individuals participate in activism. This is because connective action, unlike collective action, encourages users to contribute through personalized expression rather than through group action around a singular idea. In other words, an individual's identity with a cause can become more flexible. They argue that this makes online social movements individual-centric, non-hierarchical, and more inclusive compared to traditional movements (King 2014). Based on this theory, the drawback would be that it makes organizing potentially millions of people around a concrete belief system nearly impossible. Activism becomes more personalized and less uniform.

Literature Review

Not only have social media become an integral part of politics, they have become a key component to advocacy groups' communication strategies. A study by Obar, Zube, and Lampe (2012) found that 100% of the 53 organizations they surveyed used social media. Even more so, 67% of groups in the survey reported they use Twitter daily to communicate with followers. Considering the reliance on social media by advocacy groups, researchers have sought to analyze how these groups use social media to communicate. Lovejoy and Saxton (2012) were the first to analyze the content of nonprofit organizations' Twitter use. In order to discern the purposes of organizations' social media strategies, they developed a coding typology that categorized tweets into three groupings: information, community, action. In other words, each tweet was categorized according to whether it provided information, built community, or encouraged action (call to action). They categorized nearly 4,700 tweets and found that 59% of them were informative, but their central finding was that 16% of tweets were action-oriented. Prior to social media, digital communication almost exclusively relied on websites, which are primarily centers of information. Lovejoy and Saxton were surprised that organizations, through social media, had the opportunity to more effectively spur supporters to action but still primarily relied on social media to spread information.

Other researchers have analyzed the communicative functions of political organization tweets. Edrington and Lee (2018) used a modified version of Lovejoy and Saxton's typology to code tweets from the Black Lives Matter social movement for the purpose of determining which function (information, community, or action) generated the most likes, retweets, and replies. Similar to Lovejoy and Saxton's research, 60% of tweets were informative and action messages were less likely to be retweeted than community or informative ones. Auger (2013) categorized Facebook posts, tweets, and YouTube videos from two pairs of diametrically opposed advocacy groups. His central finding was that the provision of information was the most common characteristic. Gerodimos and Justinussen (2015) performed a content analysis on Facebook posts from Barack Obama's 2012 reelection campaign, finding that substantive posts about policy or Obama's character were more engaging as measured by likes, comments, and shares than personal appeals and promotional calls. Also, positive acclaims were more likely to be shared than other types of posts. The conclusions from this literature are that most advocacy organization social media posts are information-centric and that action-oriented messages are less likely to receive feedback from users compared to other types of messages.

In an effort to further understand which political social media messages are most popular, Pew Research Center has undertaken studies that measure the feedback toward messages that express negativity against an ideological opponent. A Pew Research Center (2017) study analyzed more than 200,000 press releases and Facebook posts from official accounts of members of Congress. Posts that expressed disagreement with the opposing party received 1.5 times more likes than posts without disagreement, three times more comments, and double the number of shares. According to Pew, this analysis was its "most extensive use of tools and methods of data science to date." Similarly, Pew researchers Hughes and Kessel (2018) studied if the 2016 presidential election impacted how users utilize Facebook's emotional reactions (angry, love, sad, haha, wow). One of their findings was that confrontational posts from lawmakers, defined as those that express opposition toward politicians or political groups, were more likely to inspire angry reactions and constituted 15% of posts from the study period.

In addition to this, researchers Zilinksy, Vaccari, Nagler, and Tucker (2020) studied tweets from celebrities who endorsed candidates in the 2016 presidential election from January 2016 to May 2018. They found that tweets that mentioned Trump, Clinton, or Sanders averaged 763 retweets versus tweets about other topics that averaged 732 retweets. Specifically, tweets about candidate Trump from Democratic-leaning celebrities on average received 1,011 retweets. Even during the Trump impeachment proceedings, an independent U.S. spice retailer was the second-highest spender on Facebook impeachment ads. The business' rationale was that its pro-impeachment ads "worked better" than any ads the company had run previously (Nguyen 2019).

Why Study This?

It is necessary to study how influential individuals and organizations use Twitter because the notion that social media are a source of people power is changing. This relates to advocacy groups because the central premise of the theory of connective action advanced by Bennett and Segerberg is that online social movements are individual-centric and non-hierarchical (King 2014). This notion is challenged, however, by evidence that suggests social media are becoming tools of powerful interests to more easily manipulate followers. In 2011, social media were praised for supposedly enabling the Arab Spring, which resulted in the downfall of many longstanding regimes across the Middle East and North Africa (Brown & Guskin 2012). The consensus was that social media upended the social order by giving more voice to citizens.

But that consensus has changed in the ensuing years. Facebook was criticized in 2014 for manipulating the news feeds of more than half a million users to be either exceedingly positive or negative as part of a psychological study (Goel 2014). Facebook also was criticized in 2018 for allowing the political consulting firm Cambridge Analytica, which worked for Donald Trump's 2016 presidential campaign, to improperly access the data of up to 87 million users (Chang 2018). Famously, Russia carried out a social media disinformation campaign that favored Donald Trump and attacked Hillary Clinton during the 2016 presidential campaign (Mueller 2019). The implication of these scandals is that social media have become tools for manipulation rather than for increased civic engagement.

Data support the notion that instead of further democratizing influence social media have actually consolidated it. Hong and Nadler (2016), measuring online presence as the number of weekly tweets from an interest group multiplied by its number of Twitter followers as a share of the sum volume of groups in the study and offline presence as the number of in-house lobbyists employed by an interest group as a share of the sum of lobbyists employed by groups in the study, found that the top 10% of organizations have 82% of the online voice versus 30% of the offline voice.

This was reinforced by Guo and Saxton (2018) who, in the first organizational-level study of social media message effectiveness, found tweets from organizations that had more followers and tweeted more were more likely to get more favorites and retweets than tweets from organizations with less followers that tweeted less. As a result, Guo and Saxton reported that a large number of advocacy groups garnered low levels of attention versus a small subset that generated high levels of attention.

Furthermore, Leetaru (2019) examined the whole of Twitter using a real-time stream of 1% of all available tweets (called the Spritzer stream), concluding that the social networking site, compared to years past, is being driven by a smaller number of users. For example, in January 2012 retweets were 20% of Twitter's volume. In October 2018, 53% of content on Twitter was retweets. He writes that "…[retweets] are defining characteristics of such a digital public forum in which a small central set of elites drive the overall conversation." This finding contrasts with the theory of connective action in that users now seem to be sharing what others are saying as opposed to providing their own individual contributions.

As an example of purported elites driving the conversation, Twitter disproportionately represents certain demographics. Wojcik and Hughes (2019) conducted a survey of 2,791 U.S. adult Twitter users, finding that they are more likely to be younger than the average American, more likely to identify as Democrats, more likely to have attained a college degree, and more likely to have a household income of at least $75,000. Likewise, Pew Research Center (2019) analyzed a random sample of adult U.S. Twitter users from June 2018 to June 2019. The organization found that 97% of tweets from U.S. adults that mentioned national politics came from just over 10% of Twitter users. The study also reported that only 22% of the American public uses Twitter and that only 13% of tweets in the study period dealt with political issues.

While certain groups may be overrepresented on Twitter, majorities of Americans say social media are integral to contemporary politics. In a survey of 5,594 U.S. adults conducted by Anderson, Toor, Lainie & Smith (2018), 69% of respondents said social media are important to get politicians to pay attention to issues. Similarly, 67% of respondents said social media are important for creating sustained movements for social change, and 65% of respondents said social media highlight important issues that do not get a lot of attention. It is clear from these results that social media are viewed as a major source of political influence.

The potential impact that social media has had on political polarization also remains unclear. Smith, Hughes, Remy, and Shah (2020) found from a survey in January that Democrats on Twitter have more ideological views than Democrats who are not on Twitter; although, it is unclear if Twitter was the radicalizing force or if more ideological individuals are attracted to the social media platform. All in all, 29% of Democrats use Twitter. 56% of Democrats and Democratic-leaning independents on Twitter describe their views as liberal or very liberal compared to 41% of non-Twitter Democrats. Similarly, 54% of Twitter-using Democrats say that presidential candidates should seek common ground with Republicans. 65% of Democrats who do not use Twitter say the same.

Gaps in the Literature

While researchers have analyzed the impact of negativity on public feedback to Facebook posts from U.S. lawmakers (Pew Research Center 2017; Hughes and Kessel 2018), there has not been a study considering such impact on either interest group social media messages or on Twitter. While multiple researchers (Lovejoy and Saxton 2012;

Edrington and Lee 2018) categorized interest group tweets according to communicative function (information-community-action), their results only showed that information-oriented tweets were the most common and that calls to action received less public feedback. These results have been mirrored in similar research (Auger 2013; Gerodimos and Justinussen 2015).

This lack of knowledge regarding which type of advocacy group tweets receive the most favorites, replies, and retweets presents challenges to individuals who are trying to further understand how social media can be used as a tool for political advocacy. Considering Twitter grants more influence to powerful actors (Hong and Nadler 2016; Guo and Saxton 2018), understanding the social media strategies of advocacy groups is integral in studying contemporary lobbying. This forms the rationale for my research question: do advocacy group tweets that are adversarial to an ideological opponent receive more favorites, replies, and retweets compared to messages that are not negative?

Methods

Twitter, much like Facebook, is a social media website, which means it encourages and enables users to interact with other users. The two sites are largely similar. While Facebook posts can be liked, commented on, or shared, tweets can be favorited, replied to, or retweeted. On Facebook, users can like the pages of advocacy groups to receive their content; on Twitter, users can follow such accounts. They do, however, differ in size. In June 2019, Facebook averaged 1.6 billion daily active users (Facebook). As of February 2019, Twitter had 126 million daily users. Twitter used to report its number of monthly active users but stopped in February 2019 after a substantial decline, choosing instead to announce its daily user statistic (Kastrenakes 2019).

Although Facebook has more users, I am choosing to study Twitter because there already has been a study on negativity's effect on political Facebook posts (Pew Research Center 2017).

For the purpose of determining if adversarial advocacy group tweets receive more public feedback than other types of tweets, I decided to analyze tweets from two pairs of diametrically opposed advocacy groups. Specifically, I chose a gun rights and gun control advocacy group and an abortion rights and anti-abortion advocacy group because these issue areas have clear ideological opponents. Auger (2013) also analyzed tweets from two pairs of diametrically opposed advocacy groups in the areas of firearms and abortion, but he included Facebook posts and YouTube videos in his analysis.

Since I am studying advocacy groups in relation to social media, it was important that the groups being researched exhibit both a sizable Twitter presence and also significant offline influence. After examining Twitter activity and political donation data on OpenSecrets.org, I decided to study the National Rifle Association (@NRA; gun rights), Everytown for Gun Safety (@Everytown; gun control), Planned Parenthood Action (@PPact; abortion rights), and Susan B. Anthony List (@SBAList; anti-abortion). Using Twitter advanced search, I collected tweets from these four organizations from Labor Day 2018 to the day after Election Day of the same year. This period encompasses the Brett Kavanaugh confirmation hearings and midterm elections.

I coded more than 2,000 tweets for this research. Retweets and replies were not included. For the coding, each tweet was given an identification number. The tweets are coded chronologically based on date and organization. Along with this, the tweet's text and a description of any visual elements, the year, month, and day that it was posted, and the number of likes, retweets, and replies it received were recorded. Following this, the tweets were coded based on their communicative functions: argumentative, agreeable, action-oriented. I chose these categories based on previous research. Obviously, the argumentative category most directly answers my research question. I added the agreeable category based on Gerodimos and Justinussen's (2015) research, which found that positive acclaims from Barack Obama's 2012 reelection campaign Facebook were more likely to be shared than other types of posts. The action-oriented label was added because it was consistently employed in past research.

Unlike past research, however, I treated these categories as yes or no questions instead of as "either…or…." Essentially, each tweet either contained argumentative, agreeable, or action-oriented language or it did not. This means that a given tweet could fall under any or all of the three categories or even none of them. This coding recognizes that many tweets do not fall under only one category. As an example, a tweet can contain both argumentative and agreeable language. This scheme allows the data to reflect the existence of both instead of forcing the coder to choose which language is dominant.

Each code was defined. Argumentative tweets were those that express disagreement with an explicit and specific public ideological opponent. Agreeable ones express support toward an explicit and specific external public ideological ally. Action-oriented tweets include language that tells the viewer to complete a specific task. A more thorough explanation of the coding scheme can be found in Appendix A. In addition to these coding categories, tweets were coded based on the multimedia that was employed in them: plain, graphic or photo, link, embedded video. In contrast from the other coding categories, tweets could only be coded for one multimedia option. A more thorough explanation of this coding scheme also can be found in Appendix A.

I recruited an additional coder in order to assess inter-coder reliability. A random sample of tweets in the study from each of the four organizations was coded. Then an inter-coder reliability test was performed between the respective sets of data using a Krippendorff alpha inter-rater reliability test. The results for each of the variables (argumentative, agreeable, action) were higher than .80. Scores that are higher than .80 under the Krippendorff test support that the coding scheme that was employed is reliable and replicable (Hayes and Krippendorff 2007).

Results

After completing the coding, I ran means tests on the overall data for likes, retweets, and replies and on data for each specific coding variable: argumentativeness, agreeableness, action-oriented language. The results can be found in Appendix B. From these tables, I chose median as a measurement over average because of the stark range between the tweet with the most respective likes, retweets, and replies and the tweet with the lowest of each of those metrics. This first table shows the median likes, retweets, and replies of the coded data.

Table 1

Overall Medians

Code	Total	Argumentative	Agreeable	Action
Number/Percent (%)	2053, 100	957, 46.6	1027, 50	800, 39
Median Likes	92	109	78	74
Median Retweets	42	56	36	41
Median Replies	4	6	4	4

Fifty percent of tweets in this study had agreeable language. Roughly 47% had argumentative characteristics, and 39% had action-oriented language. Tweets with argumentative language tended to receive more likes, retweets, and replies than the medians across those metrics for all tweets in the study. Agreeable and action-oriented tweets tended to receive fewer likes and retweets compared to the medians in those categories for all tweets in the study. Agreeable and action-oriented tweets tended to receive the same number of replies as overall tweets in the study.

Since I measured the medians for tweets with, for example, argumentative language, I wanted to measure the medians of tweets without argumentative language. I also did this for tweets without agreeable or action-oriented language.

Table 2

Medians for "Negative" Data

Code	Total	Non-Argumentative	Non-Agreeable	Non-Action
Number/Percent (%)	2053, 100	1096, 53.4	1026, 50	1253, 61
Median Likes	92	78	99	110
Median Retweets	42	32	48.5	43
Median Replies	4	3	5	4

Tweets without argumentative language tended to have fewer likes, retweets, and replies than all tweets in the dataset. Tweets without agreeable language or without action language had higher than or equal to the median likes, retweets, and replies for the whole dataset.

I also wanted to consider tweets that fell under multiple coding categories. I examined tweets that included: argumentative and agreeable language, argumentative and action-oriented language, agreeable and action-oriented language, language from all three coding categories, and language that did not fall under any of the coding categories.

Table 3

Medians for Tweets that Fall Under Multiple Categories

Code	Total	Argum. - Agree.	Argum. - Action	Agree. - Action	Ar. - Ag. - Ac.	None
Number/Percent (%)	2053, 100	388, 18.9	359, 17.5	417, 20.3	149, 7.3	284, 13.8
Median Likes	92	123	102	59	122	115
Median Retweets	42	59	59	30	66	40
Median Replies	4	6	6	3	6	3

Tweets that included argumentative and agreeable language, argumentative and action-oriented language, and all three coding categories tended to receive more likes, retweets, and replies than the total data. Agreeable and action-oriented language had lower medians for likes, retweets, and replies than the total data. Tweets that did not fall under any category had higher median likes than the total data but lower medians for retweets and replies.

I also computed the medians based on the multimedia characteristics of the tweets in the study.

Table 4

Multimedia Medians

Code	Total	Plain	Photo	Link	Video
Number/Percent (%)	2053, 100	283, 13.8	928, 45.2	633, 30.8	209, 10.2
Median Likes	92	69	97	83	159
Median Retweets	42	27	39	42	80
Median Replies	4	3	4	4	8

Median likes, retweets, and replies were highest for tweets with video. Tweets with photos or graphics had a higher median for likes than the median for all likes in the study but a comparatively lower median for retweets. Compared to the total data, tweets with links had a lower median for likes but the same median for retweets. Both tweets with photos or graphics and links had the same median for replies as the total data. Plain tweets had lower medians for likes, retweets, and replies than the medians for those metrics from the overall data.

Following this, I calculated the median likes, retweets, and replies for each of the four organizations in the study. I also calculated the percentage of tweets in each organization that fell under each category.

Table 5

Medians by Organization

NRA	**Total**	**Argumentative**	**Agreeable**	**Action**
Number/Percent (%)	237, 100	113, 47.7	143, 60.3	72, 30.4
Median Likes	1,100	1200	851	1400
Median Retweets	413	513	314	611
Median Replies	68	99	44	102
Everytown	**Total**	**Argumentative**	**Agreeable**	**Action**
Number/Percent (%)	540, 100	131, 24.3	235, 43.5	295, 54.6
Median Likes	104	127	110	81
Median Retweets	46	63	46	46
Median Replies	3	5	4	4
Susan B. Anthony List	**Total**	**Argumentative**	**Agreeable**	**Action**
Number/Percent (%)	552, 100	201, 36.4	404, 73.2	155, 28.1
Median Likes	25	26	24	13
Median Retweets	11	16	10	7
Median Replies	1	2	1	1
Planned Parenthood	**Total**	**Argumentative**	**Agreeable**	**Action**
Number/Percent (%)	724, 100	512, 70.7	245, 33.8	278, 38.4
Median Likes	118	112	166	81
Median Retweets	56	57	64	45
Median Replies	7	7	7	4

Argumentative tweets from the NRA, Everytown, and Susan B. Anthony List tended to receive more likes, retweets, and replies than their overall tweets. Agreeable tweets from the NRA tended to receive less feedback than its overall tweets; Everytown's agreeable tweets had higher medians for likes and replies and the same median for retweets compared to its overall tweets; agreeable tweets from Susan B. Anthony List had lower medians for likes and retweets and the same median replies compared to its overall tweets.

Action-oriented tweets from the NRA had the highest median likes, retweets, and replies among NRA tweets; Everytown's action-oriented tweets had a lower median for likes, the same for retweets, and higher for replies compared to its overall tweets; Susan B. Anthony List's action-oriented tweets had lower medians for likes and retweets and the same median for replies compared to its overall data.

Argumentative tweets from Planned Parenthood had lower median likes and retweets and the same median replies compared to its overall data. Agreeable tweets from Planned Parenthood had higher medians for likes and retweets and the same median replies compared to its overall data. Action-oriented tweets from Planned Parenthood had lower medians across all three metrics compared to its overall data.

The NRA tweeted the least but had the highest median likes, retweets, and replies. Susan B. Anthony List tweeted the second-most and had the lowest median likes, retweets, and replies. Among the four organizations, Planned Parenthood had the highest percentage of argumentative tweets (70.7%). Of the three codes, this was its most used one. Susan B. Anthony List had the highest percentage of agreeable tweets (73.2%). Of the three codes, this was its most used one. Agreeable also was the most used code for the

NRA tweets (60.3%). Everytown had the highest percentage of action-oriented tweets (54.6%). This was its most used code.

I also calculated which multimedia was used the most by each organization.

Table 6

Multimedia Use by Organization

Organization	Total/Percent	Plain	Photo	Link	Video
NRA	237,100	35, 14.8	73, 30.8	114, 48.1	15, 6.3
Everytown	540, 100	19, 3.5	260, 48.1	221, 40.9	40, 7.4
SBA List	552, 100	105, 19	256, 46.4	124, 22.5	67, 12.1
PP	724,100	144, 19.9	298, 41.2	215, 29.7	67, 9.3

Photos or graphics were the most used multimedia for Everytown, Susan B. Anthony List, and Planned Parenthood. Links were the most common multimedia for the NRA, and photos or graphics were its second most popular multimedia. Video was the least popular multimedia for the NRA, Susan B. Anthony List, and Planned Parenthood, and the second least popular behind plain tweets for Everytown.

From these data, it can be determined that tweets with argumentative language tended to receive more likes, retweets, and replies than tweets without it. So, I wanted to see if this relationship was supported by linear regression analysis in order to assess causation. I ran linear regression tests, analyzing the relationships between tweets with certain types of language (argumentative, agreeable, action-oriented) and their public feedback (likes, retweets, comments). A summary table of these results is in Appendix C. There were two statistically significant relationships: a positive relationship between retweets and tweets with argumentative language and a positive relationship between replies and tweets with argumentative language.

The former model reveals a positive relationship between argumentative language and retweets ($R^2 = .005$, $p < .05$). All else equal, tweets without argumentative language were expected to receive roughly 122 retweets ($b = 121.915$, $p < .05$); however, tweets with argumentative language were expected to receive an additional 75 retweets ($b = 75.470$, $p < .05$), or roughly 197 retweets total.

The latter model reveals a positive relationship between argumentative language and replies ($R^2 = .003$, $p < .05$). All else equal, tweets without argumentative language were expected to receive about 20 replies ($b = 20.011$, $p > .05$); however, tweets with argumentative language were expected to receive an additional 59 replies ($b=59.015$, $p < .05$), or roughly 79 replies total.

Still, I wanted to see if this relationship between retweets and tweets with argumentative language and replies and tweets with argumentative language persisted across each interest group in the study. So, I performed linear regression analyses on data from each group in the study. A summary table of these results also can be found in Appendix C. There was a statistically significant positive relationship between both retweets and tweets with argumentative language from the NRA ($R^2 = .17$, $p < .05$) and replies and tweets with argumentative language from the NRA ($R^2 = .022$, $p < .05$).

All else equal, tweets that were not from the NRA and were without argumentative language were expected to receive about 49 retweets ($b = 48.641$, $p < .05$); however, tweets from the NRA were expected to receive an additional 648 retweets ($b = 647.652$, $p < .05$) and tweets with argumentative language were expected to receive 72 retweets ($b = 72.272$, $p < .05$), or roughly 769 retweets combined total.

All else equal, tweets that were not from the NRA and were without argumentative language were expected to receive about -7 replies ($b = -7.215$, $p > .05$); however, tweets from the NRA were expected to receive an additional 241 replies ($b = 240.644$, $p < .05$) and tweets with argumentative language were expected to receive an additional 58 replies ($b = 57.827$, $p < .05$), or roughly 292 replies combined total.

There also was a negative statistically significant relationship between replies and tweets from the NRA with agreeable language ($R^2 = .021$, $p < .05$). All else equal, tweets that were not from the NRA and were without agreeable language were expected to receive about 44 replies ($b = 44.452$, $p < .05$); however, tweets from the NRA were expected to receive an additional 247 replies ($b = 247.278$, $p < .05$) and tweets with agreeable language were expected to receive 51 fewer replies ($b = -50.93$, $p < .05$), or roughly 240 replies combined total.

There was a positive statistically significant relationship between retweets and tweets with argumentative language from Everytown ($R^2 = .013$, $p < .05$). All else equal, tweets that were not from Everytown and were without argumentative language were expected to receive about 161 retweets ($b = 160.617$, $p < .05$); however, tweets that were from Everytown were expected to receive 104 fewer retweets ($b = -103.711$, $p < .05$) and tweets with argumentative language were expected to receive an additional 51 retweets ($b = 50.965$, $p < .05$), or roughly 108 retweets combined total.

For Susan B. Anthony List tweets, there was a positive statistically significant relationship between retweets and argumentative tweets ($R^2 = .024$, $p < .05$) and replies and argumentative tweets ($R^2 = .004$, $p < .05$). There also were statistically significant positive relationships between likes and tweets with agreeable language ($R^2 = .026$, $p <$

.05) and retweets and tweets with agreeable language ($R^2 = .023$, $p < .05$). There was a negative statistically significant relationship between likes and tweets with action-oriented language ($R^2 = .025$, $p < .05$).

All else equal, tweets that were not from Susan B. Anthony List and that did not include argumentative language were expected to receive about 173 retweets ($b = 172.543$, $p < .05$); however, tweets that were from Susan B. Anthony List were expected to receive 158 fewer retweets ($b = -158.087$, $p < .05$) and tweets with argumentative language were expected to receive an additional 58 retweets ($b = 58.045$, $p < .05$), or roughly 73 retweets combined total.

All else equal, tweets that were not from Susan B. Anthony List and that did not include argumentative language were expected to receive about 37 replies ($b = 36.828$, $p > .05$); however, tweets from Susan B. Anthony List were expected to receive 53 fewer replies ($b = -52.51$, $p > .05$) and tweets with argumentative language were expected to receive an additional 53 replies ($b = 53.227$, $p < .05$), or roughly 37 replies combined total.

All else equal, tweets that were not from Susan B. Anthony List and that did not include agreeable language were expected to receive about 441 likes ($b = 440.564$, $p < .05$); however, tweets from Susan B. Anthony List were expected to receive 500 fewer likes ($b = -500.495$, $p < .05$) and tweets with agreeable language were expected to receive an additional 171 likes ($b = 170.894$, $p < .05$), or roughly 112 likes combined total.

All else equal, tweets that were not from Susan B. Anthony List and that did not include agreeable language were expected to receive about 183 retweets ($b = 182.793$, $p < .05$); however, tweets from Susan B. Anthony List were expected to receive 181 fewer retweets ($b = -180.679$, $p < .05$) and tweets with agreeable language were expected to receive an additional 46 retweets ($b = 45.743$, $p < .05$), or roughly 48 retweets combined total.

All else equal, tweets that were not from Susan B. Anthony List and that did not include action language were expected to receive about 579 likes ($b = 578.948$, $p < .05$); however, tweets from Susan B. Anthony List were expected to receive 470 fewer likes ($b = -469.727$, $p < .05$) and tweets with action language were expected to receive 157 fewer likes ($b = -156.973$, $p < .05$) , or roughly -48 likes combined total. While the data show this is a negative relationship, obviously the data are unclear since they indicate a negative number of likes which is not possible. Further statistical analysis is needed to better understand this relationship.

For Planned Parenthood, there were three statistically significant positive relationships between tweets with argumentative language and each of the metrics for public feedback: likes ($R^2 = .004$, $p < .05$), retweets ($R^2 = .011$, $p < .05$), replies ($R^2 = .003$, $p < .05$). All else equal, tweets that were not from Planned Parenthood and that did not include argumentative language were expected to receive about 387 likes ($b = 387.428$, $p < .05$); however, tweets from Planned Parenthood were expected to receive about 177 fewer likes ($b = -177.084$, $p < .05$) and tweets with argumentative language were expected to receive 143 additional likes ($b = 142.66$, $p < .05$), or roughly 353 likes combined total.

All else equal, tweets that were not from Planned Parenthood and that did not include argumentative language were expected to receive about 138 retweets ($b = 138.291$, $p < .05$); however, tweets from Planned Parenthood were expected to receive about 85 fewer retweets ($b = -84.659$, $p < .05$) and tweets with argumentative language were expected to receive 104 additional retweets ($b = 104.388$, $p < .05$), or roughly 157 retweets combined total.

All else equal, tweets that were not from Planned Parenthood and that did not include argumentative language were expected to receive about 27 replies ($b = 26.616$, $p > .05$); however, tweets from Planned Parenthood were expected to receive about 34 fewer replies ($b = -34.14$, $p > .05$) and tweets with argumentative language were expected to receive 71 additional replies ($b = 70.677$, $p < .05$), or roughly 62 replies combined total.

I also wanted to discover if there were statistically significant relationships between the number of likes, retweets, and replies a tweet received and the multimedia that was employed in the tweet. A summary table of the linear regression results from these tests can be found in Appendix D. There were statistically significant negative relationships between tweets with links and retweets ($R^2 = .002$, $p < .05$) and tweets with links and likes ($R^2 = .004$, $p < .05$). There also was a statistically significant negative relationship between tweets with photos and retweets ($R^2 = .004$, $p < .05$).

All else equal, tweets without a link were expected to receive about 173 retweets ($b = 172.945$, $p < .05$); however, tweets with a link were expected to receive 51 fewer retweets ($b = -51.405$, $p < .05$), or roughly 122 retweets total. All else equal, tweets without a link were expected to receive about 445 likes ($b = 444.674$, $p < .05$); however, tweets with a link were expected to receive 173 fewer likes ($b = -172.518$, $p < .05$), or roughly 272 likes total. All else equal, tweets without a photo were expected to receive about 186 retweets (b = 185.787, $p < .05$); however, tweets with a photo were expected to receive 63 fewer retweets (b = -63.473, $p < .05$).

There was a statistically significant positive relationship between tweets with video and likes ($R^2 = .019$, $p < .05$) and between tweets with video and retweets ($R^2 = .03$, $p < .05$). All else equal, tweets without video were expected to receive 329 likes (b = 329.004, $p < .05$), and tweets with video with expected to receive an additional 614 likes (b = 613.713, $p < .05$), or roughly 943 total likes. All else equal, tweets without video were expected to receive 127 retweets (b = 127.413, $p < .05$), and tweets with video were expected to receive an additional 292 retweets (b = 291.568, $p < .05$), or about 419 total retweets.

I also wanted to see if there was a temporal relationship between when a tweet was posted and its public feedback. I compared tweets that were shared from September 16 through October 6 (the date when Christine Blasey Ford's accusation became public to the date Brett Kavanaugh was confirmed) to tweets that were not shared during that period. I also compared tweets that were shared from November 1 to November 7 (encompassing Election Day, the days leading up to elections, and the day after) to tweets that were not shared during that period. A summary table of these results can be found in Appendix E. There was a statistically significant negative relationship between tweets that were posted from November 1 to November 7 and retweets ($R^2 = .003$, $p < .05$). Tweets that were not posted during this time period were expected to receive about 172 retweets (b = 172.183, $p < .05$), but tweets that were posted during this period were expected to receive 65 fewer retweets (b = -65.208, $p < .05$), or roughly 107 retweets total.

But there were more nuanced results when I looked at the data by organization. For example, there were positive statistically significant relationships between tweets from Everytown during the Kavanaugh period and likes ($R^2 = .013$, $p < .05$) and retweets ($R^2 = .013$, $p < .05$). All else equal, tweets that were not posted during the Kavanagh period that were not from Everytown were expected to receive 433 likes ($b = 432.579$, $p < .05$); however, tweets that were posted during the period were expected to receive 137 likes ($b = 137.495$, $p < .05$) and tweets that were from Everytown were expected to receive 316 fewer likes ($b = -315.639$, $p < .05$), or roughly 254 total likes.

All else equal, tweets that were not posted during the Kavanagh period and that were not from Everytown were expected to receive 174 retweets ($b = 173.559$, $p < .05$); however, tweets that were posted during the period were expected to receive 51 additional retweets ($b = 50.943$, $p < .05$) and tweets that were from Everytown were expected to receive 122 fewer retweets ($b = -121.647$, $p < .05$), or roughly 103 total retweets.

Likewise, there were positive statistically significant relationships between tweets from Planned Parenthood during the Kavanaugh period and likes ($R^2 = .004$, $p < .05$) and retweets ($R^2 = .004$, $p < .05$). All else equal, tweets that were not posted during the Kavanagh period that were not from Planned Parenthood were expected to receive 398 likes ($b = 397.716$, $p < .05$); however, tweets that were posted during the period were expected to receive 131 additional likes ($b = 130.745$, $p < .05$) and tweets that were from Planned Parenthood were expected to receive 130 less likes ($b = -130.725$, $p < .05$), or roughly 398 total likes.

All else equal, tweets that were not posted during the Kavanagh period and that were not from Planned Parenthood were expected to receive 159 retweets ($b = 159.419$, $p < .05$); however, tweets that were posted during the period were expected to receive 48 additional retweets ($b = 48.225$, $p < .05$) and tweets that were from Planned Parenthood were expected to receive 48 fewer retweets ($b = -48.285$, $p < .05$), or roughly 159 total retweets.

Based on the results of the linear regression, tweets with argumentative language and tweets with video tended to receive more retweets than tweets without argumentative language or without video. Across all four groups in the study, the statistically significant positive relationship between tweets with argumentative language and retweets persisted. The model of the relationship between argumentative language and retweets only explains .5% of the variation (Appendix C), however, and the model for the relationship between video and retweets explains only 3% of the variation (Appendix D). Since these are relatively low, I decided to run a linear regression analysis on tweets that had both argumentative language and featured a video. While the statistically significant positive relationship persisted ($R^2 = .033$, $p <.05$), a tweet's inclusion of a video ($b = 280.780$, $p < .05$) had a more significant impact than a tweet's inclusion of argumentative language ($b = 55.369$, $p < .05$). Tweets that did not include argumentative language or a video were expected to receive about 103 retweets ($b = 102.701$, $p < .05$).

Considering the success tweets from Everytown had in soliciting retweets during the Kavanaugh period (Appendix E), I decided to run a linear regression analysis on tweets from Everytown during the Kavanaugh period that featured both argumentative language and a video. There was a statistically significant positive relationship (R^2 =

.042, $p < .05$) for the model. The statistical significance continued with retweets for the relationships with a tweet being posted during the Kavanaugh period (b = 56. 396, $p < .05$) and a tweet being posted with a video (b = 281.265, $p < .05$). There was a statistically significant negative relationship between retweets and the tweet coming from Everytown (b = - 102.536, $p < .05$). In this model, there was no statistically significant relationship between a tweet featuring argumentative language and retweets (b = 28.988, $p > .05$). Tweets without any of these characteristics were expected to receive about 125 retweets (b = 124.723, $p < .05$).

In an effort to increase the R^2, I decided to run an analysis with the highest R^2, thus far, from the study, which was the statistically significant positive relationship between retweets and tweets from the NRA with argumentative language ($R^2 = .170$). So, I ran a test on the relationship between retweets and tweets from the NRA that included argumentative language and a video ($R^2 = .190$, $p < .05$). I chose not to include a time characteristic (Kavanaugh or Election Day) since neither appeared to have a significant impact on NRA tweets. The positive statistically significant relationships between the three coding characteristics in the test and retweets persisted under the multivariable analysis: argumentative (b = 54.859, $p < .05$), video (b = 244.088, $p < .05$), NRA (b = 635.202, $p < .05$). Tweets without any of these characteristics were expected to receive about 33 retweets (b = 33.346, $p < .05$).

Discussion

Does argumentative language increase a tweet's public feedback?

My research question sought to answer if adversarial interest group tweets receive more likes, replies, and retweets than ones that are not negative. These data support that tweets with argumentative language do receive more public feedback than tweets without it. Argumentative tweets had the highest overall median likes, retweets, and replies compared to all of the other categories in the dataset (Table 1). Similarly, tweets without argumentative language tended to fair worse than tweets without agreeable language or action-oriented language (Table 2). This suggests argumentativeness boosts a tweet's likelihood for increased likes, retweets, and replies.

Likewise, in an analysis of tweets that fell under more than one coding option, tweets with argumentativeness as one of their defining characteristics tended to receive more public feedback than tweets that did not have argumentativeness as one of their characteristics (Table 3). Across three of the four groups in the study, tweets with argumentative language tended to receive more public feedback than their overall tweets. The exception was Planned Parenthood, but that could be attributed to 70% of its tweets including argumentative language. In comparison, none of the other groups had more than 50% of their tweets include argumentative language (Table 5).

The notion that tweets with argumentative language receive more public feedback than non-argumentative ones earned more support with the linear regression analyses. There were statistically significant positive relationships between retweets and tweets with argumentative language and replies and tweets with argumentative language. The statistically significant positive relationship between retweets and argumentative tweets persisted when the data was disaggregated to analyze each group in the study specifically (Appendix C).

Is argumentative language the reason tweets perform well?

While the statistically significant results suggest that argumentativeness is not only correlated with but causes a tweet to receive more retweets, only .5% of the variance in the model of the relationship between retweets and argumentative tweets, as one example, could be attributed to the argumentative language. Clearly, there are other factors. Looking at the data for multimedia usage, videos had higher medians for likes, retweets, and replies than the medians in those metrics for argumentative tweets (Table 4).

There also were statistically significant positive relationships between likes and tweets with videos and retweets and tweets with videos. Based on the linear regression analysis, tweets with video were expected to receive 419 total retweets and the presence of a video explained 3% of the variance (Appendix D). Compare that to tweets with argumentative language that were expected to receive 197 retweets and the presence of argumentative language explained .5% of the variance (Appendix C).

While there were no positive statistically significant relationships between a tweet's public feedback and when it was posted (Kavanaugh confirmation or around Election Day), there was for liberal organizations, specifically, during the Kavanaugh period (Appendix E). This makes sense because the liberal base was particularly energized and enraged during this time. I thought that tweets with argumentative language and video from Everytown during the Kavanaugh period would yield the highest R^2. In this analysis, 4.2% of the variance could be attributed to the relationship in the model. While there continued to be a statistically significant positive relationship between retweets and a tweet being posted during the Kavanaugh period and with a video, the statistically significant relationship with argumentative language disappeared.

Following this, I ran an analysis with the positive statistically significant relationship with the highest R^2 (retweets and tweets from the NRA with argumentative language; $R^2 = .170$) and added video as a variable. While 19% of the variance could be explained by this model, the tweet's inclusion of a video was expected to generate about five times the number of additional retweets compared to the tweet's inclusion of argumentative language. The fact that the tweet came from the NRA was expected to generate about thirteen times the number of retweets compared to the tweet's inclusion of argumentative language. This all leads to the notion that a video's impact on a tweet, specifically, is stronger than its inclusion of argumentative language. Also, there is evidence that when a tweet is posted and who shares it impacts the amount of feedback it receives.

Why do some tweets receive less public feedback?

Of course, it is also worth looking at features that may decrease a tweet's likelihood of receiving more retweets. Tweets with agreeable language and tweets with action-oriented language tended to receive less likes and retweets (Table 1). Tweets without agreeable language and tweets without action-oriented language had higher medians than tweets with the respective language (Table 2). Of tweets that had multiple characteristics, those with agreeable and action-oriented language and those that did not fall under any coding criteria had the lowest medians across all three metrics (Table 3). Within each organization, however, there were exceptions to this finding. Action-oriented tweets performed best, as measured by public feedback, for the NRA. Agreeable tweets from Everytown had the same median for retweets as its overall median and tended to receive more likes and replies compared to its overall data. As measured by public feedback, agreeable tweets from Planned Parenthood performed best (Table 5).

This mixed results picture continued when using linear regression analysis to study individual groups. There was a negative statistically significant relationship between replies and tweets from the NRA with agreeable language, but there were, for Susan B. Anthony List, statistically significant positive relationships between likes and tweets with agreeable language and retweets and tweets with agreeable language. There also was a negative statistically significant relationship between likes and Susan B. Anthony tweets with action-oriented language (Appendix C). All of this suggests that whether tweets with agreeable or action-oriented language did well or not largely depended on which organization posted the tweet. The contradictory and lack of results makes it difficult to reach any definitive statement.

In regard to the multimedia that was employed, there were statistically significant negative relationships between tweets with links and retweets and tweets with links and likes. There also was a statistically significant negative relationship between tweets with photos and retweets (Appendix D). Using median as a measurement, plain tweets had lower likes, retweets, and replies compared to the overall data. Tweets with photos tended to have a higher median for likes than overall tweets but a lower median for retweets and the same median for replies. Tweets with links had a lower median for likes but the same for retweets and replies as the overall medians (Table 4). As shown, there is evidence that suggests a tweet's inclusion of a photo or link decreases its likelihood of receiving more public feedback. That being said, nearly half of the tweets in the study featured a photo, and almost one-third included a link (Table 4). So, there is a possibility that both characteristics were overrepresented in the study, which could explain these results.

Additionally, there was a statistically significant negative relationship between tweets that were posted from November 1 to November 7 and retweets (Appendix E). While it would seem logical that tweets closer to Election Day would perform better, many of the organizations in the study shared posts that either re-endorsed candidates or congratulated victorious candidates. These tweets tended to receive low public feedback, so this could explain this surprising result.

What does this mean for future research?

These results suggest that the inclusion of argumentative language does increase a tweet's likelihood of receiving more public feedback. This is congruent with past research (Pew Research Center 2017; Zilinksy, Vaccari, Nagler, and Tucker 2020). But the results also show that multiple other variables (multimedia, time, organization that shares it) can impact the number of likes, retweets, and replies that a tweet receives. Specifically, a tweet's inclusion of a video was shown to have a greater effect than its inclusion of argumentative language. So, future research needs to consider the multiple variables that can impact how well a tweet performs as measured by public feedback.

The question of why argumentative tweets receive more public feedback, however, emerges from this research. It could be answered, in part, by Twitter's algorithm. Prior to 2016, Twitter users saw every tweet from every person they followed in chronological order with the most recent at the top of the feed. This changed when the social media company instituted an algorithm. The algorithm is a software that evaluates tweets and promotes ones it thinks the user will appreciate the most. In other words, users see more tweets from the people they interact with most. Importantly, this allows for popular tweets to be seen more widely (Oremus 2017). Relating the algorithm to this research, tweets with argumentative characteristics may receive increased public feedback. And the algorithm may then share those tweets more broadly than it would other non-argumentative tweets that receive less public feedback.

But how does this impact interest group use of social media? Pew Research Center (2019) reported that only 22% of Americans use Twitter, and a relatively small subset of tweets from those users are about politics. Still, Anderson, Toor, Lainie & Smith (2018) found that 69% of survey respondents said social media are important to get politicians to pay attention to issues. And the vast majority of members of Congress are on Facebook, Twitter, and YouTube (Straus 2018). But while the majority of Americans are not on Twitter, a majority say social media are important. Journalist Ezra Klein, in an interview about his recent book on U.S. political polarization, said social media primarily affects elites. He assumes that most U.S. political elites are on Twitter. “They’re stuck in a hyper-polarized informational system, and it influences the decisions they make, the candidates they support, the messages they emphasize, the stories they focus on,” Klein said (Newton 2020). He then argues that more polarized elites create a more polarized public.

While public officials are on Twitter, I think it is incorrect to assume, as Klein did, that they are active users. Their accounts could be run by staff. Still, a social media account offers constituents, and therefore interest groups, a direct connection to members. For example, Susan B. Anthony List and Planned Parenthood Action often shared tweets that were directly addressed to public officials. I assumed this was part of their respective strategies to mobilize their followers, but, perhaps, their intended audience was the representative himself?

Considering the algorithm's effect on how information is consumed on Twitter, a content analysis of a specific organization's tweet history may not be a useful way to study the site. This is because a user, typically, does not see all of the content that an organization posts. Instead, it might be more helpful, in order to study argumentativeness on social media, to perform a content analysis on a specific user's feed. This method would allow researchers to analyze how much of a person's feed features tweets with argumentative language. It would be interesting if the algorithm promotes mostly argumentative tweets. If this is the case, how does this impact advocacy groups? If certain messages are being seen more, it follows that other messages are being seen less. It is feasible that a user may primarily see argumentative content from an organization, even if it mostly does not post content with argumentative language. How does this impact the perception of interest groups? More broadly, what is the effect of this on the minority of Americans who use Twitter for political purposes?

It also is necessary to consider cultural factors that may contribute to angry tweets receiving more public feedback. Iyengar et al (2012) performed research on data collected from national and cross-national surveys in order to study affective polarization. Most research on political polarization is done so from the perspective of differences in policy preferences, but they decided to analyze it by considering the extent to which partisans view each other negatively. They found that, on average, the rating of the respective other party had dropped by about fifteen points since 1988. They wrote, "…the mere act of identifying with a political party is sufficient to trigger negative evaluations of the opposition, and exposure to prolonged media-based campaigns only reinforces these predispositions." Their research shows how argumentativeness on social media could be the result of cultural partisan strife; nonetheless, considering that social media are "prolonged media-based campaigns," the researchers also suggest that social media contributes to this phenomenon, as well.

Slate's former senior technology writer said after Twitter initiated its algorithm that the site should not be construed as a marketplace of ideas: "But as Twitter gets better at showing users the tweets that most resonate with them, the risk is that it's also getting better at reinforcing their biases and abetting their construction of alternate realities—not a marketplace of ideas, but a battlefield pocked with foxholes" (Oremus 2017). Even the individual who created the retweet button for Twitter said the function needs to be reformed because it "incentivize[s] extreme, polarizing, and outrage-inducing content" (Kantrowitz 2019). Social media offer interest groups a powerful way to reach more citizens more quickly than they have been able to in the past. Tweets with argumentative language from interest groups, in particular, receive more public feedback than tweets without such language. And Twitter's algorithm appears to further expand the reach of these tweets. It could be argued that this is a function of democracy – an organized interest informing and mobilizing the public against a shared ideological opponent. Twitter, and social media broadly, has changed how the U.S. political system, and therefore interest groups, function. Future research should consider if this new political communication landscape actually promotes civic engagement for more citizens and, if not, how that can be achieved.

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Appendix A – Coding Scheme

You've been invited to take part in Sean Newhouse's research study on criticism and praise in interest group tweets. For this project, I am looking at tweets from the NRA (@NRA), Everytown (@Everytown), Susan B. Anthony List (@SBA), and Planned Parenthood Action (@Ppact) from Labor Day 2018 (9/3) to the day after Election Day 2018 (11/7).

First, create a column in Microsoft Excel or a similar product for Tweet IDs. Each organization needs a consistent ID. For example, tweets from the NRA could be "1001, 1002, 1003…." But tweets from Everytown could be "2001, 2002, 2003…." An ID corresponds to a tweet, so the first tweet from an organization on Labor Day 2018 would be "x001."

In the adjacent column, copy and paste the corresponding tweet text. You will have to copy the text into a plain text editor first. Also, provide a brief description of any visual elements to the tweet. For example, is there a graphic? Who is on the graphic? What does it say?

Next, list the year, month, and day the tweet was posted in separate columns.

Then, record the number of likes, retweets, and replies it received in separate columns.

Most of the remaining questions are y/n questions. The first one is if the tweet is argumentative. Mark "1" if there's argumentative language and "0" if there's not. **Argumentative tweets express disagreement with an explicit and specific public ideological opponent.**

Express disagreement: The tweet has to portray someone or something in a negative light. This usually takes the form of direct criticism but consider context. Anytime

Everytown, for example, mentions the NRA it's more than likely criticism whether there is critical language or not.

Explicit and specific: The opponent has to be named. A tweet that vaguely criticizes or that disagrees with an unspecified "they" does not count. If the tweet doesn't list the name of a specific person or organization, it could still fall under these criteria so long as there's a negative characteristic, such as "senators who support x should be voted out of office."

Public Ideological Opponent: The opponent has to be a public figure. For this research, public figure is defined as an individual or entity who would be known to most of the followers of the page in question. The figure has to be mentioned or shown. Elected officials, candidates for public office, public officials, political parties (variations of Republican and Democrat), general terms that connotate specific examples (i.e. elites, Hollywood, lobbyists), companies, advocacy organizations, and states/countries all qualify under this category.

Example: Attack ad

In the next column, record if the tweet is agreeable. Mark "1" if there's agreeable language and "0" if there's not. **Agreeable tweets express support toward an explicit and specific external public ideological ally.**

Express support: The tweet has to portray someone or something in a positive light. This usually takes the form of direct support but consider context. Some individuals and entities are inherently supported whether there's specific language or not.

Explicit and specific: The supporter has to be named. A tweet that vaguely praises or that agrees with an unspecified "they" does not count. If the tweet doesn't list the name of a specific person or organization, it could still fall under these criteria so long as there's a positive characteristic, such as "senators who support x should remain in office."

External public ideological supporter: The individual or entity receiving praise cannot be primarily associated with the organization sending the tweet. Essentially, if the organization praises itself then it's not agreeable. The supporter has to be a public figure. For this research, public figure is defined as an individual or entity who would be known to most of the followers of the page in question. The figure has to be mentioned or shown. Elected officials, candidates for public office, public officials, political parties (variations of Republican and Democrat), companies, advocacy organizations, and states/countries all qualify under this category.

Volunteers, armed citizens, young people, shooting victims, unborn babies, women, and minority groups, as some examples, are not public figures. Some people from these groups, however, have become public figures.

Example: (Celebrity) endorsement

<u>Considerations</u>

1. Historical figures are not public figures.
2. If the organization sending the tweet is highlighting a partnership with another organization, the partnering organization **does not** qualify as an external supporter.
3. Everytown and Moms Demand Action partner so much that they should be treated as the same organization.
4. Students Demand Action is an organization under Everytown.
5. Ballot initiatives and proposed federal rules **do qualify** as public opponents and supporters for this research.
6. Everytown frequently refers to a #GunSenseMajority. Sometimes this refers to a majority of voters and sometimes to a majority in Congress. It only qualifies under this definition when it refers to members of Congress.

In the next column, mark “1” if there’s action-oriented language and “0” if there is not. For this research, **action-oriented means language that tells the viewer to complete a specific task.** Essentially, there has to be a verb whose subject is “you” (i.e. [You] vote.)

The action has to direct a specific task. In other words, the person reading the tweet can either complete the task or not. Here are some words that almost always count: vote, share, read, click, watch, learn. Some words that almost never count are: support, encourage, believe.

Action-oriented tweets also typically provide the means to complete the requested task.

Twitter polls, by their very nature, are action oriented.

<u>Considerations</u>

1. Planned Parenthood often asks its followers to #PinkOutTheVote. While this doesn’t technically qualify because “pink” isn’t a verb, it’s close to #GetOutTheVote and the intention is clear. So, this is an exception.

In the last column, note the multimedia employed in the tweet.

Mark “1” for **plain tweets** (no multimedia used). It’s just text. Twitter polls fall under this category.

Mark “2” if the tweet has a **graphic or photo**.

Mark “3” if the tweet includes a **link**. This usually manifests as shared articles or bitly links.

Mark “4” if the tweet includes an embedded **video**.

<u>Considerations</u>

1. Regarding gifs, if it could work as a video – mark it as 4. If not, mark it as 2.
2. If there is a link to a video (the video is not embedded in the tweet), mark it as 3.
3. If there is a bitly link and graphic or video, mark it as 2 or 4. This is because the video or graphic would be more visually dominant than the bitly link.

Considerations for the whole project

1. Only include original tweets. Do not include retweets or replies from the organization in the study.
2. Each tweet in a thread should be treated individually.

Appendix B – Means Tests

Likes Retweets Replies * Argumentative

Argumentative		Likes	Retweets	Replies
Not present	Mean	353.1743	121.9151	20.0109
	N	1096	1096	1096
	Median	77.5000	32.0000	3.0000
	% of Total N	53.4%	53.4%	53.4%
	Range	41799.00	14300.00	2900.00
present	Mean	435.3532	197.3856	79.0261
	N	957	957	957
	Median	109.0000	56.0000	6.0000
	% of Total N	46.6%	46.6%	46.6%
	Range	21797.00	10099.00	20900.00
Total	Mean	391.4817	157.0955	47.5207
	N	2053	2053	2053
	Median	92.0000	42.0000	4.0000
	% of Total N	100.0%	100.0%	100.0%
	Range	41799.00	14300.00	20900.00

Likes Retweets Replies * Agreeable				
Agreeable		Likes	Retweets	Replies
not present	Mean	368.3674	156.7300	67.1072
	N	1026	1026	1026
	Median	98.5000	48.5000	5.0000
	% of Total N	50.0%	50.0%	50.0%
	Range	10997.00	3500.00	20900.00
present	Mean	414.5735	157.4606	27.9533
	N	1027	1027	1027
	Median	78.0000	36.0000	4.0000
	% of Total N	50.0%	50.0%	50.0%
	Range	41799.00	14300.00	2900.00
Total	Mean	391.4817	157.0955	47.5207
	N	2053	2053	2053
	Median	92.0000	42.0000	4.0000
	% of Total N	100.0%	100.0%	100.0%
	Range	41799.00	14300.00	20900.00

Likes Retweets Replies * Action

Action		Likes	Retweets	Replies
not present	Mean	430.1197	156.5092	60.1109
	N	1253	1253	1253
	Median	110.0000	43.0000	4.0000
	% of Total N	61.0%	61.0%	61.0%
	Range	41798.00	14300.00	20900.00
present	Mean	330.9650	158.0138	27.8013
	N	800	800	800
	Median	74.0000	41.0000	4.0000
	% of Total N	39.0%	39.0%	39.0%
	Range	21799.00	10100.00	2000.00
Total	Mean	391.4817	157.0955	47.5207
	N	2053	2053	2053
	Median	92.0000	42.0000	4.0000
	% of Total N	100.0%	100.0%	100.0%
	Range	41799.00	14300.00	20900.00

Appendix C – Summary Tables of Linear Regression Results (Relationships Between Public Feedback Metrics and Coding Characteristics both Overall and by Organization)

	Likes		Retweets		Replies	
Overall	R^2	b	R^2	b	R^2	b
(Constant)		353.174*		121.915*		20.011
Argumentative	0.001	82.179	0.005*	75.478*	0.003*	59.015*
(Constant)		368.367*		156.73*		67.107*
Agreeable	0	46.206	0	0.731	0.001	-39.154
(Constant)		430.12*		156.509*		60.111*
Action	0.001	(-)99.155	0	1.505	0.001	-32.31
	Likes		**Retweets**		**Replies**	
NRA	R^2	b	R^2	b	R^2	b
(Constant)		158.347*		48.641*		-7.215
NRA		1722.019*		647.652*		240.644*
Argumentative	0.171*	73.674	0.17*	72.272*	0.022*	57.827*
(Constant)		210.133*		96.990*		44.452*
NRA		1727.108*		652.057*		247.278*
Agreeable	0.17*	-36.043	0.166*	-30.322	0.021*	(-)50.93*
(Constant)		203.592*		70.743*		28.616
NRA		1720.241*		651.303*		239.171*
Action	0.17*	-27.448	0.165*	28.653	0.019*	-22.34
	Likes		**Retweets**		**Replies**	
Everytown	R^2	b	R^2	b	R^2	b
(Constant)		467.35*		160.617*		35.783
Everytown		(-)305.957*		(-)103.711*		-42.264
Argumentative	0.01*	9.885	0.013*	50.965*	0.004*	49.029
(Constant)		459.549*		192.352*		85.229*
Everytown		(-)306.73*		(-)119.83*		(-)60.961*
Agreeable	0.01*	25.211	0.011*	-7.472	0.003*	-43.327
(Constant)		488.561*		180.766*		70.316*
Everytown		(-)298.886*		(-)124.057*		-52.191
Action	0.011*	-47.382	0.011*	22.994	0.002	-23.269
	Likes		**Retweets**		**Replies**	
SBA	R^2	b	R^2	b	R^2	b
(Constant)		494.624*		172.543*		36.828
SBA		(-)441.677*		(-)158.087*		-52.51
Argumentative	0.022*	33.495	0.024*	58.045*	0.004*	53.227*
(Constant)		440.564*		182.793*		74.551*
SBA		(-)500.495*		(-)180.679*		-51.605
Agreeable	0.026*	170.894*	0.023*	45.743*	0.003	-26.298
(Constant)		578.948*		210.074*		81.009*
SBA		(-)469.727*		(-)169.061*		(-)65.957*
Action	0.025*	(-)156.973*	0.021*	-19.305	0.003*	-40.428
	Likes		**Retweets**		**Replies**	
PP	R^2	b	R^2	b	R^2	b
(Constant)		387.428*		138.291*		26.615
PP		(-)177.084*		(-)84.659*		-34.14
Argumentative	0.004*	142.66*	0.011*	104.388*	0.003*	70.677*
(Constant)		424.025*		179.312*		75.828*
PP		-119.216		(-)48.369*		-18.679
Agreeable	0.002	18.989	0.002	-10.312	0.001	-43.418
(Constant)		474.558*		172.805*		62.997*
PP		(-)124.845*		-45.781		-8.109
Action	0.003*	-100.209	0.002	1.118	0.001	-32.378
*p < .05						

Appendix D - Summary Table of Linear Regression Results (Relationships Between Public Feedback Metrics and Multimedia Characteristics)

	Likes		Retweets		Replies	
	R^2	b	R^2	b	R^2	b
(Constant)		380.931*		157.067*		42.729*
Plain	0	76.539	0	0.205	0	34.762
(Constant)		443.348*		185.787*		66.484*
Photo	0.002	(-)114.744	0.004*	(-)63.473*	0.001	(-)41.951
(Constant)		444.674*		172.945*		41.544*
Links	0.004*	(-)172.518*	0.002*	(-)51.405*	0	19.385
(Constant)		329.004*		127.413*		45.154*
Video	0.019*	613.713*	0.03*	291.568*	0	23.248
p < .05						

Appendix E - Summary Tables of Linear Regression Results (Relationships Between Public Feedback Metrics and Temporal Coding Characteristics both Overall and by Organization)

	Likes		Retweets		Replies	
	R^2	b	R^2	b	R^2	b
(Constant)		353.835*		143.211*		45.305*
Kavanaugh	0.002	123.463	0.002	45.535	0	7.267
(Constant)		167.123*		72.926*		19.1
Kavanaugh		85.009		31.059		1.87
NRA	0.171*	1718.958*	0.165*	647.079*	0.019*	241.253*
(Constant)		432.579*		173.559*		59.678*
Kavanaugh		137.495*		50.943*		9.828
Everytown	0.013*	(-)315.639*	0.013*	(-)121.647*	0.002	(-)57.614*
(Constant)		487.697*		193.068*		63.663*
Kavanaugh		69.903		25.586		-0.078
SBA	0.023*	(-)437.117*	0.021	(-)162.806*	0.002	(-)59.947*
(Constant)		397.716*		159.419*		48.065*
Kavanaugh		130.745*		48.225*		7.725
PP	0.004*	(-)130.725*	0.004*	(-)48.285*	0	-8.224
	Likes		Retweets		Replies	
	R^2	b	R^2	b	R^2	b
(Constant)		421.256*		172.183*		43.07*
Election	0.002	-128.688	0.003*	(-)65.208*	0	19.238
(Constant)		222.531*		97.379*		15.236
Election		(-)129.469*		(-)65.502*		19.128
NRA	0.172*	1723.008*	0.168*	648.573*	0.019*	241.325*
(Constant)		512.339*		207.672*		58.929*
Election		(-)156.816*		(-)76.168*		14.34
Everytown	0.013*	(-)321.541*	0.014*	(-)125.283*	0.002	(-)55.985*
(Constant)		510.23*		204.277*		57.198*
Election		8.038		(-)15.889		40.948
SBA	0.022*	(-)448.568*	0.021*	(-)161.805*	0.003*	(-)71.228*
(Constant)		482.272*		195.976*		44.978*
Election		(-)161.657*		(-)78.064*		18.206
PP	0.004*	(-)151.388*	0.006*	(-)59.034*	0	-4.735
*p < .05						