Tweeting PP: an analysis of the 2015–2016 Planned Parenthood controversy on Twitter

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Abstract

Objectives—We analyzed Twitter tweets and Twitter-provided user data to give geographical, temporal and content insight into the use of social media in the Planned Parenthood video controversy.

Methodology—We randomly sampled the full Twitter repository (also known as the Firehose) (n=30,000) for tweets containing the phrase "planned parenthood" as well as group-defining hashtags "#defundpp" and "#standwithpp." We used demographic content provided by the user and word analysis to generate charts, maps and timeline visualizations. Chi-square and t tests were used to compare differences in content, statistical references and dissemination strategies.

Results—From July 14, 2015, to January 30, 2016, 1,364,131 and 795,791 tweets contained "#defundpp" and "#standwithpp," respectively. Geographically, #defundpp and #standwithpp were disproportionally distributed to the US South and West, respectively. Word analysis found that early tweets predominantly used "sensational" words and that the proportion of "political" and "call to action" words increased over time. Scatterplots revealed that #standwithpp tweets were clustered and episodic compared to #defundpp. #standwithpp users were more likely to be female [odds ratio (OR) 2.2, confidence interval (CI) 2.0–2.4] and have fewer followers (median 544 vs. 1578, p<.0001). #standwithpp and #defundpp did not differ significantly in their usage of data in tweets. #defundpp users were more likely to link to websites (OR 1.8, CI 1.7–1.9) and to other online dialogs (mean 3.3 vs. 2.0 p<.0001).

Conclusion—Social media analysis can be used to characterize and understand the content, tempo and location of abortion-related messages in today's public spheres. Further research may inform proabortion efforts in terms of how information can be more effectively conveyed to the public.

Implications—This study has implications for how the medical community interfaces with the public with regards to abortion. It highlights how social media are actively exploited instruments for information and message dissemination. Researchers, providers and advocates should be monitoring social media and addressing the public through these modern channels.

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Keywords

Planned Parenthood; Social media; Twitter; Abortion

1. Introduction

On July 14th, 2015, the Center for Medical Progress, an antiabortion organization posing as a biotechnology firm, began releasing videos online of Planned Parenthood employees discussing the purchase of fetal tissue for research purposes [1]. These videos contained surreptitiously recorded conversations that were edited to imply misconduct on the part of Planned Parenthood. Although the videos were discredited [2], they gained widespread media coverage and ignited public debate over abortion care and research with fetal tissue in the United States (US). A significant political response ensued, including congressional hearings, legislative attempts to make Planned Parenthood ineligible for federal funding and strong antiabortion rhetoric from presidential candidates. Social media platforms such as Twitter, Facebook and Instagram both reflected and influenced the public discourse of this controversy [3,4].

Twitter is a free microblogging media tool that forms a valuable repository of publically messaged opinions [5–7]. Approximately one quarter of adults online use Twitter [8]. Users are able to post messages of 140 characters (called a "tweet") to either the general public or a group of followers, who subscribe to posts from individual users. While companies often use Twitter to track consumer trends, its data repository of over 310 million monthly users is also now used by health researchers [9]. Related work has included the use of Twitter as a predictive tool for epidemiological spread of disease, measurement of public sentiment on health policy changes and even exploration of using social media language analysis to prospectively follow patient health [10–12].

While much of the interest in Twitter centers around monitoring ambient discussions in the public sphere, users employ Twitter to strategically spread messages and information in order to influence others [13–15]. Twitter employs several platform functions that increase visibility and interest in tweets. Hashtags ("#") assigned to keywords express affiliations to various digital social publics and dynamic topic themes ("threads") [16,17]. Users can also repost a previously tweeted post of another user from their own account, which is known as a "retweet" or direct tweets at other specific users by including their username in the tweet ("mentions"). These both allow messages to be amplified through a new set of followers. Finally, because tweets are limited in characters, they often link to additional websites with more content including blogs, news articles, images and videos.

Abortion is one of the most frequently discussed medical procedures on social media platforms [18]. In the case of the Planned Parenthood video controversy, users took to Twitter with two very opposite intentions of influencing the discussion of abortion [19]. This public debate had political, financial, medical and legal consequences for abortion provision. The objective of our research was to describe the public discourse on this controversy in terms of both content being shared and strategies used to disseminate information on Twitter. We compared the demographic and content characteristics of tweets from the group-defining

hashtags "#defundpp" and "#standwithpp" to obtain novel insight into the public debate on abortion.

2. Methods

We conducted a mixed-methods, retrospective, repeated cross-sectional study using Twitter data between July 14, 2015, and January 30, 2016, a 180-day span that begins with release of the first video and concludes just after the indictment of two employees from the Center for Medical Progress [2]. We used both qualitative and quantitative methods to compare messaging around this issue among proabortion (represented by #standwithpp) and antiabortion (represented by #defundpp) advocates. We chose these two hashtag campaigns in particular because they were both the most trending hashtags used at the time as well as championed by the major advocacy groups in question. #standwithpp was used and continues to be used directly by Planned Parenthood, major news outlets (*CNN*, *Newsweek*, *Mic* and *Bustle*, among others), politicians and celebrity advocates. While antiabortion users tweeted a variety of hashtags, #defundpp was used by legislators and public figures and has headlined anti-Planned Parenthood rallies.

Our study was deemed exempt by the Oregon Health & Science University institutional review board.

2.1. Database

We collected data using Crimson Hexagon (Crimson Hexagon, Boston, MA, USA; 2016), a licensed social media analytic tool that samples **the entire collection of tweets on Twitter, known as the *Firehose***, with unbiased and statistically consistent categorical proportions that is available for an institutionally negotiated fee [8,20]. During our inquiry period, a total of 6,884,998 tweets contained the phrase "planned parenthood." Also during this time, 1,364,131 tweets contained an antiabortion message using the hashtag "#defundpp," and 795,791 tweets contained a proabortion stance utilizing the hashtag "#standwithpp." For each of these phrases, we sampled 10,000 random tweets over this time period.

2.2. Variables

For each tweet, Twitter provides certain information related to the user account of the tweet (Table 1). Additionally, if provided by the user, Crimson Hexagon can also give location data associated with the Twitter account including country, state, and city or urban area; the author's gender; and the author's Klout score. Klout score is a validated, industry-accepted measure of "social influence" based on the author's presence and follower count across several social media platforms [21,22]. Klout scores have a range of 1–100, with higher scores corresponding to greater strength and spread of influence.

We uploaded our tweet sample to the open web app Visage (Column Five, Irvine, CA, USA; 2016) to create topic graphs that helped us understand the most prevalent themes in the tweets. The tweets were then queried for the most frequently mentioned words and categorically coded based on the three themes that dominated the conversation: "political," "action" and "sensational." "Political" words were defined by any association with a political institution or movement (i.e., hillaryclinton, republican). The "action" category

included verbs calling for a particular activity (i.e., support, donate). Finally, "sensational" terms were defined as such because they employed dramatic or visceral imagery (i.e., chop, murder, war). Neutral, descriptive words such as "planned parenthood" or "with" were excluded. In order to limit researcher bias in categorizing these terms, two investigators independently coded the 200 most common words. In the event of a disagreement, a third investigator arbitrated the final category. Table 2 contains an example of list of the top 40 most tweeted words and their category designations.

We also wanted to examine the use of statistical or data-based arguments. We found that use of the "%" symbol was almost always associated with statistical statements such as "87% of Planned Parenthood revenue comes from abortions!" We also assessed for use of platform-specific messaging strategies including retweets, links to external websites, "mentions" of other users (excluding retweets) and association with other threads (additional hashtags "#"). For geographical categorization, we adapted preexisting US census regions (West, Midwest, South and Northeast) [23].

2.3. Analysis

We analyzed the output through a variety of qualitative and quantitative techniques in order to characterize the origin, content and cadence of the conversation. We used tabulations, descriptive statistics and graphs to examine sociodemographic variables and tweet content. Chi-square and t tests were used to compare differences in content, statistical references and dissemination strategies by hashtag (indicating proabortion vs. antiabortion affiliations). We generated repeated cross-sectional geographic plots and scatterplots over time using RAW, an open web app that creates custom vector-based visualizations using the D3.js JavaScript library (Density Designs, Milan, Italy; 2016). Additionally, because tweeting is highly correlated with real-time information, these were examined in relationship to known significant events that occurred during this time period (e.g., Republican Presidential Primary debates, shooting at the Colorado Springs Planned Parenthood). We used Stata 13.0 (StataCorp LP, College Station, TX, USA; 2013) and Microsoft Excel 14.4.3 (Microsoft Corporation, Redmond, WA, USA; 2010) for analysis.

3. Results

Our final data set utilized 30,000 tweets from 18,869 users. We first examined specific author characteristics to identify differences in location, gender and social influence by hashtag used. Fig. 1 depicts the geographical distribution of #defundpp and #standwithpp tweets. #defundpp tweets were much more likely to occur in the American South (44% vs. 29, p<.001), while #standwithpp was seen disproportionately in the American West (26% vs. 19%, p<.001) and Northeast (19% vs. 12%, p<.001). Equal proportions of #defundpp and #standwithpp tweets came out of the Midwest (17%). Hashtag use was also differentiated by gender. #standwithpp tweets were predominately female (66% vs. 34%, p<.001), while #defundpp tweets were more likely to be male (53% vs. 47%, p<.001). Moreover, #defundpp users had significantly higher social influence (mean Klout score 47.8 vs. 41.4, p<.001) and more followers of their accounts (median 1578 vs. 544, p<.001).

We compared messaging tactics between #defundpp and #standwithpp campaigns by looking at both the content of tweets as well as strategies used to amplify messaging. There was no significant difference in use of statistical arguments (1% vs. .9%, p=.385). Our word analysis using coded designations also demonstrated differences in the #stand-withpp and #defundpp content. For the general thread "planned parenthood," 15.8% of words were categorized as "political," 9.7% as "action" and 11.4% as "sensational." For #defundpp specific tweets, we found that of the most common words, 36.9% of tweets were "political," 11.1% were "action" and 19.2% were "sensational." Meanwhile, for #standwithpp, 23.4% were "political," 15.8% "action" and 5.1% "sensational." We analyzed how the use of these words evolved over time in the public discourse (Fig. 2). While initial tweets predominantly used "sensational" words, over time, the proportion of politically associated tweets or "action" tweets increased.

Twitter-specific messaging strategies, such as including external links, mentions, retweeting and use of additional hashtags, are used to amplify messaging on social media. We examined whether #standwithpp and #defundpp tweets used these techniques differently. We found that #defundpp users were significantly more likely to insert external links (83% vs. 78%, p<.001), mention another user (40% vs. 37%, p<.05), as well as retweet previous user comments (86% vs. 65%, p<.001). #defundpp users were also much more likely to use additional hashtags to link their tweets to other threads (mean hashtags 3.3 vs. 2.0, p<.001).

Finally, we created various scatterplots over time to better understand the relationship of our demographic variables with tweet output and significant events. Fig. 3 is a scatterplot of #standwithpp and #defundpp tweets plotted over time with significant events marked on the timeline. Visually, it appeared that the #standwithpp tweets were episodic over this time and highly clustered around major events. #defundpp tweets appeared to have more consistent output over the study period. To quantify this, we compared tweets that occurred within 1 week of these events and found that #standwithpp tweets were far more likely to occur during this window (55% vs. 39%, p<.001).

4. Comment

Social media platforms such as Twitter play an important role in information dissemination, idea amplification and digital reflection of public sentiment [5,24,25]. In this study, we provide an analysis of public discourse on abortion and fetal tissue research controversy on Twitter. Important differences were identified in both the content shared by users and the methods used to disseminate messaging by pro- and antiabortion advocates. There were also significant demographic differences in geography, gender and social media engagement.

This study also provides one of the first attempts to formally analyze tweet content by examining messaging tactics using platform functions and word analysis. We found that antiabortion tweets appeared to use more dissemination strategies such as co-hashtagging mentions and retweeting. We were also able to use Twitter to monitor the evolution of this debate over a period of time. Our findings suggest that the Planned Parenthood debate, while originally fanned by the imagery implied in the videos, evolved as a political sound bite with increasing mentions in the context of politics and political action.

Our study shows that social media reflect many of the attitudes and opinions animating the public discourse of abortion provision. Previous research focusing on political events pertaining to abortion also found a robust public response on Twitter [26]. While our analysis similarly focuses on a period of significant controversy and public attention, it provides some new insight into the greater abortion discourse as a whole. Because Planned Parenthood is abortion's most visible US institution, we believe that it is fair to extrapolate anti-Planned Parenthood sentiment as antiabortion sentiment and, similarly, pro-Planned Parenthood postings as reflective of a proabortion sentiment. It has been shown that personal perspectives on social media leanings are often heavily biased by self-selecting social circles and algorithmically curated media feeds to match the readers' opinions [27,28]. As a result, without separate research inquiry, it may not be evident to many people that antiabortion posts dominated this discussion almost 2:1 during this period or that these posts came from more "influential" users. Similarly, it may be surprising that while the large body of evidence about the safety of abortion supports its unregulated provision [29,30], both sides appeared to employ statistical arguments with equal frequency.

There are significant limitations to this analysis. An inherent limitation to any analysis of a social media platform is that there will be population biases reflective of the platform's user base [31]. Twitter users tend to be younger, better educated, wealthier and more ethnically diverse [32]. Second, our study is limited by the types of data available from the Twitter Firehose. This data set is not constructed for public health research. Thus, key demographic information is not available or is restricted to self-report (gender and location), limiting our interpretation. Furthermore, if self-reported data are systematically missing, this can bias results. Third, hashtag analysis carries inherent biases that can skew data because hashtags themselves are user-defined surrogates. There may be some classification errors (for example, it is possible that some users are linking tweets to hashtags of the opposite sentiment to influence or infiltrate that dialog), and tweeting trends in these hashtag samples may not be externally valid to larger populations [33,34]. Fourth, in addition to words, tweets often contain images or links. These are important pieces of content that at this point we are unable to analyze. Fifth, this analysis is cross-sectional to a specific period of high-volume social media engagement around this topic. Results during this time should not be extrapolated to subsequent time periods. Finally, while we provided unique information about what is contained in the discourse, we cannot measure the impact of the message. There are some platform outcomes such as "likes" that hold potential as surrogates, but further research is needed to develop mechanisms for extracting these data. However, our study is one of the first attempts to examine a social media data set for abortion-related content using both quantitative and qualitative methods. We believe that our analysis significantly develops a nascent field.

There is important insight to be gained from studying medical issues like abortion on social media. We are increasingly aware that scientific data siloed to conventional medical journals may have little impact on public knowledge or perception [35]. In other recent examples such as transgender bathroom laws and gun violence, we have seen that public discourse can lead to political reactions and consequences [36,37]. Information regarding abortion is easily and often distorted, and distorted information may be the first information received by the public at large [38]. Research on the presence of distorted medical information on social

platforms provides some insight about what the public is *actually* seeing and saying. Moreover, analysis such as this may inform proabortion efforts by describing how information can be effectively conveyed to the public.

As the interface of transmitting medical information happens increasingly outside the medical office and in the digital world, medical research needs to expand outside of traditional media to influence these spheres. Public discourse can be considered an important outcome for measuring the impact of research, particularly research on abortion and reproductive health. We hope that our study will encourage further rigorous, multidisciplinary inquiry into this field.

Acknowledgments

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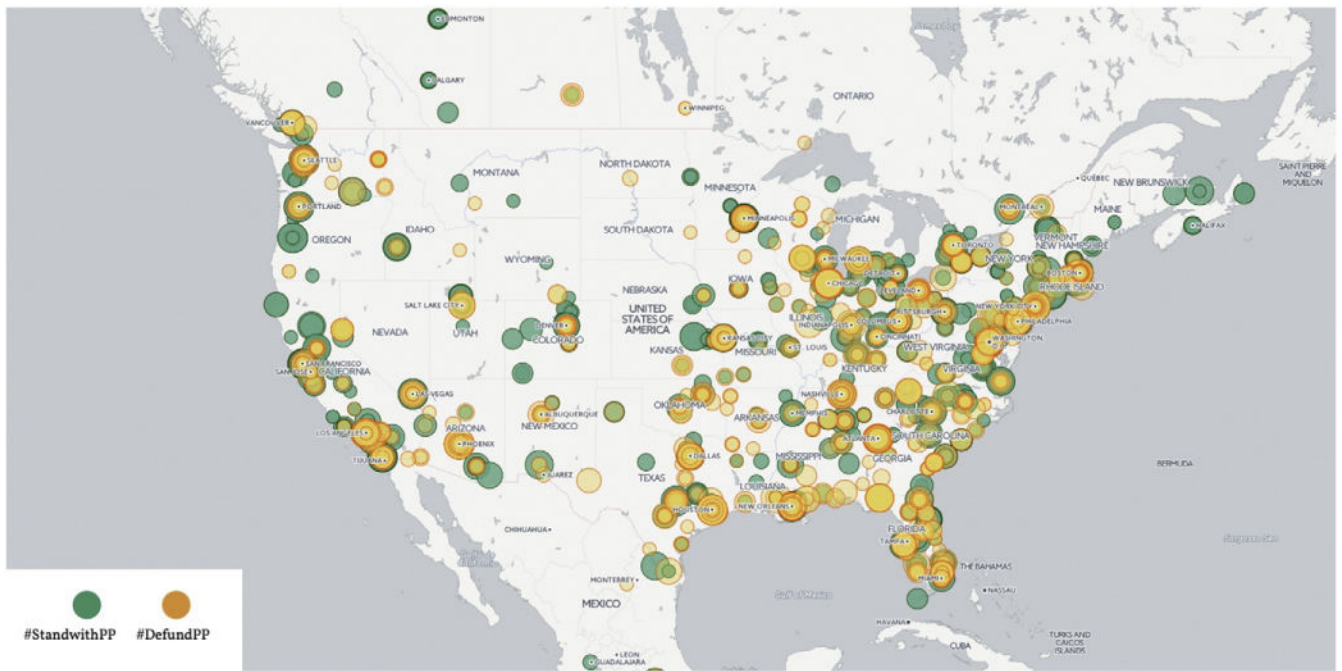
Fig. 1.
Geographic distribution: geographic origin of tweets containing "planned parenthood" sorted by those containing "#standwithPP" and "#defundPP." The size of the circle represents the relative Klout score (social influence) of the account.
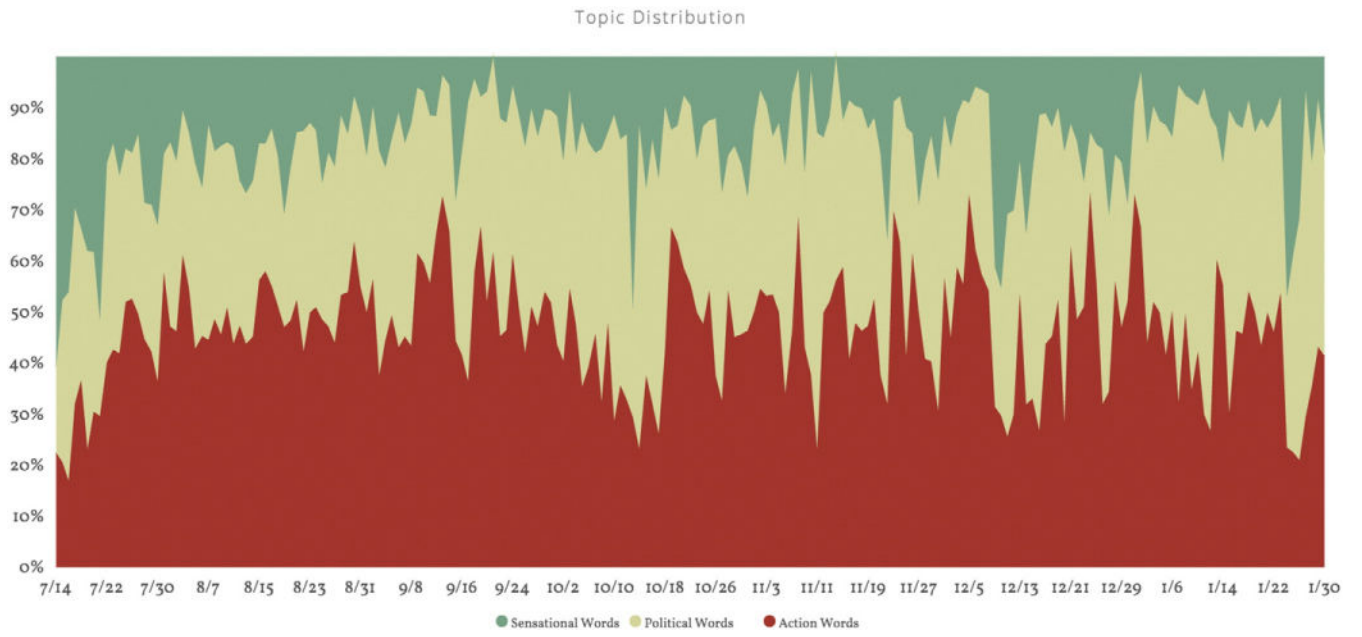
Fig. 2.
Topic distribution: use of "sensational," "political" and "action" words over time in tweets containing "planned parenthood."
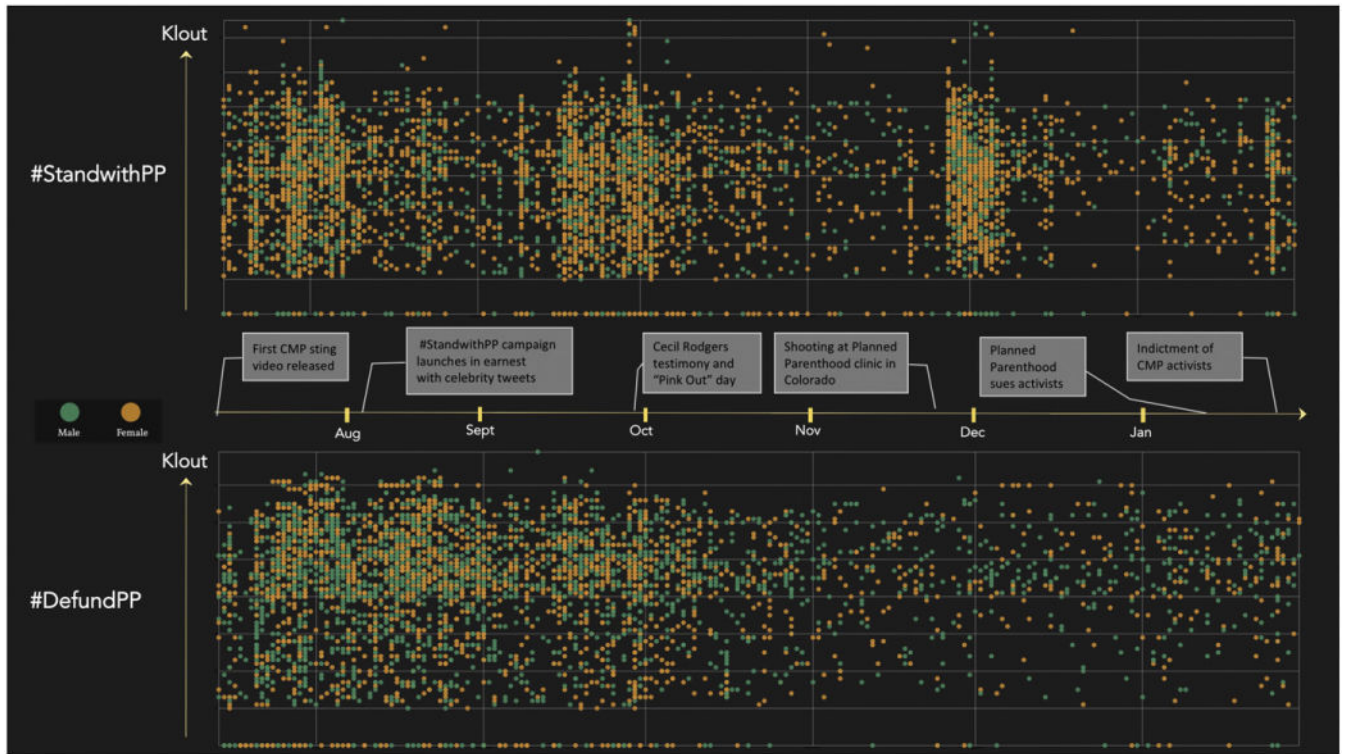
Fig. 3.
Tweets over time: volume of tweets by gender containing "#standwithPP" and "#defundPP"
over the time period of July 14, 2015, to January 30, 2016. The vertical axis plots the
relative Klout score of the user.

Table 1

Data categories provided by Twitter Firehose used in this analysis

Category	Definition
Identifier	Twitter database ID
Date and time	Timestamp of when tweet was published
Link	URL for accessing original tweet
Tweet	Tweet text/content
Author handle	Username associated with Twitter account
Author name	If given by author
Geographical location	By country, state/region and city if available
Klout score	Measure of social influence (scale 1–100)
Gender	If given by author
Posts	Number of previous posts author had made up until the time of tweet
Followers	Number of other Twitter users following this account at time of tweet
Following	Number of accounts this Twitter user is following at time of tweet

Table 2

Top 40 most tweeted words from #planned parenthood, #defundpp and # standwithpp and their category designations

"planned parenthood"	#	Sort	"#defundpp"	#	Sort	"#standwithpp"	#	Sort
planned	841	E	#pjnet	291	P	planned	186	E
parenthood	827	E	#ppsellsbabyparts	228	S	parenthood	179	E
#plannedparenthood	175	E	#tcot	146	P	women	168	E
defund	84	A	planned	136	E	@ppact	157	P
via	71	E	mt	126	E	health	145	E
baby	69	S	parenthood	121	E	#plannedparenthood	110	E
abortion	63	E	baby	103	S	care	77	E
videos	60	E	#prolife	99	P	support	76	A
funding	49	P	#wakeupamerica	99	A	@ppfa	70	P
women	44	E	defund	99	A	against	70	E
#defundpp	42	A	#plannedparenthood	94	E	abortion	63	E
parts	41	S	#unbornlivesmatter	84	S	stand	51	A
babies	40	S	abortion	83	E	#prochoice	50	P
aborted	37	S	@ppact	75	E	reproductive	50	E
body	33	S	#cruz2016	64	P	show	47	A
#ppsellsbabyparts	32	S	body	63	S	pp	46	E
against	31	A	parts	62	S	stop	46	A
gop	31	P	#trump2016	61	P	republicans	44	P
#standwithpp	30	A	#uniteblue	61	P	@sensanders	43	P
#tcot	30	P	babies	61	S	#uniteblue	42	P
obama	30	P	life	60	E	attack	41	E
defunding	29	A	@jstines3	57	P	#abortion	40	E
health	28	E	#ccot	55	P	#prolife	40	P
republicans	28	P	#cruzmissile	42	P	defund	40	A
congress	27	P	chop	40	S	attacks	39	E
people	27	E	shop	39	S	@hillaryclinton	38	P
support	26	A	stop	35	S	access	37	E
texas	26	E	women	35	E	healthcare	37	E

"planned parenthood"	#	Sort	"#defundpp"	#	Sort	"#standwithpp"	#	Sort
@ppact	25	P	pp	34	E	women's	36	E
hillary	25	P	don't	31	E	#solidarity	34	P
clinton	24	P	hillary	31	P	today	34	E
attacks	22	E	#praytoendabortion	29	A	change	33	A
chop	22	S	want	29	E	don't	33	E
shop	22	S	like	28	E	need	33	A
fund	21	A	@leahr77	27	E	profile	32	E
shooting	21	S	unborn	27	S	right	32	P
want	21	E	@lifenewshq	26	P	people	31	E
#prolife	20	P	can't	26	E	#p2	30	P
abortions	20	E	need	26	A	cut	30	A
bill	20	P	#defundplannedparenthood	25	A	#pinkout	29	P

Key: P = political, A = action, S = sensational, E = excluded.