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Listening to #2A: Applying a Qualitative Method to Twitter Dialogue

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Abstract

In this article, we present a project that explored the application of an established qualitative methodology to a novel source of data: microblog postings on the social media platform Twitter, also known as tweets. In particular, we adapted Consensual Qualitative Research (CQR; Hill, Thompson, & Williams, 1997) for use in this analysis. The coinciding aim of the project was to study the cultural impasses that seemed to characterize U.S. society surrounding the 2016 presidential election. Publicly available tweets bearing the hashtag #2A were selected for examination; this hashtag indicated the user's intention to direct the posting to the attention of Twitter users in the context of the Second Amendment, which refers to citizens' right to bear arms. The article describes the process by which CQR was modified for this use, profiles the exploratory findings, and present suggestions for subsequent similar research undertakings.

Keywords

Social Media, Twitter, Consensual Qualitative Research

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Listening to #2A: Applying a Qualitative Method to Twitter Dialogue

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In this article, we present a project that explored the application of an established qualitative methodology to a novel source of data: microblog postings on the social media platform Twitter, also known as tweets. In particular, we adapted Consensual Qualitative Research (CQR; Hill, Thompson, & Williams, 1997) for use in this analysis. The coinciding aim of the project was to study the cultural impasses that seemed to characterize U.S. society surrounding the 2016 presidential election. Publicly available tweets bearing the hashtag #2A were selected for examination; this hashtag indicated the user's intention to direct the posting to the attention of Twitter users in the context of the Second Amendment, which refers to citizens' right to bear arms. The article describes the process by which CQR was modified for this use, profiles the exploratory findings, and present suggestions for subsequent similar research undertakings. *Keywords: Social Media, Twitter, Consensual Qualitative Research*

"This is like the biggest focus group someone could ever imagine," stated a software company administrator in a recent New York Times technology article (Clifford, 2012; para. 25). The article profiled the upsurge in efforts to cull the immense amount of information that is represented by Twitter conversations and other social media dialogue. To date, these efforts have been led by market researchers and corporations hoping to maximize the profitability of their products and services. For example, Twitter data is frequently examined through some form of sentiment analysis, a computational approach to identifying language that suggests positive or negative attitudes toward a product or other target, and then using statistics derived from frequencies to calculate prevailing opinions and trends (e.g., Zimbra et al., 2018).

However, social media studies have also entered academic literature (Snelson, 2016), and psychologists and other social scientists could find social media to be a particularly important venue for their research, given the vast group of interlocutors and the relatively spontaneous nature of the dialogue. The in-vivo, contemporaneous nature of social media conversations about cultural topics holds particular promise for social scientists who study sociocultural issues. Along these lines, we wondered about the possibility of moving beyond frequency-based approaches in the analysis of this material via a qualitative methodology that would allow a more nuanced glimpse of the meanings within the dialogue. Framing such a project as exploratory, we were also interested in what we could learn from Twitter conversations about the sharp cultural divisions and attitudinal differences that were underscored at the time of the 2016 U.S. presidential election. Such trends and the importance of studying them are not, however, confined to a US context—the same upturn in political and cultural divisiveness has been noted on a global level (Amnesty International, 2017). In this article, we describe our work to explore these possibilities via a modified consensual qualitative research analysis of Twitter dialogue surrounding gun ownership.

Twitter and Social Scientists

With the current versions of both Facebook and Twitter emerging in 2006 (McFadden, 2018) and Instagram following in 2010 (Brown, 2018), social media represents a relatively new landscape for data analysis related to the study of human communication. Whereas Facebook and Instagram incorporate a focus upon interactions with friends, the microblogging platform Twitter lends itself readily to spontaneous, wide-ranging communications among its estimated 126 million daily users (Shaban, 2019) who may be known or unknown to each other. Via Twitter, researchers can access public exchanges focused on a vast array of themes, topics, or events; datasets of public tweets are available from Twitter's own Application Programming Interface (API) or from third-party companies who access the API on their customers' behalf for a fee. Users can add a feature called a *hashtag* to their 280-character tweets. A hashtag is an appended keyword or phrase that refers to a topic of interest and that is denoted by the initial character #. The hashtag allows users who are interested in a particular theme to search for and identify each other, functioning thereby as a virtual location in which users can communicate with each other.

As mentioned, the analysis of Twitter data has proven invaluable to marketers, yet its value extends beyond corporate applications. Jones and Silver (2019) listed accessibility and ecological validity as advantages offered by Twitter data, along with the fact that it tends to be less biased by low participation rates and demand characteristics. Kern et al. (2016) pointed out that "social media provides an active laboratory, far removed from the contrived small-scale experiments that have long dominated psychology" (p. 507). At the same time, the authors observed that psychologists who would like to engage with social media data will likely have had little guidance in how to do so. They presented an approach to social media analysis that bridged psychological concepts with computer science, describing the possibilities for mining social media on a large scale for quantifiable data points such as survey responses, "likes," and counts of word usages. In this way, theoretically derived research questions regarding the relationships between, for example, user characteristics and the frequencies of different classes of words can be addressed statistically.

Accordingly, psychologists have contributed automated linguistic analyses of psychologically relevant topics that include, for example, a study that revealed that suicide-related Twitter posts tended to feature more references to death, and more uses of the first person pronoun (O'Dea et al., 2017). Along these lines, researchers are creating computerized elaborations of frequency counts, such as analyses of the presence of particular keywords within Tweets (Brady et al., 2018), and a statistical classification of lexical variation in Tweets according to gender (Bamman et al., 2014). Jones and Silver (2019) compared the content of Tweets against a list of 114 anxiety-related words to explore reactions to a false missile alert issued in Hawaii, finding that expressions of anxiety increased 4.6% on the day of the false alert and escalated steadily during the actual alert period. Patton, MacBeth, Schoenebeck, Shear, and McKeown (2018) conducted one of the few qualitative studies of Twitter content with their examination of grief expression on Twitter. In so doing, the authors applied "a deep, textual analysis" to a corpus of 408 tweets from a particular user's Twitter network, explaining that "a deep read is a type of textual analysis in which annotators use outside knowledge such as context to interpret textual data" (p. 3). In addition, Kreis has used critical discourse analysis to examine Twitter users' discursive strategies, revealing the criminalizing depictions of refugees in a #refugeesnotwanted corpus (2017a) and illuminating U.S. President Donald Trump's provocative political brandishing of Twitter communication (2017b).

Zappavigna (2011) pointed out that the searchable quality of electronic data presents multiple options for turning up instances of particular content that could be available for such a deep read. She discussed the potential to go beyond lists of search results to study the "communities of shared value" formed by people via the "hive mind," or the stream of continuous online conversation (p. 789). In particular, Zappavigna identified hashtags as a kind of metadata whose primary function is to invite and establish affiliation: "The hashtag… broadly presupposes a virtual community of interested listeners who are actively following this keyword" (p. 791). In using hashtags, according to Zappivigna, we are "labeling the ideation that we are going to axiologize around" (p. 799). Twitter hashtags, therefore, can become hubs for online community discussion of values, as well as locators by which individuals can find opportunities for participation in these discussions. Once inside, participants can experience a forum for support, expansion of their original views, and ideas for activism. Using hashtags to develop and maintain attention to particular social issues has been called "hashtag activism" (Bogen et al., 2019, p. 4).

The Aims of the Project

The current project was developed from two objectives that coincide with the preceding discussion, as will be described below. One had to do with the range of possibilities for social media to serve as social science data, particularly with regard to consensual qualitative research. The second was related to our team's central interest in research related to social inclusion and exclusion; as a university-based team of researchers, we have conducted several qualitative studies in this area over the past decade. The data that we analyzed included formats that are typical to many qualitative studies: transcribed individual interviews (e.g., Smith et al.,2016; Smith et al., 2017) along with a few focus group transcriptions (e.g., Smith & Romero, 2010). We found Consensual Qualitative Research to be a useful methodological approach in our previous studies (CQR; Hill et al., 1997). With an ongoing consensus-based team process at its heart, CQR allows for a naturalistic, interactive approach to the exploration of nuanced issues as it balances the effects of researcher differences in the interpretation and coding of participant narratives.

Briefly, in the classic form of CQR, participants are interviewed using a semi-structured interview protocol. When the interviews have been transcribed, a small team of researchers (in our studies, usually three) develops a list of domains—or broad topic areas—via consensus that are proposed to subsume the data within the interviews. Each member independently reads through the transcripts and assigns the data into the domains; they subsequently meet to discuss these assignments and establish modifications according to their consensus. Domain headings, domained material, and the raw data are now submitted to an auditor, who is a fourth member of the team not involved in the coding itself. The auditor may provide feedback to the team here and/or at future points in the analysis process. Next, core ideas are abstracted within each domain for each interview, and subsequently these core ideas are examined within domains, but across participants. After identifying similarities within domains across cases, team members brainstorm a list of categories that describe the data in each domain.

We value CQR as a qualitative approach and especially appreciate its team-based, consensual nature. It affords researchers the opportunity to become closely involved with the data while also offering the benefit of other sets of eyes and other points of view. However, CQR stages and procedures were designed for a completely different sort of data set—relatively few participants who each contribute more extensive amounts of narrative. With its many users and snippets of dialogue, Twitter data presents precisely the opposite. We wondered if (and how) we could adapt the CQR process to the analysis of social media dialogue to the largest naturally occurring focus group imaginable? We decided to explore this question with regard to the culturally charged atmosphere that surrounded the 2016 presidential election.

Listening to the #2A Community

As referenced earlier, our work has focused broadly on the relationship between psychological practice and the sociocultural structural forces—like classism and racism—that relegate some groups to the cultural margins while others are maintained at the center of access to power, resources, and civic protections (e.g., Smith, 2015; Smith, 2010). *Social exclusion* and *social inclusion* are general terms that can be used to describe the action of these forces across different forms of structural oppression. At the time of the 2016 U.S. presidential election, we were among many social science observers of the striking, seemingly accelerating divisions and exclusionary animosities that seemed to characterize U.S. society.

What data might be available by which to gauge and interpret these divisions beyond our own viewpoints? We began to discuss ways of "listening in" on these sociocultural impasses—situations in which little progress ever seemed to be made toward resolution, as the opposing opinions of individuals were so deep-rooted that compromise seemed unlikely. In reflecting on our social media feeds, we shared an awareness that we existed within a specific progressive "political bubble," and we were interested in openly learning more about the other thought communities to which we were rarely exposed. Especially as psychologists, we were cognizant of the value that our field—a field that prioritizes the conceptualization of interpersonal relationships and dynamics—could eventually bring to our understanding of these gaps and divisions.

For its breadth and of-the-moment nature, Twitter suggested itself as a promising social media platform by which to access public sentiment within and across cultural impasses. As a way to narrow our focus, we debated various hashtags that could help us capture groups of prevailing sentiments. As mentioned, hashtags are words or phrases that are appended to a tweet and are preceded by a hash mark. Hashtags pinpoint a keyword or topic of interest, enabling social media platforms to index their users' posts and make them searchable by other users. In other words, once a user searches a specific hashtag, they are shown a page that aggregates all posts incorporating that same hashtag. In deliberating various hashtags, we sought one that (a) was broad enough to invite various impasses and tensions mentioned, and (b) that might particularly capture the impasse that we perceived to exist between the supporters of President Donald Trump and the supporters of his Democratic counterparts.

After deliberation, the hashtag #2A—referring to the Second Amendment to the U.S. Constitution—was selected. The Second Amendment to the U.S. Constitution refers to the right to bear arms, and reads as follows: "A well-regulated militia being necessary to the security of the free state, the right of the people to keep and bear arms shall not be infringed" (The Constitution of the United States, Amendment II [U.S. Const. amend. II]).

Dialogue around this hashtag seemed promising based on its contemporary social relevance with regard to public shootings, gun use, and the types of guns allowed in the U.S.—conversations that are not only frequently associated with political affiliations but that also have class—and race—related implications. #2A also seemed to be an opportune hashtag given its potential associations with mounting anti-Muslim and anti-immigrant rhetoric at the time of the Trump presidential election. Along the same lines, #2A seemed to dovetail with the racism-related tensions that coincided with the 2016 presidential election: gun rights themselves have been closely associated with racial dynamics via legislation like Florida's Stand Your Ground Law, by which individuals are permitted to use deadly force when they fear bodily harm, and which was cited in the defense of the killer of Trayvon Martin, an unarmed Black teen. For all these reasons, #2A stood out as a viable location at which to listen in on a variety of the tensions that might be part of the national dialogue.

Method

The Twitter universe is, of course, too vast to be apprehended in its totality, and in order to carve out a data set within it, we took guidance from other researchers. We followed Zappavigna (2011) in aiming "not to construct a representative corpus of the linguistic activity on Twitter, but instead to conduct a case study in which field variables, that is, the topic of the tweets, was held relatively constant to afford a rich investigation of meaning-making in a single domain on Twitter" (p. 792). Having selected #2A as our domain, we gathered our corpus of tweets in proximity to a relevant cultural event—the 2016 presidential election—while acknowledging the impossibility of knowing what proportion of total commentary this corpus represented (Whiting et al., 2019). Like Bogen et al. (2018), we collected a sample of tweets containing a particular hashtag, removed all retweets (or tweets having non-original content), and then specified the remaining tweets as a corpus for study.

More specifically, the social media analytics platform Tweetbinder was used to procure two sets of tweets captured directly from the Twitter stream. Capture parameters for each were set at 5000 tweets bearing the hashtag #2A, with each capture period beginning at 2 pm, which is located within the peak volume hours for Twitter that are generally estimated to range between noon and 3 pm EST. All tweets posted during the capture times in English in the United States were entered into the data sets. The first data set was drawn approximately four months before the 2016 U.S. presidential election (July 22nd, 2016). This data set contained 5560 postings in all, with 1585 (or 28%) of these being original tweets (the others were retweets of other postings). The second was created approximately four months after the inauguration of the newly-elected U.S. president Donald Trump in 2017 (April 7th, 2016). It contained 5578 postings, with 1758 (or 31%) original tweets. In this way, two data sets were created; the original #2A tweets from each year comprised the corpus for each sample, hereafter referred to as the 2016 and 2017 data sets.

As will be explained below, every tweet within each #2A data set was assigned by research team members to one or more categories pertaining to content theme—although all tweets bore the hashtag #2A, the textual content of the tweets varied widely, with some having no overt connection to the connotation of the hashtag. Interpretation of content themes was not dependent on any particular word usage within the tweet, rather, content themes were interpreted by team members who read each tweet for meaning and then refined their shared understanding of its meaning through consensus. This process of assigning meaning categories to a tweet will be referred to as "coding."

In order to most fully permit divergent meanings to emerge from each of the two data sets, the two data sets were coded by two separate teams working independently of each other. Team members were graduate students in counseling psychology. The total number of team members was 14, and the period of the project stretched over a summer break during which some team members graduated and were replaced by new team members. During the first year, each team had four members; during the second year, each had five. Among the 14, five team members were White, four were Asian American, three were Arab or Arab American, and two were African American. Twelve identified as women, with the remaining two identifying as men. The project was supervised by a White female faculty member.

CQR's traditional series of gradated data reduction stages was not appropriate to our project, given the dramatic brevity of a Tweet in comparison to a full interview narrative. Nevertheless, we adhered carefully to CQR's hallmark process: independent coding by team members, who then argue each code to consensus to arrive at a final category framework. Each team developed an emergent coding structure for their own data set without knowing the categories that had been developed by the other team, as knowing about and/or attempting to apply the other teams' structure would have conveyed potentially biasing expectations regarding the meaning structure of that data set. Within teams, themes were inductively derived by individual team members for each tweet, who then met as a group to reach consensus. Using the constant comparison approach, categories that emerged from team consensus were compared to the data on an ongoing basis and continuously assessed regarding the overall developing structure; refinements along the way were also argued to consensus. Some tweets lacked sufficient clarity and/or content to enable them to be categorized by the team and were therefore coded as *unclear*. In 2016, there were 109 unclear tweets, which left 1476 that were coded for content. In 2017, 220 were unclear, leaving 1538 that were codable.

Results

Following the completed coding of both data sets, we obtained an analysis of the estimated groupwide characteristics of each #2A corpus from Demographics Pro, an analytic platform that infers anonymized, aggregated demographic group profiles via a computerized algorithm that is based on publicly-available information offered in user profiles and communications. According to the anonymized groupwide analyses of the accounts contained in our data sets, the 2016 users estimated to be 96% White and 68% male, while in 2017, they were 97% White and 87% male. In 2016, the most frequently identified state of residence was estimated to be California at 16% followed by Texas at 12%; in 2017 it was Texas at 12% followed by California at 10%. Approximately half of the users in each year had over 1000 Twitter followers of their own (48% and 50%).

Table 1 displays the thematic category structure as interpreted by the two separate analysis teams. As shown, the 2016 data set was analyzed as having 27 content-related themes, and the 2017 data set was analyzed as having 29 content-related themes.

Table 1. Thematic Categories and Number of Codes Assigned by Corpus Year

	2016 Category	Code Frequency	2017 Category	Code Frequency
1	Pro 2A	359	Gun Friendly	838
2	Advertisement	217	Aficionado	728
3	Guns Keep Us Safe	180	Self-Protection	333
4	Terrorism	168	Visibility	246
5	Anti-Gun-Control	134	Stupid Liberals	230
6	Gun Information	127	Sales	186
7	Females and Guns	123	Pro-Trump	136
8	Anti Hillary	109	Civic Participation	116
9	Anti-Obama	107	Islamophobia	88
10	Conservative Positions	105	and Guns	83
11	Pro Trump	102	Heteronormativity	76
12	Gun Enthusiast	97	Military	76
13	Racism	85	Militant Revolution	63
14	Information	71	Racism	60
15	Fear of Government	68	Religion	60
16	Call to Action	56	Preppers	46
17	Pro-Military	51	Fake News	46

18	Anti Liberal	51	Anti-Obama	23
19	Nationalism	44	White Nationalism	15
21	Stupid Liberals	45	Anti-Gun	14
22	Guns are Sexy	42	Blue Lives Matter	12
23	Pro Law Enforcement	27	Anti-Trump	12
24	Pro Gun Family	26	Classism	6
25	Entertaining	25	Mental Health	6
26	Religion	22	Anti-Hillary	6
27	Mental Health	17	All Lives Matter	5
28			Anti-Abortion	4
29			Black Lives Matter	3
Total		2458		3517

As might be expected from an unstructured, emergently derived coding process, individual differences appeared among the category structures derived by the two independent working teams. Both teams received the same general orientation to the task and knew that they were free to assign multiple codes to a single tweet as per team consensus. In practice, the 2017 team tended to assign multiple codes more frequently, with an average of 2.3 codes per tweet. In comparison, the 2016 team assigned an average of 1.6 codes per tweet.

Once the thematic codings were completed by each team, the two teams met to examine their results side-by-side for the first time. Each team presented an overview of the coding results from their corpus, and then the two teams compared and contrasted the two data sets, as well as their own experiences of their immersion within the data set that they worked on.

Subjective Team Experiences of the Results

As the teams considered the presentation of each other's results, they shared their impression that the 2017 corpus conveyed a greater feeling of energy and enthusiasm relative to 2016. As one team member put it, "They seem excited about the [presidential] candidate who won and they now feel freer to speak up." Team members remarked on the sense of anger and perceived unfair treatment within both data sets by tweeters who were presumed to be White. They noted the frequent utilization of racist and Islamophobic rhetoric in the expression of these sentiments. One team member summarized this position as "It's like they're saying, it's unfair how people who are inferior to me get more rights than I do—or the same rights that I do." Both teams also noted the demeaning language in #2A regarding political liberals, who were portrayed as stupid and hypocritical. Team members were struck by the conflation of gun ownership with patriotism and pro-military sentiments. "It almost felt like being a gun owner is *equivalent* to being patriotic," commented one. Team members noticed that they encountered no gun-related discussion about white shooters (such as in publicized accounts of school shooters or police shootings of Black men) in the data sets.

Team members also presented to each other the elements of the data sets that most surprised them. No one had expected the fear of government theme that emerged within #2A, especially in 2016—the notion that, for some, ownership of a personal firearm is motivated by belief in the eventual need for citizens to defend themselves not from outsiders but from the U.S. government itself. Along these lines, the Twitter #2A data sets represented the first time that many team members had encountered the so-called "prepper" movement —people who believe that the likelihood of catastrophic national civil unrest and/or natural disasters is high, and that individuals must prepare to defend themselves against life-threatening circumstances (e.g., Feuer, 2016). Many team members had expected to discover more active debate about gun use, given the strong opinions that exist on both sides of this issue, but there was very little anti-gun sentiment expressed in association with #2A—2017 alone featured a relatively small *Anti-Gun* category. The strong heteronormative emphasis of the data sets surprised some team members, as did the use of women's sexuality to sell guns. Finally, team members had not expected the high number of gun sales pitches that they encountered.

Team members also shared the affective experience of their work with the data sets. Many tweets were explicitly racist; some led the researchers to Nazi or "dark web" sites; the activities of illegal gun sellers were suggested. One team member summarized the experience by calling it "emotionally taxing. I found myself desensitizing or numbing myself." Team members discussed their developing understanding of the positions reflected in #2A, although this understanding rendered the material no less disturbing. Team members felt vividly the fear that seemed to suffuse the #2A tweets, with one describing the #2A mindset as "The world is a scary, dangerous place, and everyone who is trying to take away my gun is making me more unsafe."

Discussion

In this section, we describe the meanings of the emergent thematic categories and outline possible interpretations. As mentioned, we chose to analyze each corpus independently by two separate teams in the interest of preserving the opportunity for categories to be derived emergently and without prejudice according to the categories found in the other set of tweets. For this reason, the category structure is different for each year, offering an opportunity for consideration of both the similarities and the differences between the two. At the same time, this procedure also means that a direct, category-by-category comparison is not possible. For that reason, the impressionistic nature of the following descriptions should be borne in mind. Tweets from the corpus are quoted in italics, and each tweet exemplified below had the hashtag #2A appended to it in addition to the quoted text.

Top Categories: Support and Advocacy for Gun Ownership

Not surprisingly, given that every Tweet bore the #2A hashtag, the most tweeted categories in each year referred to the theme of the hashtag itself: *Pro 2A* in 2016 and *Gun Friendly* in 2017. In fact, what may be more surprising is that a greater proportion of tweets in each year did *not* receive codes related to a hashtag to which it was directly connected. This finding underscores the function of a hashtag to not only communicate directly regarding the interest that it represents, but also to bring a posting about something else to the attention of a community that presumably shares that interest.

Although *Pro 2A* (2016) and *Gun Friendly* (2017) parallel each other in meaning, their wording conveys the different character of each corpus as experienced by the coding teams. In 2016, coders responded primarily to the frequent specific mention of Second Amendment constitutional rights that suffused the corpus. Several of the other top categories that year developed related themes of perceived threat as indicated by *Guns Keep Us Safe, Terrorism*, and *Anti-Gun-Control*. The latter is obviously closely related to *Pro 2A*, yet the team interpreted a distinctly different character within those two categories. *Pro 2A* contained tweets that were patriotic in tone as they advocated for the right to bear arms; they emphasized individual rights and constitutional freedoms. *Anti-Gun-Control* tweeters were more defiant and less constitutional in tone (*You can have my gun when you take it from my cold dead hands*).

2017's top category, *Gun Friendly*, was interpreted by coders as support for guns and hunting as a way of life. *Aficionado* was a close second in 2017, and was a theme representing hobbyists and enthusiasts tweeting expository, specialist, and/or editorial content about particular guns (*The Myth of the .38 Snub Nose Revolver as a Good First Gun*). It could be said, therefore, that 2017's top categories referred to appreciation for firearms and support for their broad availability, with a self-defensive category, *Self-Protection,* as a runner-up to those (*Lord, make me fast and accurate. Let my aim be true and my hand faster than those who wish to harm me and mine*). Gun appreciation was codified by the 2016 team as well, but their category *Gun Enthusiast* was further down the list. *Gun Information* also came behind the defense-oriented categories in 2016; this category contained content that overlapped with 2017's *Aficionado* in that it described highly-regarded guns and their features or assets. In 2017, Twitter content that pertained specifically to individuals' defensive use of firearms—*Self-Protection*—came after the gun appreciation categories.

#2A and Self-Protection

Guns as a means of protection against others were referenced within each corpus, yet the enemy to be vanquished seemed to shift from 2016 to 2017. In 2016, a contingent of users specified the Obama led U.S. government itself as the enemy, with *Fear of Government* making an appearance within the 2016 category structure. In 2017, the team did not code the emergence of a category that conveyed a fear of one's own government; however, *Islamophobia* suggested a specific anti-Muslim sentiment—a fear of outsiders—within the corpus. It seemed to us that the shift in #2A tweeters' fears highlighted not only their distrust of the Obama administration but also their enthusiasm for President Trump, a White president who articulated gun-friendly sentiments and initiated a ban on Muslims entering the United States.

On the other hand, although President Barack Obama's record on gun control has been described as relatively weak (Murse, 2019), he has been portrayed as one of the most anti-gun presidents in the history of the US by the director of the National Rifle Association Institute of Legislative Action's (NRA-ILA) Public Affairs. For example, the NRA issued such statements as "President Obama's obsession with gun control knows no boundaries" (NRA-ILA, 2019; para. 3). Such pronouncements dovetail with the mistrust that pro-2A tweeters articulated. Not only may they have believed that the Obama administration did not have the best interest of its own citizens in mind, it also appears that they were strongly opposed to government attempts to limit their right to own weapons that they could use to defend themselves.

Relatedly, the Trump administration was led by a relative supporter of gun ownership, leaving groups such as Muslims and Arabs to serve as #2A motivators (*An Islamofascist agenda is underway! #WakeUpAmerica #WakeUpWesternCivilization*) for continued advocacy (*Disarmament is a death sentence in our current terror-tolerant societies. It is a citizen's job to kill terrorists*). In either case, #2A tweeters expressed their belief that, without arming themselves with a gun, they would be unable to defend themselves from anticipated threats. They conveyed the expectation that they would eventually have to take matters into their own hands, and that the U.S. government—even with a leader who is aligned with many of their ideals—could not adequately protect them. The 2017 category *Preppers* captures this generalized ongoing fear of impending catastrophe and the conviction that individuals would at that time be on their own to either sink or swim (*The Threat of Civil Unrest—Preppers Who've Relaxed Under Trump Have No Idea the Hell That Is Coming*).

Call to Action / Civic Participation / Militant Revolution

In coding the data, team members observed that tweeters in both years advocated for gun ownership that was free as possible from government statutes or oversight. At the same time, the relevant categories seemed to capture a divergence in tweets that were similar in content but different in tone. In 2016, tweeters frequently called for increased *Civic Participation* in association with the #2A agenda—that is, for the changing of relevant laws through greater civic involvement (*God, Guns, and Freedom! Join us as we light up Twitter with 2A tweets!*) along with *Calls for Political Action* (*Stop the erosion of our 2A rights! Rally at the statehouse at 10 am*). In 2017, coders responded to the salience of tweeters who called for continuing *Militant and/or Revolutionary Change* of the system itself (*Our government must be fully replaced by those who care about the people's rights!*). The different tones to which our coding teams responded suggests the possibility of a shift in attitude and mood within the #2A community. In 2016, tweeters advocated for relatively tame, within-system methods of replacing candidates who were not sufficiently pro-gun. In 2017, with the backing of a new president whom they felt was aligned with their beliefs, tweeters seemed emboldened to call for insurgency to defend against remaining individuals who may oppose them (*With A Half-Installed Coup D'Etat, Maybe You Should Join Your State Militia And Help Guard Your State*).

Racism, Islamophobia, and White Nationalism

Both 2016 and 2017 coders noted the use of racist themes and subtexts to promote #2A messages (*Palistinian authority publicizes rules for beating wives. Let's get more multiculuralism or should it be called delusionalism!*). These included tweets that utilized racist dog-whistle language (*Protecting oneself from thugs with a gun isn't taking the "law" into your own hands, it's taking your "life" into them*), and messages that were generally anti-immigrant (*No Trespassing, if U don't understand #English, let me use my 12 gauge*) and/or xenophobic (*Guess what else I walk with my dog? #2A Now get the eff out of my country*). The categories *White Nationalism* and *Nationalism* contained related content that furthermore advocated for the protection or promotion of Whites (*What is the appropriate response to a race which seeks which seeks to genocide yours? #MAGA*) with the utilization of additional hashtags like *#BlackLiesMatter*.

Anti-Liberal and Pro-Trump Tweets

Anti-Hillary Clinton sentiment was categorized as a theme within the #2A data sets for each year, but its prevalence was less apparent in 2017 in the aftermath of the election of her opponent, Donald Trump. Similarly, Anti-Obama tweets predictably dropped in prevalence within the 2017 category structure. Disapproving commentary in general about political liberals was a notable theme in each year (*Islamism AGAIN. Ruining the WORLD. Keep letting them in, DUMB Liberals. #2A Bang, bang*) with the 2016 team coding it as two separate categories: *Anti-Liberal* captured criticism of liberal policies, while *Stupid Liberals* contained derisive or mocking references to liberals (*San Francisco State University: another sucky left-wing shithole to avoid*). In keeping with the anti-liberal leanings of the #2A data sets, the eventual winner of the 2016 presidential election (*Good work from OUR Brave @POTUS!*) received primarily favorable mention (*Another promise kept! This @POTUS doesn't disappoint, and I knew he wouldn't. Success begets success*), although a few tweeters used #2A to share a different view *(#trump, he's Moronic #POTUS*). The 2017 category *Fake News*, a phrase popularized by President Trump, also reflected generally anti-liberal content (*Watch the new @NRA ad bringing the fight to the NYT and all the lying, violent leftist media*).

Reaching Out Within the #2A Community

Each data set contained categories that corresponded to the use of a hashtag as a way to metaphorically post a message on a community bulletin board. The bulletin board function was represented by 2016's *Information* and 2017's *Visibility* categories, in which a variety of informational tweets conveyed announcements or bits of information on a variety of topics that ranged from the environment (*Green power is the wave of the future!)* to preferred comic books (*The Amazing Spider-Man (2015 4th Series) is out*). Similarly, prominent categories like 2016's *Advertisement* and 2017's *Sales* contained tweets that hoped to bring products—often but not always guns—to the attention of potential #2A customers. Statements and outreach to the community regarding *Religion* and religious events were noted in each year, as were tweets that expressed and/or promoted support for police officers and the military.

#2A, Gender, and Sexuality

The #2A community used Twitter to express their perspectives on gender and sexuality, and in this regard, some general observations can be made that apply to both data sets. There were several tweets that used the hashtag to garner an audience for discriminatory and hateful messages regarding homosexuality, including instances where our team encountered links to homophobic images or external sites that had nothing to do with guns or the Second Amendment. Heterosexuality, on the other hand, was presented positively; moreover, women were used to make guns look sexy and entertaining. Content differed between users who appeared to be women, and others who appeared to be men who were tweeting about women (and guns). Male tweeters were vocal about their rights to acquire and own guns, as well as their feelings toward anyone who was seen as a threat to that right. Other tweets that related to women and guns were associated with entertainment, protection, and family. Overall, women's presence within #2A seemed primarily reflective of men's references to women rather than women using their own voices.

Gender-Related Categories

The category *Females and Guns* was developed for the 2016 data set to encompass all tweets related to women and guns. These tweets ranged from references to leisure and/or entertainment to politically-toned messages (*"The most misogynistic thing a society can do is hamper the ability of women to protect themselves"*). *Guns Are Sexy* reflected the strategy of using sex and women for marketing purposes; one tweeter was an apparent gun enthusiast who sold videos of herself using her guns in sexy outfits. *Pro-Gun Family* was a 2016 gender—referenced category that encompassed content related to guns as a part of family life. Tweets in this category included such examples as a video of a father teaching his daughter to shoot, and advocacy for protection of family life through the Second Amendment. Women made an appearance in this category via tweets that urged mothers to own guns for the protection of their children. In fact, the NRA tweeted a campaign called *"Moms Like Me."* The team who analyzed the 2017 data spotted similar themes that they captured with the category *Women and Guns*. As in 2016's *Females and Guns,* this category encompassed all tweets with content related to women and guns. *Heteronormativity,* another 2017 gender-referenced category, included such messages as tweets that were linked to an external site titled *The Art of Manliness* or that generally affirmed traditional gender roles.

Minor Categories

Some categories appear in the structural table with only a few entries. In each year, these included the *Mental Health* category, which referenced mental health in some way (*#gunsense will use suicide as a justification for burdening our #2A rights. They do nothing to increase mental health care for suicidal people*). In addition, the 2016 team coded jokes with the code *Entertaining*. In the 2017 data set, the team added codes to denote the number of tweets that carried the "Lives Matter" hashtags in addition to #2A: *#BlueLivesMatter*, *#AllLivesMatter*, and *#BlackLivesMatter*. The 2017 team also coded a small number of tweets that contained *Social Class* and *Anti-Abortion* references.

Through the Eyes of the #2A Community

Via the lens provided by our qualitative category structure, a general portrait emerges from the #2A corpus—a portrait of values, views, and the world of their aspirations. This sample of 2Aers want to view the US as a powerful country that can protect itself from external threats, but they do not fully trust the US government to assure their own safety. They feel strongly that their everyday personal safely requires that they be individually armed, a right that they believe is guaranteed by the U.S. Constitution. They are angered by what they call "political correctness" and believe that commentary or critique of their views on guns, religion, or race are misguided, stupid, and pretentious. Their cultural identifications align with Whiteness and Christianity, and they want to be free to self-segregate with regard to race and religion; ; others are viewed as intruders in spaces that are rightfully theirs. Those individuals who are seen as unprepared for the encroachment of dangerous others are described as gullible and vulnerable. 2Aers express frequent fear of danger and of losing power in the nation and/or the world, and the opportunity to freely own and carry guns is closely identified with the maintenance of their power.

Limitations and Lessons Learned

As with all qualitative findings, the discussion here is understood to reflect the subjectivities of the researchers and the characteristics of this particular sample. As mentioned, the independent coding of the two data sets does not allow for direct comparison, so our commentary on their correspondences is speculative. Although we utilized a qualitative methodology that incorporates consensus as a check on individual biases, all researchers in this study came from the same graduate program in the northeastern region of the United States, one that has an emphasis on multicultural approaches to psychology, and this shared perspective should be borne in mind.

Another limitation involves the indeterminate yet likely presence of bots and trolls among our corpus of Twitter users. Bots are computer-automated Twitter accounts that are programmed to post content; trolls post provocative content for its own sake and/or to promote a particular agenda, sometimes from fake accounts. The prevalence of these accounts has been estimated variously. Twitter has suggested that approximately 5% of its users are spammers or trolls, and that 8.5% are automated (Timberg & Dwoskin, 2018) while Varol et al. (2017) estimated the number of bots to be somewhere between 9% and 15% of all Twitter accounts. Demographics Pro, the platform that created our demographic group profiles, applies an algorithm that is designed to eliminate fake accounts from its results, but the broader influence of bots within Twitter generally cannot be ruled out in the consideration of our findings.

In general, we came away from this exploratory project believing that consensual qualitative research elements can be as useful in the analysis of social media narratives—and for the same reasons—as it with more conventional data. This is not to minimize the usefulness of the quantitative approaches that underlie such endeavors as sentiment analysis. Depending on one's goals, frequency-based analyses can clearly be advantageous: for a company whose interest is in the number of specific mentions of their product, a computer program that can move through thousands of Tweets and count up those mentions is clearly the most effective way to assess Twitter data. However, not all the meanings conveyed in Twitter dialogue can be gathered in such a straightforward way; entries into our categories were often derived from nuanced and/or indirectly stated communications. Moreover, just as with conventional data, consensual qualitative research methods allow for themes to emerge that researchers did not anticipate and would not have specified for analysis beforehand, as in the case of *Fear of Government*. Proposed procedures and recommendations that derive from this project are as follows:

1. Decide in advance what aspect(s) of each tweet will be analyzed and coded. In this article, we present the analysis of content-related themes within the corpus. However, we considered other elements of the data that could also have been analyzed. For example, we noted that some tweets contained images, while others contained links to websites or other media. These features could have been analyzed and either coded separately or in relation to the themes. We also explored the possibilities regarding the coding of affect within the tweets, noting that some seemed to convey anger, pride, disgust, or some other emotional tone. We were interested in all these elements and would consider extending our approach to comprise them in future research.

2. Initiate an emergent establishment of category structure as well as the process by which the team will code the tweets. We initiated our procedure based on our experience with CQR methods, but we were in unknown territory as we worked with tweets and we refined our method in the process of this study. Again, our process was to have two teams of four or five researchers working with two separate data sets of approximately 1500 tweets each, one data set from 2016 and the other from 2017. Without communicating with each other, the two teams proposed and refined the category structure for their data sets by working with one subset of tweets at a time. For example, team members might agree to work independently on the categories for a group of 100 tweets in preparation for their next consensus meeting. Independently, each researcher read through the 100 tweets and assigned one or more codes (i.e., category names) to each tweet. Of course, when researchers were working with the first group of tweets, there were no existing categories and all were proposed emergently; for subsequent groups, tweets could either be assigned to existing categories and/or received newly proposed codes. When team members met, they discussed the coding of each of the 100 tweets to consensus. When the team agreed that a new code was needed, the team undertook a review of the previous coding to see if the new code should be retroactively applied anywhere. Going forward, we would utilize this sequence more efficiently from the beginning of the project.

3. Collaboratively evaluate the coding process on an ongoing basis. It is important for team members to take time to discuss and review the reasoning behind their use of categories and the rational for proposing new categories (or collapsing existing ones). Along these lines, we continued to discover tweets that challenged our assumptions about the essential parameters of established categories. For example, the 2016 team ultimately created two categories that originally seemed similar yet corresponded to tweets that the members ultimately found to be different: *Pro 2A* and *Anti-Gun-Control*.

4. Document the team's process. It is helpful to conclude each consensus meeting by creating documents that reflect evolving team codes and consensus, which can then be shared with team members to use going forward. For this purpose, we eventually decided to use an Excel spreadsheet that had the text of each tweet in the corpus listed in a column—so the spreadsheet for each corpus had approximately 1500 rows, and as many columns as there were categories. Additional columns were added for each category, with a 1 entered in the columns that indicated the coding for a particular tweet. Each row, therefore, lists the tweet and the categories that were assigned to it. In addition, we created a compendium of all categories used thus far, and updated it following each consensus meeting, referring to this as the codebook. We established this practice in the course of the present study; in the future, we would include it from the outset.

5. Incorporate an auditor. One of the elements of CQR that we did not import into this process—and retrospectively, we wished that we had—is the participation of an auditor. Looking back, both our coding teams felt that the opportunity for outside input would have aided their work. Requesting more audits early in the process would be most helpful, as that is the time that the team is becoming acclimated to the consensus process and is refining its coding standards. For example, the first audit could come after a team had coded 10% of the tweets; the second might come after 20%, and then a third could be conducted at the halfway mark. The auditor could review all the team's materials, including the codebook and the spreadsheet showing codes assigned thus far. The auditor could then offer suggestions with regard to the meaning and consistency of the categories and/or any possible redundancies.

Concluding Comments

Calling for new methods in an age of new media, Barden (2013) pointed out that familiar paradigms for data collection and analysis may not fully lend themselves to new modalities of interpersonal communication. He described the need to create innovative experimental methodologies in order to undertake this analysis and described striving for an adaptation of existing methodologies that is pragmatic and flexible rather than "methodologically 'pure'" (p. 10). With this project, we hope to further encourage the flexible application of established qualitative methodologies in new social science data settings—applications that can better allow social scientists to learn from the multifaceted, ongoing communication of views and values that flourishes within Twitter hashtag communities.

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