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#DoctorsSpeakUp: Lessons learned from a pro-vaccine Twitter event

Beth L. Hoffman[a,b,c,*], **Jason B. Colditz**[b,c], **Ariel Shensa**[d], **Riley Wolynn**[b,c], **Sanya Bathla Taneja**[b,c], **Elizabeth M. Felter**[a], **Todd Wolynn**[e], **Jaime E. Sidani**[b,c]

[a]Department of Behavioral and Community Health Sciences, Graduate School of Public Health, University of Pittsburgh, 130 De Sotto Street, Pittsburgh, PA 15261, United States

[b]Division of General Internal Medicine, Department of Medicine, University of Pittsburgh, School of Medicine, 1218 Scaife Hall, 35505 Terrace Street, Pittsburgh, PA 15261, United States

[c]Center for Behavioral Health, Media, and Technology, University of Pittsburgh, School of Medicine, 230 McKee Place, Suite 600, Pittsburgh, PA 15213, United States

[d]Department of Physical Therapy, University of Pittsburgh School of Health and Rehabilitation Sciences, 4028 Forbes Tower, Pittsburgh, PA 15260, United States

[e]Kids Plus Pediatrics, 4070 Beechwood Blvd, Pittsburgh, PA 15217, United States

Abstract

Background: In response to growing anti-vaccine activism on social media, the #DoctorsSpeakUp event was designed to promote pro-vaccine advocacy. This study aimed to analyze Twitter content related to the event to determine (1) characteristics of the Twitter users who authored these tweets, (2) the proportion of tweets expressing pro-vaccine compared to anti-vaccine sentiment, and (3) the content of these tweets.

Methods: Data were collected using Twitter's Filtered Streams Interface, and included all publicly available tweets with the "#DoctorsSpeakUp" hashtag on March 5, 2020, the day of the event. Two independent coders assessed a 5% subsample of original tweets (n = 966) using a thematic content analysis approach. Cohen's κ ranged 0.71–1.00 for all categories. Chi-square and Fisher's exact tests were used to examine associations between tweet sentiment, type of account, and tweet content (personal narrative and/or statement about research or science). Accounts were analyzed for likelihood of being a bot (i.e. automated account) using Botometer.

Results: Of 847 (87.7%) relevant tweets, 244 (28.8%) were authored by a Twitter user that identified as a parent and 68 (8.0%) by a user that identified as a health professional. With regard

[*]Corresponding author at: Graduate School of Public Health, University of Pittsburgh, 130 De Sotto Street, Pittsburgh, PA 15261, United States. beth.hoffman@pitt.edu (B.L. Hoffman).

Declaration of Competing Interest
The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Todd Wolynn is co-founder of "Shots Heard Round the World" and was involved in the promotion of the #DoctorsSpeakUp event. Todd Wolynn has received funding from Merck Corporation and Sanofi Pasteur Inc. for conference travel, lodging, and consulting, but not during the time this study was conducted.

Appendix A. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.vaccine.2021.03.061.

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to sentiment, 167 (19.7%) were coded as pro-vaccine and 668 (78.9%) were coded as anti-vaccine. Tweet sentiment was significantly associated with type of account ($p < 0.001$) and tweet content ($p = 0.001$). Of the 575 unique users in our dataset, 31 (5.4%) were classified as bots using Botometer.

Conclusions: Our results suggest a highly coordinated response of devoted anti-vaccine antagonists in response to the #DoctorsSpeakUp event. These findings can be used to help vaccine advocates leverage social media more effectively to promote vaccines. Specifically, it would be valuable to ensure that pro-vaccine messages consider hashtag use and pre-develop messages that can be launched and promoted by pro-vaccine advocates.

Keywords

Twitter; Social media; Anti-vaccine; Health communication

1. Introduction

Vaccine hesitancy—the delay or refusal of vaccination despite its availability—has been identified by the World Health Organization as one of the top ten threats to global health [1]. Although vaccine misinformation has circulated for decades, messages on social media platforms appear to be amplifying its spread and facilitating the connection of anti-vaccine activists worldwide [2-4]. Additionally, individuals who rely on social media for information are more likely to be misinformed about vaccines than those who rely on traditional media, such as television news programs [5]. This misinformation can lead to real-world harms, such as decreased vaccination rates and the resurgence of vaccine preventable disease. For example, measles was eradicated in the United States, but the disease resurfaced largely due to vaccine refusal [6,7].

In response to concerns about the propagation of anti-vaccine misinformation and connections on social media, the organization “Shots Heard Round the World” (i.e. “Shots Heard”) launched in 2019 [8]. Dedicated to aiding health professionals who are targeted for advocating for vaccines online, “Shots Heard” consists of a fully vetted Facebook group and listserv of individuals that support the distribution of scientific information about vaccines and adherence to evidence-based vaccination schedules. The mission of the organization’s response network is for “Shots Heard” volunteers to come to the aid of individuals, organizations, and medical practices being targeted by anti-vaccine activists. For example, in November 2019, Shots Heard gained international attention by coming to the aid of Brad Bigford, a traveling nurse practitioner who received thousands of comments from individuals against vaccines [9]. Shots Heard again garnered international attention in January 2020 after coming to the aid of Cincinnati-based pediatrician Nicole Baldwin, whose TikTok video about the importance of vaccines was met with anti-vaccine comments as well as harassment and personal threats [9].

Following these two events, Zubin Damania, MD, known colloquially as ZDoggMD on social media, posted a video to his YouTube channel calling all healthcare professionals and pro-vaccine advocates to speak up in support of vaccines using the hashtag #DoctorsSpeakUp on March 5, 2020 on the social media platform Twitter [10]. A hashtag is created automatically when the author puts the '#' symbol before a word, and allows users to click on a linked word or phrase and navigate to other mentions of it, facilitating conversation on the topic [11]. Many health organizations and campaigns have successfully used hashtags to promote their messages [12]. In the days leading up to the event, news reports surfaced that the anti-vaccine movement was preparing to use the #DoctorsSpeakUp hashtag on Twitter on March 5, 2020 to spread misinformation about vaccines [13].

Given these reports, we aimed to systematically examine Twitter messages (i.e. tweets) related to the #DoctorsSpeakUp event. The primary aims were to determine (1) characteristics of the Twitter users who authored these tweets, (2) the proportion of tweets expressing pro-vaccine compared to anti-vaccine sentiment, and (3) the content of these tweets.

2. Methods

2.1. Sample selection

Data were collected using Twitter's Filtered Streams Application Programming Interface (API) and the Real-time Infovellience of Twitter Health Messages (RITHM) software framework [11]. Data potentially included all publicly available tweets with the "#DoctorsSpeakUp" hashtag that were posted from midnight March 5, 2020 until the following midnight (United States Eastern Time), which corresponds to the day of the #DoctorsSpeakUp o event on Twitter. This elicited 106,275 tweets, of which 86,943 were retweets of other tweets and 19,332 were original tweets.

A 5% subsample of original tweets (n = 966) was selected using RITHM "HashSpear" functionality. The HashSpear procedure uses tie-adjusted Spearman ranked correlations to compare the frequency of top hashtags in random subsamples of data (i.e., n = 966) to the frequency of those hashtags in the full dataset (i.e., n = 19,332). In this process, iterative subsamples are drawn and the Spearman coefficient is calculated for each subsample, then the subsample with the strongest correlation is retained [11,14]. In the current study, the top 61 hashtags were included based on face validity of their relevance to the topic, and each of these had at least 50 occurrences in the primary data (See Appendix 1).

This study was approved by the University of Pittsburgh Institutional Review Board (PRO19080214). To protect tweeters from identification, we paraphrased all example tweets included in the text and tables.

2.2. Codebook development

To achieve a sample of tweets that were specific to the #DoctorsSpeakUp event, we included a code for *relevance*. Tweets that did not pertain to vaccination (i.e. "*When will #DoctorsSpeakUp that we need covid testing?*") were deemed not relevant. The first coding category pertained to the *type of account* that authored the tweet, coding if the Twitter user who authored the tweet self-identified, either in the user's Twitter bio or the tweet itself, as a health professional, parent, and/or organization. These account types were informed by the nature of the event (i.e. calling on healthcare professionals and organizations to tweet about vaccines) and prior research suggesting anti-vaccine social media content is often generated by those who identify as parents [2]. An account was coded as an organization if the Twitter bio contained information clearly identifying the account as belonging to an organization (e.g. link in bio to organization's website). An account was not coded as an organization if it was the personal account of someone affiliated with an organization (e.g. "reporter for local news organization"). Accounts that were suspended, deleted, or unclear were coded as unknown.

The second coding category was *sentiment* (i.e. pro or anti-vaccine). Pro-vaccine sentiment was operationalized as the tweet expressing support of healthcare workers that administer vaccines and/or vaccines themselves, and anti-vaccine sentiment was operationalized as the tweet expressing opposition to healthcare workers that administer vaccines and/or vaccines themselves.

The third coding category pertained to *content*, with sub-codes for narratives and/or presentation of statements about research or science. This coding category was informed by best practices of risk communication and prior research examining vaccine content on social media. Specifically, risk communication best practices emphasize the use of evidence-based information and/or narratives and anecdotes when communicating about public health topics [15]. Additionally, prior research suggests vaccine content on social media contains both narratives related to vaccination and/or presentation of statements about research or science [2,16]. The final codebook presented clear definitions and examples for each code (Table 1).

The codebook was validated through analysis by two coders of 100 relevant tweets that were not included in the final sample.

2.3. Coding procedures

We used an iterative coding process that involved double-coding by independently working human coders, adjudication of disagreements, and codebook clarification. Coders were provided with the tweet text and a link to each tweet online. All relevant tweets that remained publicly available at the time of coding were viewed on Twitter.com so that links to external content could be assessed when possible. However, the text from unavailable tweets was still included in thematic analysis to preserve comprehensiveness of the original data. Inter-rater reliability was assessed using Cohen's κ and disagreements were adjudicated between the two coders, with the lead author having the final determination. After four rounds of this process, inter-rater reliability was considered good to excellent (Cohen's κ 0.71–1.00) for all categories [17]. Coders then independently coded the remaining tweets.

2.4. Analysis

For each coding category, we calculated descriptive statistics and used a thematic content analysis approach [18]. Codes were not mutually exclusive. For example, a tweet that mentioned vaccinating one's child because 1 in 500 children with measles dies from the disease would be coded as containing both a narrative and presentation of a statement about research or science. We coded both textual and visual (e.g. pictures, videos) content present for each tweet. For the thematic content analysis, coders reviewed tweets within each of the codes for thematic trends, highlighting specific words or phrases within tweets that exemplified the emergent themes. Coders also wrote annotations and memos throughout the coding process, which were reviewed with supervising researchers to refine the themes identified.

We used Chi-square and Fisher's exact tests to examine the associations between tweet sentiment (pro- and anti-vaccine) and type of account (parent, professional, both parent and professional, and organization) and tweet sentiment (pro- and anti-vaccine) and content (personal narrative, statements about research or science, and both personal narrative and statements about research or science). Tweets of "unknown" authorship or those without specific content (i.e. personal narrative or statements about research or science) were not included in the Chi-square or Fisher's exact tests, but were still included in the thematic content analysis.

In addition to the content analysis by human coders, we also used the Botometer application to analyze Twitter users that authored tweets in our dataset for likelihood of being a bot (i.e. automated account) [19]. Botometer uses over 1000 features from the Twitter user profile to determine the probability that an account is completely automated [20,21]. Consistent with prior research, all user accounts with a bot probability higher than 0.43 were classified as bots [22]. Tweets authored by suspected bots were included in the content analysis to provide a comprehensive assessment of what Twitter users viewing the #DoctorsSpeakUp hashtag on the day of the event were exposed to.

3. Results

A total of 847/966 (87.7%) of tweets were deemed relevant to the #DoctorsSpeakUp event.

3.1. Type of account

The content analysis by human coders found that, of relevant tweets, 244 (28.8%) were authored by a Twitter user that identified as a parent, 68 (8.0%) were authored by a user that identified a health professional, 42 (5%) were authored by a user that identified as both a health professional and a parent, 35 (4%) were authored by a user that identified as an organization, and the remaining 458 (54%) were unknown. Twitter users who identified as a health professional or a parent and health professional and tweeted pro-vaccine content often included their credentials (e.g. MD, MPH, PhD) in their Twitter username or referenced their specialty (e.g. #pediatrician) in their Twitter biography. Almost a quarter of tweets authored by an account where the user identified as a health professional or a parent and health professional were anti-vaccine. Additionally, approximately 50% of tweets authored by an organization were anti-vaccine. These accounts often included the terms pro-information and pro-science in their Twitter biography.

In our dataset, 130 users authored two or more tweets with the majority of these users authoring tweets expressing anti-vaccine content. Of the 575 unique users in our dataset, 31 (5.4%) were classified as bots using Botometer. The Botometer API could not determine the probabilities for 19 (3.3%) accounts due to the profiles being private, suspended, deleted, and/or lacking sufficient user content for analysis. Of the 141 users who authored pro-vaccine tweets, 2 (1.4%) were classed as bots using Botometer and 3 (2.1%) could not be determined. Of the 422 users who authored anti-vaccine tweets, 29 (6.9%) were classed as bots using Botometer and 19 (3.3%) could not be determined.

3.2. Tweet sentiment and content

Of relevant tweets, 167 (19.7%) were coded as expressing pro-vaccine sentiment, 668 (78.9%) were coded as expressing anti-vaccine sentiment, and 12 (1.4%) were considered neutral in sentiment.

3.3. Description of pro-vaccine tweets

Within the pro-vaccine tweets, 23 (13.8%) contained a personal narrative. These tweets often mentioned the tweet author not seeing cases of vaccine preventable diseases due to vaccines, or a personal connection to someone who is immunocompromised (e.g. "*My niece is why I vaccinate. She had a transplant at 9 mo of age, then cancer, so is on immunosuppressants and cannot receive live vaccines. #DoctorsSpeakUp #ParentsSpeakUp*"). Additionally, 28 (16.8%) pro-vaccine tweets contained a statement about research or science, often including statistics on deaths from vaccine-preventable diseases (e.g. "*#DoctorsSpeakUp Vaccines prevent 2–3 million deaths per year!? That is why it is so important to get your #vaccines! #VaccinesWork*").

Thematic content analysis of pro-vaccine tweets that were not coded as either a personal narrative or research/science found these tweets mostly consisted of general statements such as "*vaccines are safe and effective*" or "*preventing disease is better than treating disease*." Another theme observed was tweets mentioning nurses being powerful advocates for vaccination and/or the hashtag #NursesSpeakUp (e.g. *"Nurses are excellent advocates for vaccines. If you're a nurse, don't be afraid to speak up! #DoctorsSpeakUp # NursesSpeakUp*"). Several tweets also included videos of a healthcare provider speaking directly into the camera about supporting vaccines.

3.4. Description of anti-vaccine tweets

A total of 64 (9.6%) anti-vaccine tweets contained a personal narrative (e.g. *"My child's pediatrician said to stop vaccines after my son developed autism 14 years ago. When will #DoctorsSpeakUp*") and 239 (35.7%) contained a statement about research or science (e.g. "*When will # doctorsspeakup about a 54% increase in child chronic illness and that life expectancy is falling?*"). Anti-vaccine tweets coded as containing a statement about research or science often included claims that vaccines cause neurological problems including seizures and autism, and links to videos of anti-vaccine activists claiming that vaccines have not been adequately tested for safety and efficacy via large-scale randomized control trials. Further qualitative analysis of anti-vaccine tweets revealed that approximately 20% (n = 131) of the tweets were identical to one of the six suggested tweets from an infographic shared on Twitter by anti-vaccine activists (Fig. 1).

Thematic content analysis of anti-vaccine tweets that were not coded as either a personal narrative or research/science found these tweets often contained the first suggested tweet in Fig. 1 (*"When will # DoctorsSpeakUp that the #vaccines harm and kill children?*"). Other themes observed were tweets mentioning that health professionals vaccinate because of financial compensation (e.g. "*when will # DoctorsSpeakUp about receiving money from insurance companies for vaccinating children?*") or health professionals not being well educated about vaccination (e.g. "*when will # DoctorsSpeakUp that they don't get any real vaccine education?*").

3.5. Associations between tweet sentiment and type of account

Tweet sentiment was significantly associated with type of account ($p < 0.001$). When examining the tweets in each type of account (those authored by parents, by health professionals, and by both parents and health professionals) by tweet sentiment, the proportion of tweets that were pro- or anti-vaccine sentiment varied (Table 2). For example, among tweets authored by parents, only 3.7% were pro-vaccine compared to 96.3% that were anti-vaccine. Conversely, among tweets authored by health professionals, 79.4% were pro-vaccine and 20.6% were anti-vaccine. Complete results are presented in Table 2.

3.6. Associations between tweet sentiment and content

Tweet sentiment was significantly associated with tweet content ($p = 0.001$). When examining the proportion of tweets in each content category (personal narrative, research or science, and a combination of personal narrative and research or science) by tweet sentiment, a greater proportion of each content category contained anti-vaccine sentiment (Table 2). Of particular note were tweets containing research or science; while almost 90% of these tweets contained anti-vaccine sentiment, only 10% contained pro-vaccine sentiment.

4. Discussion

Our analysis of representative tweets related to the #DoctorsSpeakUp event on March 5, 2020 provides insight that can guide future vaccine advocacy on social media. The event, which was spontaneously created by pro-vaccine social media personality ZDoggMD, originated as a way to leverage social media to bring together healthcare professionals and pro-vaccine advocates [10]. However, just over 75% of relevant tweets in our sample expressed anti-vaccine sentiment, supporting news reports that suggested the anti-vaccine movement mobilized prior to the event to use the hashtag to spread misinformation about vaccines [13].

Extrapolating the findings from our analysis of a 5% subsample to the full sample of tweets collected suggests that there were approximately 4287 pro-vaccine tweets during the #DoctorsSpeakUp event. This indicates that the #DoctorsSpeakUp event was fairly large in relation to other researched public health Twitter hashtag events. For example, the #DoctorsSpeakUp event generated more tweets in a day than the cervical cancer prevention event #SmearForSmear generated over the course of one week ($n = 3019$) [23].

Overall, our findings suggest that many pro-vaccine advocates are not incorporating best practices of risk communication in their messages. Effective risk communication messages include components such as open and transparent evidence-based information, careful stakeholder-informed planning, and the use of narrative and anecdotes, among other strategies. [15,24]. Compared to pro-vaccine tweets, in our sample, anti-vaccine tweets more often exhibited qualities of effective risk communication, namely providing evidence in the form of statements about research or science (even if it was not correct), and/or using personal narratives.

With regard to our analysis of Twitter users who authored tweets in our sample, we found that almost a quarter of tweets authored by an account where the user identified as a health professional or a parent and health professional were anti-vaccine, and approximately 50% of tweets authored by an organization were anti-vaccine. This is particularly concerning as these professionals and organizations marketed themselves as pro-information and pro-science, which may also be compelling to vaccine hesitant individuals.

Moreover, although a greater percentage of users who authored anti-vaccine tweets were classified as bots compared to users who authored pro-vaccine tweets (6.9% vs. 1.4%, respectively), the percent of bots in our sample was slightly lower than previous studies examining bots who tweet about vaccines [25,26]. However, content analysis of tweets revealed that approximately 20% of anti-vaccine tweets were copied from an infographic that was disseminated on Twitter by anti-vaccine activists prior to the #DoctorsSpeakUp event (Fig. 1). The relatively low percent of bots in our sample in addition to findings from the content analysis suggest a highly coordinated response of anti-vaccine individuals. Consistent with previous literature, it may be useful to conceptualize these users as devoted anti-vaccine antagonists [27].

An emerging issue in social media health communication is the co-opting of hashtags by those opposed to the campaign message. Social media health communication is evolving rapidly, and there are few evidenced-based recommendations for how best to use hashtags. The Centers for Disease Control and Prevention's *Social Media Guidelines and Best Practices for Twitter*

Profiles was last updated in 2011, long before hashtag co-opting was commonplace [28]. Likewise, the American Medical Association and the American Public Health Association's recommendations on using social media simply suggest using hashtags [29,30].

Therefore, based on the findings from this study, we offer the following guidelines for future pro-vaccine social media events. First, it may be valuable for event organizers to be trained in best practices for risk communication in order to utilize these principles to increase the reach and effectiveness of the event [15]. As outlined by Covello, the seven best practices in public health risk communication are: (1) accept and involve stakeholders as legitimate partners, (2) listen to people, (3) be truthful, honest, frank, and open, (4) coordinate, collaborate, and partner with other credible sources, (5) meet the needs of the media, (6) communicate clearly and with compassion, and (7) plan thoroughly and carefully [15]. Below we outline additional guidelines and the corresponding risk communication best practice(s) they encompass.

Second, leverage partnerships to create a broad coalition of vaccine advocates (best practice #4). Although ZDoggMD maintains a relatively large social media following with, as of this writing, 275,000 subscribers to his YouTube Channel and 62,500 followers on Twitter, our results suggest his reach and influence pales in comparison to the devoted anti-vaccine antagonists who opposed the event. Combining efforts with multiple national and international vaccine advocates and promoting the event through targeted announcements via multiple channels (e.g. social media accounts, email listservs, organization websites) may be effective at increasing the number of pro-vaccine individuals participating and their respective engagement.

Third, maximize inclusivity by considering multiple pro-vaccine stakeholders when creating the hashtag and including these stakeholders in the hashtag development process (best practices #1 and #5). The #DoctorsSpeakUp hashtag did not represent the full complement of pro-vaccine activists that participated in the event, leading to additional hashtags such as #NursesSpeakUp" and #ParentsSpeakUp. Having multiple hashtags dilutes the ability to track messages and may have skewed the number of pro-vaccine tweets in this analysis smaller. While it may be necessary to have more than one hashtag to encompass multiple stakeholders, maximizing inclusivity during hashtag development may streamline event-related hashtags and increase pro-vaccine engagement.

Fourth, generate a list of suggested tweets, and disseminate them to potential participants prior to the event. For the #DoctorsSpeakUp event, the ability of this strategy to increase engagement was well-illustrated by the anti-vaccine antagonists. Suggested tweets could be developed during the hashtag development process with careful consideration to reading level, accessibility, and stakeholder feedback obtained via email listservs or focus groups (best practices #2 and #7). Suggested tweets could then be disseminated to potential participants during event promotion.

Fifth, provide event participants with training and examples for responding to messages clearly and with compassion (best practices #3 and #6) For example, vaccine advocates could be given examples for how respond to messages from vaccine hesitant individuals with information that addresses their specific concern in an empathetic manner [2]. Event participants could also be encouraged to share morbidity and mortality data for vaccine-preventable diseases alongside anecdotes about treating patients with vaccine-preventable diseases. Advocates could also be encouraged to use images, such as a picture of oneself getting a vaccine [24].

These guidelines can provide a basis for efforts by vaccine advocates working to encourage acceptance of COVID-19 vaccines, particularly in light of a recent news report suggesting that devoted anti-vaccine antagonists may be co-opting related hashtags [31]. Additionally, these guidelines can be utilized to develop social media campaigns to encourage vaccine uptake more broadly. The recently published SPHERE (Social media and Public Health Epidemic and REspone) framework highlights the similarities between the spread of information on social media and the spread of epidemic disease [32]. In particular, while social media can be a contagion for misinformation, proactive communication by health professionals has the potential to inoculate the public against misinformation. Generally accepted data indicate that, at most, only 1–2% of the population is anti-vaccine, whereas 20% can more accurately be described as vaccine hesitant [33]. Moreover, health professionals are highly trusted, with prior research suggesting a provider recommendation is the strongest predictor of adolescent human papillomavirus (HPV) vaccination, and provider engagement of HPV vaccine hesitant parents can lead to same-day vaccination [34].

Thus, it is imperative that healthcare providers capitalize on this trust by engaging with the public beyond the walls of the exam room. Our findings highlight the importance of carefully considering hashtag use, ensuring that messages from health professionals follow principles of risk communication, and pre-developing messages that can be launched and promoted by pro-vaccine advocates.

6. Limitations

The results of this study should be considered with the following limitations. First, this study was designed to collect tweets that specifically included the hashtag #DoctorsSpeakUp on the day of the advertised event, and therefore is not representative of all vaccine-related tweets. Second, as the risk communication principles outlined by Covello that we used to guide our coding categories were first published in 2003 [15], our analysis may not have captured advancements in risk communication practices published since then. Third, our coding categories of narratives and statements about research or science were quite broad; it may be beneficial for future research to use more narrow coding categories that could allow for the generation of more specific direction with regard to messaging. Fourth, interpretation of tweets using qualitative analysis can be subjective, although we minimized subjectivity through a systematic coding procedure and the use of experienced coders. Finally, some accounts had been deactivated or removed from the Twitter platform between data retrieval and analysis, thus making it impossible to analyze them using Botometer. Additionally, while we observed activity consistent with “trolls” (i.e., individuals who misrepresent their identity and create discord on social media) from many of the accounts that authored anti-vaccine tweets, it was beyond the scope of this study to determine if these accounts were indeed trolls.

7. Conclusions

In conclusion, this analysis of tweets related to the #DoctorsSpeakUp event on March 5, 2020 found that, despite originating as a way to leverage social media to bring together healthcare professionals and pro-vaccine advocates, over 75% of tweets were anti-vaccine. Additionally, anti-vaccine tweets were significantly more likely than pro-vaccine tweets to exhibit qualities of effective risk communication, namely providing evidence in the form of statements about research or science (even if it was not correct), and/or using personal narratives. The relatively low percent of bots in our sample combined with our content analysis of tweets suggests a highly coordinated response of devoted anti-vaccine antagonists to the #DoctorsSpeakUp event. As public health professionals develop future health communication campaigns to promote vaccines and work to address the Infodemic of COVID-19 misinformation, it would be valuable for them to carefully consider hashtag use, ensure that messages follow principles of risk communication, and pre-develop messages that can be launched and promoted by pro-vaccine advocates.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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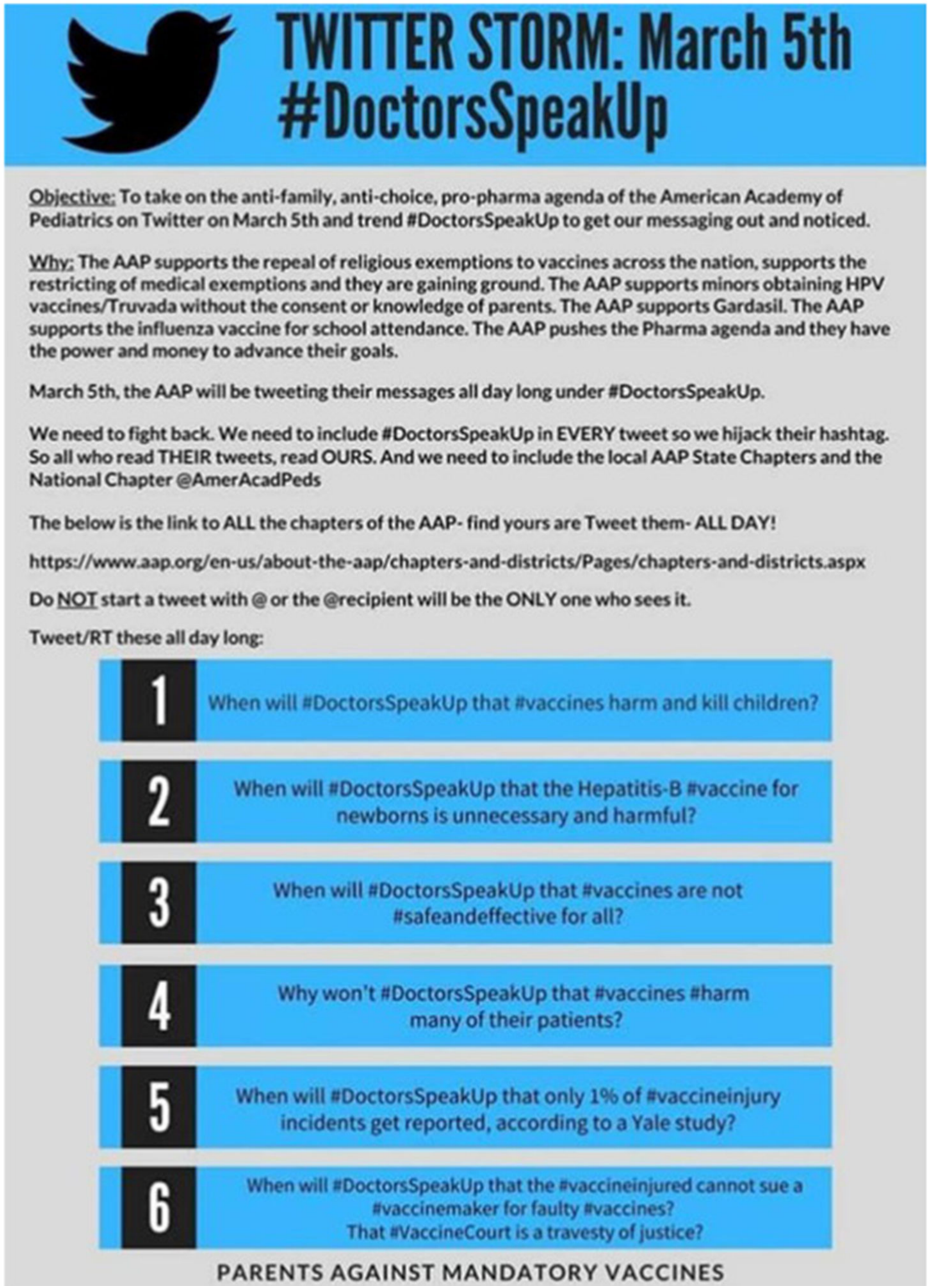

Fig. 1.

Infographic shared on Twitter by anti-vaccine activists the day prior to the #DoctorsSpeakUp event.

Table 1

Definitions for categorical codes and example tweets.

Code *Sub-code*	Definition	Examples
Relevant	The tweet includes references to the #DoctorsSpeakUp campaign or has content about vaccines or vaccine-preventable illness.	• When will #DoctorsSpeakUp that vaccines harm and kill children? • Vaccines are safe and effective, they save lives. Make sure to stay up to date on all immunizations. Protect yourself and protect the people around you. #DoctorsSpeakUp #VaccinesSaveLives #VaccinesWork NOT Relevant • I saw this trending and thought it was about doctors speaking up with truth about Coronavirus. Nope they still aren't doing that #DoctorsSpeakUp • All medications have side effects, yes or no?_ #DoctorsSpeakUp
Type of account		
Healthcare professional	The bio or tweet text identifies the author as a healthcare/public health professional.	• BIO: Pediatric resident. Keeping kids and their families safe and healthy. • BIO: Nurse practitioner searching for the truth in medicine amongst lies and corruption
Parent	The bio or tweet text identifies the author as a parent.	• BIO: Mom of a vaccine injured autistic child • BIO: Husband and father working to make healthcare better
Organization	The bio or tweet text identifies the author as an organization.	• BIO: A non-profit organization dedicated to protecting families from influenza • BIO: Providing parents recourses to make informed decisions, focusing on raising children in healthy environments
Sentiment		
Pro-vaccine	The tweet is in support of healthcare workers that administer vaccines and/or vaccines themselves.	• We vaccinate for our kids and for our community #parentsspeakup #DoctorsSpeakUp #vaccines-savelives #yesonSB163 • Vaccines are extremely safe. Not being vaccinated is unsafe. #DoctorsSpeakUp
Anti-vaccine	The tweet is against healthcare workers that administer vaccines and/or vaccines themselves	• When will #DoctorsSpeakUp that #vaccine hepB is unnecessary and harmful for newborn babies? • When will # DoctorsSpeakUp about how there are zero safety studies on the CDC vaccination schedule? When will doctors wake up and see the increased rates of autism, Type 1 diabetes, and a host of other issues that are not a coincidence?
Content		
Narrative	This account contains a personal or secondary narrative. The tweet includes "I", "my", "she", "he" within the narrative.	• I was an 18 and in good health until I got my first round of vaccines for college. Within hours my everything changed. I almost died because my digestive system was paralyzed. By refusing to educate yourself about vaccines, you're hurting children. Please educate yourself. #doctorsspeakup

Code *Sub-code*	Definition	Examples
		• I have vaccinated my own sons and nephews; they are all very healthy. They do not have any of the diseases anti-vaxxers claim vaccines cause #doctorsspeakup”
Research/Science	The tweet contains references to research/science (does not have to be accurate). This includes links to scientific articles or claims that the general public may perceive to be backed by science.	• When will #DoctorsSpeakUp that only 1%of #vaccineinjury incidents get reported, according to a Harvard study? • #Influenza and #Pneumonia are the eighth leading case of death in the US in 2017. Both of these have vaccines available which prevent and decrease risk of #Sepsis and #mortality. #VaccinesSaveLives #SepsisAwareness #DoctorsSpeakUp #TweetRN #NursesSpeakUp

Table 2

Distribution of tweet codes among the whole sample and by tweet sentiment.

Tweet code	Whole sample n (%[a])	Tweet sentiment	
		Pro-vaccine Row (Column) %[a]	Anti-vaccine Row (Column) %[a]
Type of account[b]			
Parent	244 (28.8)	3.7 (5.4)	96.3 (34.7)
Health professional	68 (8.0)	79.4 (32.3)	20.6 (2.1)
Parent and health professional	42 (5.0)	76.2 (19.2)	23.8 (1.5)
Organization	35 (4.1)	48.6 (10.2)	51.4 (2.7)
Unknown[c]	458 (54.1)	12.3 (32.9)	87.8 (59)
Content[b]			
Personal narrative	85 (10.0)	26.8 (13.8)	73.2 (9.6)
Research or science	263 (31.5)	10.3 (16.8)	89.7 (35.7)
Personal narrative and research or science	5 (0.6)	20.0 (0.6)	80.0 (0.6)
None[c]	494 (58.3)	24.1 (68.8)	75.9 (54.1)

[a]Row percents may not equal 100 due to rounding.

[b]Significantly associated with tweet sentiment ($P < 0.001$ and $P = 0.001$, respectively) using Chi-square and Fisher's exact test to accommodate low cell frequency.

[c]Omitted from Chi-square and Fisher's exact test analyses.