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Original Research Article

Characterizing twitter user topics and communication network dynamics of the "Liberate" movement during COVID-19 using unsupervised machine learning and social network analysis

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ABSTRACT

This paper analyzes online user conversation topics and discourse on Twitter related to the "Liberate" Protest movement in reaction to social distancing guidelines at the early stages of the COVID-19 pandemic. Interdisciplinary approaches in big data, machine learning, content analysis, and social network analysis (SNA) were used to characterize the communicative behavior, conversation themes, and network structures of Liberate protest supporters and non-supporters. Tweets were content coded and grouped within topic clusters produced from an unsupervised machine learning algorithm using natural language processing. An analysis of topic clusters found that tweets that support the protests are highly concentrated and have higher volumes of replicated tweets. Protest Supporters were also more likely to retweet other users while Non-Supporters were more likely to include a URL from an outside media source and produce a unique tweet. SNA was also used to assess the characteristics of retweet networks and found that the Protester Supporter network had a more centralized structure and was strongly influenced by a political organization, in contrast to the Non-Supporter network that had a larger number of smaller and more evenly-sized nodes and more driven by media personalities and commentators. Collectively, these characteristics indicate that protest supporters had more centralized, consistent and disseminated discourse protesting COVID-19 social distancing requirements compared to non-supporters who were more diverse in their criticism of the Liberate movement and generally more fragmented in their support of public health measures. Results from this study provide important insights into pandemic communication dynamics of opposing twitter communities, including in the context of those who oppose and support public health measures in a highly politicized social and online environment. Results are important in the context of assessing the messages, communication propagation and overall activities of social media communities in response to basic public health measures needed to contain this post-digital era global pandemic.

1. Introduction

Starting in March 2020, the lives of citizens across the United States were upended by the emergence of the COVID-19 pandemic. On March 23rd, the U.S. Centers for Disease Control and Prevention (CDC) distributed the first set of guidelines outlining how individuals could mitigate their risk for Coronavirus infection. This advice introduced "social distance" into the public discourse, imploring individuals to minimize physical proximity to others outside of their household by maintaining 6 feet of distance when interacting. While these measures differed based on jurisdiction (including variation at the local, city, county, and state level), many US communities closed down public areas to avoid mass gatherings, and many local businesses and restaurants closed or relied on delivery and online commerce to continue operations

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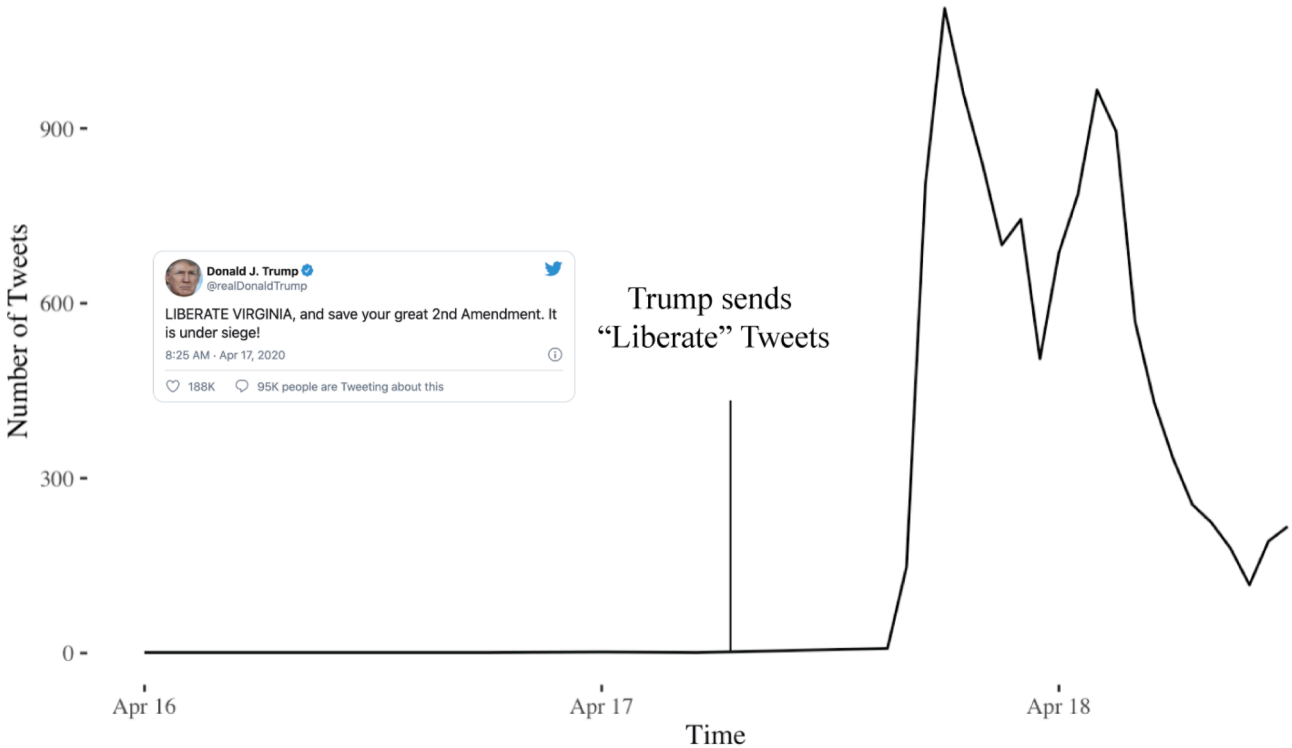


Fig. 1. Number of signal tweets with keyword "Liberate" by hour.
Note: Only 45 tweets containing the word "Liberate" were captured from April 1st–16th.

[1,2].

In the absence of a federal mandate, and as state governments and local municipalities enacted 'Stay at Home' recommendations or 'Shelter-in-place' orders, by April 10th more than 95% of the American population was under advisement to minimize their activity and risk for infection [3]. These recommendations suggested citizens to stay indoors and only venture outside one's residence for essential errands unless they were classified as an 'essential worker'. Additionally, many state, non-government organization/non-profits, and business-led advertising campaigns promoted social distancing as a form of social and personal responsibility, such as the state-wide, multimedia "Stay Safe, Stay Home" campaign in Oregon [4] and a campaign lead by healthcare leaders (including a former U.S. Surgeon General) in which the public was asked to "stay at home as much as possible" and "avoid all crowds" [5] . Despite these initial efforts to promote, and in some cases, enforce social distancing, many members of the public began to show signs of restlessness and dissent towards these orders.

During mid-April 2020, a series of "Liberate" protests in opposition to public health measures were organized around city halls nationwide by protesters who demanded an end to lockdown restrictions [6]. In the state of Michigan, which at the time had one of the largest per capita outbreaks in the country, and in response to the Governor's decision to extend the state's stay-at-home mandate up to May 15th, "Liberate" protesters gathered in the state capitol on April 15th in a show of protest that quickly gained global attention [7,8]. Further, during the Liberate Movement's early stages, U.S. President Donald Trump expressed his support by tweeting on April 17th "LIBERATE MICHIGAN," "LIBERATE MINNESOTA," and "LIBERATE VIRGINIA, and save your great 2nd Amendment. It is under siege!" to his over 80 million followers [9]. Evidence suggests that his tweets further fueled the Liberate Movement. In Minnesota, for example, protestors rallied outside the Governor's residence shortly after the tweets and demanded the economy be reopened and stay-at-home mandates be lifted [10]. Importantly, public policy until then had been guided by recommendations of epidemiological models [11], with most countries issuing stay-at-home orders in response to a model generated by Imperial College London published in late March [12]. The Liberate protests, however, made visible an emerging social movement against this scientifically based public health consensus of outbreak control.

It is worth noting that while the majority of Americans did not support the Liberate protests [13] during the initial course of the COVID-19 pandemic, non-compliance to social distancing mandates were not limited to Liberate protestors or Trump supporters. One week after the initial Liberate protests, tens of thousands of people violated social distancing guidelines in packed beaches in Southern California [14]. Additionally, smartphone movement data revealed a significant decline in social distance adherence beginning on April 14th, three weeks after the same data had shown consistent compliance [15]. By June, the Liberate protests were no longer the only protests to occur during the COVID-19 pandemic: in response to the death of African American George Floyd in late May at the hands of a police officer, Black Lives Matter (BLM) protests erupted in every major American city in response to racial injustice and police brutality [16]. Unlike the Liberate protests, BLM social protests did not explicitly support the violation of social distancing orders, and recent data indicates that cities and counties with BLM protests did not experience greater upticks in COVID-19 cases compared to districts without protests [17,18].

Stances on social distancing, however, have quickly evolved from an issue of individual and community solidarity with public health into one of polarized political ideologies, to the point that party affiliation, political leanings, and certain voting demographics can be inferred based on whether an individual supports or claims association with the Liberate Protests [8]. The politicization of views, reactions, and policies towards the COVID-19 pandemic is also reflected in individual self-reported behavior, with Gallup polls from mid-April 2020 reporting 75% of Democrats and 58% of Independents having worn a mask in the previous 7 days compared to only 48% of Republicans [19]. Hence, the COVID-19 Liberate movement is not merely an expression of personal preference or sentiment towards public health measures; rather, it is likely an expression of overlapping cultural, social and political

processes that are converging into rising tribalism, nationalism, political polarization, and divisiveness exacerbated by the epidemic.

Instead of collective behavior being motivated by an efficient and trusted flow of evidence-based information, the Liberate protests highlight that segments of the population may have their knowledge, perception and behaviors influenced by social and cultural dynamics that directly contravene needed public health measures. Given the potential negative implications for individual and community health of the Liberate and similar movements, as well as the opacity of the social and cultural dynamics driving it, we examined social media user networks that both supported and opposed the Liberate protests. We did this to better characterize how their networks operate, disseminate information, and what topics they engage with in online dialogue. This was accomplished using interdisciplinary approaches in big data, machine learning, content analysis, and social network analysis (SNA) to characterize the communicative behavior, prevalent topics, and network structure of Liberate protest supporters and non-supporters by analyzing user conversations on the popular microblogging social media platform Twitter.

2. Data and methods

2.1. Overview

The aims of this study focused on using big data, machine learning, content analysis, and SNA to identify and characterize Twitter messages related to the COVID-19 Liberate Protests and their relevant online user groups and communities. To carry out these aims, the study was conducted in 2 distinct phases: (1) data collection and processing; and (2) data analysis using unsupervised machine learning approaches in combination with manual annotation of Twitter topics and user-generated messages, which we describe below (see Figure A1 for summary of methods). All data collection and analyses were done in the computer programming languages Python and R.

2.2. Data collection and processing

Tweets were accessed through the public streaming application programming interface (API) from Twitter. We used virtual machines deployed on Amazon Web Services (AWS) cloud-based computing services to collect tweets first filtered for general COVID-19-related keywords including: “covid19”, “corona”, “coronavirus”, “coronavid19” as used and validated in prior COVID-19 Twitter studies [20,21]. From this initial corpus of general COVID-19 tweets, we then filtered the dataset for the keyword “Liberate” (including tweets that contained #liberate), as it is widely used to describe the Liberate movement in the context of both pro-liberate and con-liberate user-generated conversations and sentiment. Data collection was set for the period between April 1st, 2020 to April 20th, 2020, however the vast majority of the tweets were generated between April 17th - 20th when widespread media coverage, Liberate protests, and national debate about the Liberate movement was at its peak. In fact, from April 1st – 16th we only detected 45 tweets that contained the term “Liberate”. As seen in Fig. 1, the Liberate discussion on Twitter occurred after Trump voiced his support of the Liberate movement, which shows a spike in tweets with the word “Liberate” shortly after he tweeted. After data collection and filtering, we collected 34,672 tweets in total that included both a COVID-19 general term and the term “Liberate”. Each tweet contained the text content of the tweet and additional metadata such as user information, time stamp, media (e.g. images, videos), and any associated hyperlinks.

2.3. Data analysis using unsupervised machine learning

In order to quickly identify themes present in our corpus of tweets that included both general COVID-19 terms and “Liberate”, we employed an unsupervised machine learning approach that did not require a pre-labelled training set to identify topics of interest. Unsupervised machine learning approaches that leverage topic modeling and natural language processing (NLP) are designed to detect patterns in the data and summarize the content of the entire tweet corpus into distinct highly correlated topics, which are then reviewed and selected for the purposes of identifying clusters of Twitter social media conversations that include discussion of the Liberate movement in the context of user-generated attitudes, sentiment, and reaction originating from the public (i.e. not merely tweets from the media, social bots, or aggregators, “signal” data).

Furthermore, this allowed us to identify and exclude topic clusters of tweets that included the word “liberate” in the text of the tweet but were not user-generated or did not express attitudes and behaviors of users who associated or had opinions about the Liberate movement (i.e. “noise” data). For example, tweets that originated from news/media organization, public service announcement tweets, and tweets including “Liberate” that were not about the protests, were excluded based on topic clusters reviewed and identified (explained below). Unsupervised topic modeling strategies are particularly suited for sorting short text into highly prevalent themes without the need for predetermined coding or a training/labelled dataset to classify specific content, such as in the case of emerging social movements, protests, and other emergency events. We utilized the Biterm Topic Model (BTM) that identifies patterns in short texts that has been used in prior studies [22,23] examining a wide variety of topics, including self-reporting of COVID-19-related symptoms on Twitter and other public health issues of concern [20].

BTM is a topic clustering method that generates similar text into the same set of topics and is particularly well suited for short text (such as the 280 character limit for tweets). The corpus of tweets containing the “Liberate” keyword was categorized into highly correlated topic clusters through BTM based on splitting all text into a bag of words and then producing a discrete probability distribution for all words for each theme that places a larger weight on words that are most representative of a given theme [22]. While other natural language processing algorithms use unigrams or bigrams for splitting text, BTM uses “biterms” which is a combination of two words from a text (e.g., the text “go to school” has three biterms: “go to”, “go school”, “to school”) and models the generation of biterms in a collection rather than documents [24]. BTM was used for this study because biterms directly model the co-occurrence of words which increases performance for sparse-text documents such as tweets. Conducting BTM analysis is done initially by setting the BTM topic number (k) and “n” words (for the first round of analysis we set at $k = 10$, $n = 20$ to cover several possible topics). A coherence score is then used to measure how strong the top words from each topic correspond to its respective topic. For this study the model with $k = 20$ was chosen because it had the highest coherence score compared to the other models tested.

Based on the BTM output, we identified topics with “signal” characteristics in order to eliminate news and non-protest related tweets from our filtered dataset. Topics were removed from further analysis if they met the following conditions:

(a) Contained a term or set of terms associated with media reporting (not including media employees, personalities, and other commentators expressing their opinions), which would make it more likely to originate from a news outlet that is only reporting the event and not the opinion of an individual user (e.g. “trump” + “tweeted”, “Liberate” + “started”, “capitol” + “closed”);
(b) Contained a term or set of terms associated with viral videos (e.g., “video” + “viral”), which would make it more likely for that discourse to be related to one particular incident captured by protesters that was not generalizable to larger public behaviors, attitudes or sentiment;
(c) The volume of tweets in the topic was less than 1% of the total tweets in the dataset.

In addition to the criteria above, which relied on reviewing terms in

Table 1
Examples of content coded tweets.

Support Protest:
(1) @realDonaldTrump @FoxNews this Covid-19 is overrated.... it's over LIBERATE WEST CHESTER!!!
(2) LIBERATE OUR COUNTRY! Governors headed for messy fight over coronavirus restrictions
Against Protest:
(1) These "liberate" protests should be called "right to die" protests. Professional protesters arguing to be able to mingle during a pandemic with a contagion that has no present cure holding signs like "COVID-19 is a lie" while wearing a hazmat suit mask goggles and gloves.
(2) They are acts against the United States! AKA: Treason!
(3) You really want to catch the Corona don't you?
Reporting Protest:
1 A protest of Walz's COVID-19 response called "Liberate Minnesota" is set to occur today from noon to 3PM

BTM topic model outputs, we also reviewed the top 10 retweeted tweets in each cluster to assess if they originated from a news/media organization. We also calculated the ratio of the number of "followers" to "following" for all Twitter user accounts identified within a cluster in order to assess whether aggregated account statistics were more characteristic of bot traffic (i.e. bots generally have a much higher proportion of "following" compared to "followers", a term also known as "astroturfing" in the context of disinformation campaigns) [25]. In the topic clusters selected for analysis in this study (below), none had a news report in the top 10 retweeted tweets, the ratio of followers to following was approximately 3:1, and the average account date of creation was 6.02 years before April 17th 2020, indicating that these clusters did not exhibit characteristics of accounts that are similar to bot-like traffic/accounts.

The combination of this process allowed us to use BTM to filter out thousands of noise-related tweets unrelated to the study aims in addition to themes with low conversation volume. We then isolated "signal" tweets with specific relevance to our study that were further analyzed to explore the specific topics and sentiment of these conversations. Topic clusters that exhibited word groupings, frequencies, and characteristics related to user attitudes, knowledge, and behavior associated with the Liberate movement had their associated tweets extracted and then manually labelled to specifically identify parent themes and sub-themes. From the 34,672 tweets collected for this study filtered for the keyword "Liberate", 19,393 tweets were used for analysis based on 10 out of 20 topics outputted by our unsupervised machine learning methodology that exhibited Liberate characteristics of interest and met our inclusion criteria.

2.4. Content coding of liberate tweets

When manually annotating tweets detected after BTM, our inductive coding approach focused on a parent classification of assessing whether a tweet supports the protests (i.e., expresses a positive reaction towards Liberate Protests), does not support the protests (i.e., expresses a negative reaction), or is only reporting on the protests without stating an opinion or exhibited neutral user sentiment (see Table 1 for examples). Tweets within each topic that were not related to the protests were coded as "irrelevant" and removed from further analysis as noise. URLs associated with signal tweets, such as links to outside news articles (or in cases of "retweets" the link to the original tweet) were coded using the same criteria. User-generated messages with URLs that led to external websites were also coded for whether they belonged to a national media outlet (e.g., NYTimes, Wall St Journal, CNN, Fox) or to a local news source. A total of 3830 unique tweets were extracted from the original 19,393 and were manually annotated by first and second authors. Posts were coded independently and achieved high intercoder reliability for results (kappa = 0.90). Disagreements in coding were resolved by consensus with first and second authors upon consultation with senior author (last author). After manual qualitative content coding, 17,776 (91.7%) of all 19,393 tweets were classified as signal (i.e. related to the Liberate movement) and were then further assessed for qualitative characteristics to reveal themes based on the most popular tweets related to each topic cluster (see Table A1 in appendix for percentage of unrelated tweets broken out by topic).

In order to observe differences between politically opposed users as well as overarching themes from the content of tweets, the data was organized into two levels for analysis: the User level, which attributed individual tweets to each Twitter account associated with the dataset, and the Topic level, which organizes the tweets thematically based on our unsupervised machine learning methodology. Content of the tweet text was coded as either supporting or opposing the liberate protests, which was then used to create our sub-classification of users as *Protest Supporters* or *Non-Supporters*. Additionally, t-tests were used to detect statistically significant differences between sub-classification groups. Content of URLs associated with tweets from an identified user sub-classification were also coded for political stance and whether they were linked to an outside media outlet. Comparisons among topics were based on percentage of support and opposition towards the protests, as well as number of "unique" tweets (i.e., tweets that were not a retweet from another user without added commentary) grouped within each topic. Twitter users were classified as "Protest Supporter" if more than 50% of their tweets showed a positive reaction towards the Liberate Protests. Of the total number of Twitter users assessed in the 17,776 signal posts, 44.1% were classified as Protest Supporters. Conversely, 53.0% of users had at least 50% of their tweets that expressed negative sentiment against the Liberate movement (labeled as "AGAINST Protest" in Table 5) while only 1.6% were classified as "REPORT Only," signifying that at least 50% of their tweets mention the Liberate Protests without taking a stance. Due to the low number of *Report Only* users, *Report Only* and *AGAINST Protest* users were combined together as "Non-Supporters" for further comparisons with *Protest Supporters*.

Additionally, replication of tweet text was measured to observe message resonance throughout each topic. Tweets were grouped by text content, associated link, and BTM topic to produce the number of unique tweets. A metric we calculated and introduced in this study as "Echo" was used to represent the ratio of total tweets per topic by the number of unique tweets, as depicted in the following formula:

$$E = T/u$$

Where $\boldsymbol{E}$ = the Echo measure, $\boldsymbol{T}$ = Total number of tweets by topic, and $\boldsymbol{u}$ = Number of unique tweets by topic. An Echo closer to 1 signifies a higher number of unique tweets within a given topic, while an Echo with larger values reflects higher replication levels of the same message. In the context of Twitter, replicated text among tweets suggest that users are retweeting without inserting additional comments, their own opinion, or expressing sentiment, while retweets that add commentary to the original source are expressions of unique opinion. Echo was important to measure in the context of assessing both the diversity of Twitter conversations within topic and the replication and propagation of tweets across the broader Twitter network.

2.5. Social network analysis

Social Network Analysis (SNA) was conducted on the user networks to reveal how users interact with one another through their retweet behaviors and to characterize the information transmission of messages throughout the network. In the model presented in this paper, each node is a Twitter user and each link between nodes represent a retweet. The source node is the user who produced the original tweet while the target is the user who retweeted. When visualizing the network, nodes colored Red represent *Protest Supporters* while Blue is used for *Non-Supporters*. The first network visualization depicts users from both groups while two subgraphs were created to visualize differences in communication

Table 2
Description of topics.

Topic	Category	Topic stats	Top 3 tweets	Retweet count
1	*Backlash Against Protesters*	**% Total Tweets**: 5% **Support**: 10% **Against**: 89%	These "liberate" protests should be called "right to die" protests. Professional protesters arguing to be able to mingle during a pandemic with a contagion that has no present cure holding signs like "COVID-19 is a lie" while wearing a hazmat suit mask goggles and gloves.	229
			Pres Trump said governors "call the shots" for opening their states. Today he tweeted "LIBERATE MINNESOTA" (as well as MI and VA). A "liberate Minnesota" protest is now being organized in front of the MN governor's residence. So much for supporting the Govs. #coronavirus	228
			Liberate the PPE	200
2	*Backlash Against Trump Administration*	**% Total Tweets**: 5% **Support**: 16% **Against**: 80%	"As the governor, I along with this staff are fighting a biological war. I don't have time to fight twitter wars".	480
			Incredible report on the Senate call with Pence's COVID taskforce- @ timkaine asks about Trump's "LIBERATE" tweets, Pence basically says we'll continue to work with the Governors but Donald will, you know, ask the people to launch an insurrection… NBD.	69
			LIBERATE AMERICA from impeached criminal, liar, white supremacist, sexist, fraud, concentration camp runner, Nazi defender, admitted sexual predator, enemy enabler, violence inciter, and coronavirus incompetent @realDonaldTrump! Raise your hand if you agree!	47
3	*Backlash Against Trump Administration*	**% Total Tweets**: 3% **Support**: 9% **Against**: 91%	I hope everyone realizes @realdonaldtrump tweets inciting violence is to distract from the news he warned NATO & Israel in NOVEMBER about COVID & didn't protect AMERICA! @mitchellreports @MSNBC @FoxNews Liberate America Liberate Virginia Liberate Michigan	319
			#LiberateAmericaFromTrump Trump has failed in each instance. The people of America will cope with #coronavirus through their willingness to cooperate with their governors & the medical community. We will do this to protect ourselves our families & society. Liberate The USA!	24
			Somebody Please LIBERATE AMERICA From This Corona-Spreading Clown	21
4	*Backlash Against Trump Administration*	**% Total Tweets**: 5% **Support**: 13% **Against**: 83%	@GovInslee on Trump's liberate tweets: Trump's tweets "encourage illegal and dangerous acts. He is putting millions of people in danger of contracting COVID-19. His unhinged rantings and calls for people to "liberate" states could also lead to violence. We've seen it before".	219
			Liberate America from democrat tyranny. The Corona crisis has shown just how dangerous these people are. Democrat Gov. Whitmer of Michigan even went so far as stopping people from planting gardens or painting their home during the lockdown.. but going to buy weed was "essential"	135
			Trump is calling for his followers to liberate the states from the social distancing measures that are staving off an even greater COVID-19 death toll. Bill Barr is now poised to support Trump's call for insurrection by turning to the federal courts.	133
5	*Backlash Against Trump Administration*	**% Total Tweets**: 5% **Support**: 9% **Against**: 86%	LIBERATE THE WHITE HOUSE from the madman that's more pleased to salute North Korean military leaders than he is to helping Americans get the COVID tests needed to fight this virus!	284
			Yah, these people screamed Liberate America just like our Moron-in-Chief. They knew a deadly virus circulating. A virus less contagious than COVIDBut idiots said it was just the flu. "Only" a 2.5% fatality rate. COVID? Estimates: 2–4% 40,000 of them died by the end of the month.	91
			Stephen Moore a member of Trump's council to open up the USA is helping to facilitate "liberate" rallies against social distancing.	82
6	*Backlash Against Fox News*	**% Total Tweets**: 4% **Support**: 3% **Against**: 97%	Trump's dangerous "LIBERATE" tweets represent the views of a small minority, but one that's being actively promoted by Fox News	407
			Fox News Sunday to Liberate America My heart breaks for Health care workers & ICU nurses as this mistake will greatly impact them and their families. Here comes the rise in COVID ICU patients and death. No one to thank but @trump	205
			The "Liberate" armed activists seem to have been instigated from within the Trump Administration,in particular by a group linked to DeVos. That's covert activity to foment insurrection against a sovereign government. That's sedition. Which is treason.	17
7	*Liberate America*	**% Total Tweets**: 23% **Support**: 85% **Against**: 12%	HUGE: @JudicialWatch Subpoenas Google for Clinton Emails; @realDonaldTrump Should Appoint Special Counsel to Investigate Clinton/Obama/Biden PLUS Liberate America from #Coronavirus Shutdowns. Big Update: [URL]	817
			I appreciate @RealDonaldTrump's pushing to get country open again. No more excuses – ALL governors should go ahead and open up their states NOW with some sensible checks in place. Over 22 million Americans can't wait weeks and weeks for "testing " etc. LIBERATE AMERICA!	790
			Does Google have Hillary Clinton's Bleach Bit Emails?	581
8	*Backlash Against Protesters*	**% Total Tweets**: 18% **Support**: 9% **Against**: 87%	If we're going to liberate something it should be the data so we can see the real impact of COVID on every community	98
			Liberate Michigan? Protesting stay-at-home orders during a pandemic isn't patriotic. It's like the Boston Tea Party if the colonists tossed the tea in the harbor then jumped in themselves and drowned dragging a few innocent bystanders down with them.	58
			@[REDACTED] #Liberate death. Such a poor choice. #TrumpVirus #coronavirus #PencePandemic #hoax @realDonaldTrump	25
9	*Backlash Against Trump Administration*	**% Total Tweets**: 10% **Support**: 34% **Against**: 66%	*45 was enraged when 2 people died from Ebola and called the 12 469 deaths in a year from H1N1 a disaster. Now he's calling [TEXT CUT OFF]	1194
			700 000 Americans have been stricken by the COVID-19 virus. 36 000 Americans are dead. Trump's endless blundering has reached the level of crimes against humanity. #MinnesotaStrong #WhyImNotVotingForTrump #WhiteHousePressBriefing "Liberate" "As a Minnesotan" "As a Virginian"	481
			That's bc 4 Americans were left to be murdered in Benghazi by our own Government when stand down orders were issued. Co [TEXT CUT OFF]	120
10	*Liberate America*	**% Total Tweets**: 21% **Support**: 86% **Against**: 14%	I won't snitch on you fellow Americans if you go to church take your child to the playground show your unmasked face in public buy a non-essential item go for a drive to visit your family or just because or try to work to feed your family. #Coronavirus LIBERATE AMERICA	3706
			[NAME REDACTED] is a Patriot! Nothing stops him! He keeps fighting for all Americans!_	7
			I won't either.	3

Note 1: Retweet can signify either approval or disapproval of the original tweet based on whether the user adds commentary.
Note 2: Category based on Top 3 Tweets and stance percentage for characterizations.

Table 3
Tweet analysis by BTM topic.

Topic	Total tweets	Unique tweets	Echo	% Support protest	% Against protest	% Report
1	968	106	9.13	10	89	1
2	866	118	7.34	16	80	4
3	539	79	6.82	9	91	0
4	835	86	9.71	13	83	4
5	827	78	10.6	9	86	5
6	783	114	6.87	3	97	0
7	4048	34	119.06	85	12	3
8	3291	2508	1.31	9	87	4
9	1847	32	57.72	34	66	0
10	3796	73	52.00	86	14	0

Table 4
URL Analysis by BTM Topic.

Topic	% With URL	% URL - Twitter	% URL - Media	% URL - Support	% URL - Against	% URL - Report
1	91	85	60	39	46	12
2	86	67	12	8	61	25
3	61	47	4	5	39	51
4	80	56	45	10	43	29
5	82	65	15	5	56	31
6	88	35	71	0	82	17
7	94	82	3	85	3	6
8	5	67	3	0	1	68
9	94	91	0	0	91	9
10	100	97	0	99	0	1

***Note*:** URLs coded as "not relevant to protests" are not included in table. The column "% URL – Twitter" shows what percentage of the associated URLs from each topic are from Twitter while "% URL – Media" shows the percentage of URLs that link to an outside media source. Higher percentages of*% URL – Media* suggests that the conversation associated with the corresponding topic might be more influenced by media outlets.

Table 5
Twitter user analysis – protest supporters vs non-supporters.

	N	Percent of Total Users
Protest Supporter	6747	**44.1**
AGAINT Protest	8107	**53.0**
REPORT Only	245	**1.6**
Number of Total Twitter Users	15,295	

Average% of tweets	Non-supporter ($n = 8548$)	Protest supporter ($n = 6747$)
Include URL	88.2%	98.5%
URL Media	20.2%	<1%
URL Twitter	75.6%	89.3%
Unique Tweet	24.7%	4.1%

***Note*:** All differences between Non-Protest Supporters and Protest Supporters are statistically significant, $p < 0.05$.

patterns between *Protest Supporters* and *Non-Supporters*. Additionally, all networks use a layout created for visualizing large network graphs [26]. Due to its usage in previous research examining political discussion networks [27], modeling social influence processes [28], and increased usage in publication across disciplines [29], an Exponential Random Graph Model (ERGM) was used to detect statistically significant structural features between *Protest Supporter* and *Non-Supporter* networks. An ERGM is a statistical model that simulates alternative configurations of the observed network in order to determine the likelihood of a given structural feature, such as connections between nodes which is referred to as 'degrees' in SNA analysis. Within the context of Twitter data and this study, the term 'out-degree' refers to when a node is retweeted by another user.

3. Results

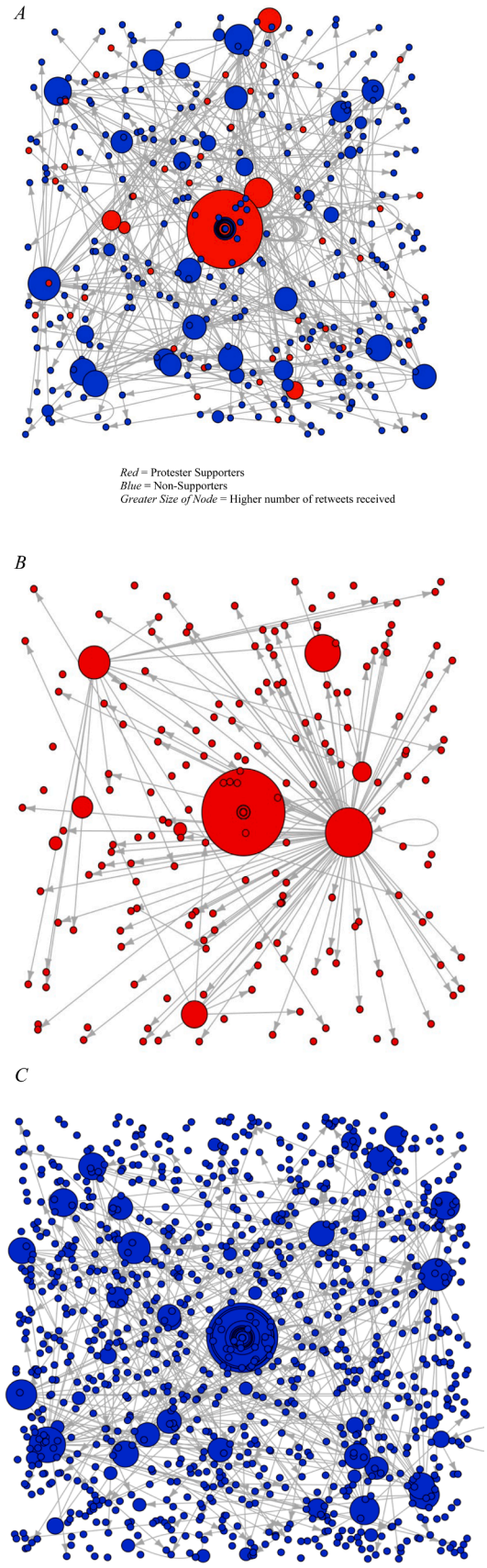
3.1. Content analysis & characterization

Grouping tweets into BTM topic clusters allowed us to identify high-level themes throughout the overall Twitter Liberate discourse and observe replication rates of messages associated with each Topic. In order to gain a more in-depth understanding of the discourse associated with each Topic (both pro and against), the Top 3 tweets based on retweet count were selected to observe what messages were most prominent within each BTM cluster. Table 2 describes the 10 Topics chosen for analysis based on the top 3 tweets with descriptive statistics of sub-topic classifications also reported in the *Topic Stats* column. Each sub-topic was classified as one of the following sub-topics based on the conversations generated by users including: "Backlash Against Protesters," "Backlash Against Trump Administration," "Backlash Against Fox News," and "Liberate America," with *Liberate America* as the only classification among the Topics that exhibited predominant support of the Liberate Protests.

For example, the sub-topic "Backlash Against Protesters" included tweets from users criticizing the rationale of Liberate protestors, expressing support for government officials, and calling for more protective measures. The sub-topic "Backlash Against Trump Administration" included tweets from users expressing direct criticism towards President Trump or one of his associates, specifically in relation to how the administration reacted to the pandemic. "Backlash Against Fox News" is composed of tweets that criticize Fox News in being complicit with the Trump administration and broadcasting misinformation that could be responsible for an increase in mortality related to COVID-19. In stark contrast, "Liberate America" consisted of tweets that call for an end of lockdown measures and encourages Americans to disregard stay-at-home mandates.

Among the topics with a majority of anti-Liberate tweet topics, the topics with the highest volume of were Topic 8 (18% of tweets) which was classified as *Backlash Against Protesters* and Topic 9 (10% of tweets) classified as *Backlash Against Trump Administration*. *Backlash Against Trump Administration* is also the most frequently used classification among the topics, and when compared to the other classifications that predominately express negative reactions towards the protests (i.e., *Backlash Against Protesters* and *Backlash Against Fox News*) *Backlash Against Trump Administration* topics typically have a higher volume of pro-Liberate tweets as most prominently seen in Topics 2, 4 and 9. In contrast, Topic 6, which is the only topic classified as *Backlash Against Fox News* had the lowest volume of pro-Liberate tweets among all topics (3% in support of Liberate Protests). Thus, *Protest Supporters* were more likely to react to discussions expressing negative criticism targeted specifically towards the Trump Administration than to other thematic critiques of the Liberate Protest movement.

While support for Liberate Protests was distributed across multiple observed topics, the majority of Pro-Liberate tweets were concentrated in two highly clustered topics (Topics 7 and 10, which are both classified in the *Liberate America* category) as shown in Table 3. The two topics that show the most positive sentiment towards the protests were also the largest: 85% of tweets in Topic 7 and 86% in Topic 10 supported the



(caption on next column)

Fig. 2. Communication network via retweets – protest supporters vs non-supporters.
Figure 2A – Protesters & Non-Protesters
Red = Protester Supporters
Blue = Non-Supporters
Greater Size of Node = Higher number of retweets received
Note: Due to large number of Twitter users within the network, not every node and edge are depicted in visualization
Figure 2B – Protesters (Non-Protester Nodes Removed)
Figure 2C – Non-Protesters (Protester Nodes Removed).

protests, and these topics combined to consist of 44% of the total tweets in the dataset. Additionally, Topic 7 showed the highest rate of replicated tweets compared to other topics, with 34 unique tweets producing 4048 tweets and an Echo score of 119.06. Other topics that exhibited high levels of support for Liberate protests also appeared to have higher replication rates as seen in Topics 9 (classified as *Backlash Against Trump Administration)* and 10 that have the second and third highest Echo of 55.97 and 52.00 respectively, while also showing the highest percentages of support for the protests after Topic 7 (although the majority of tweets in Topic 9 still take a negative stance on the Liberate movement). This indicates that pro-liberate posts were highly concentrated in thematic messaging (likely due to replication/retweets) and were most widely disseminated and shared.

In contrast to the two highly concentrated topics with high volume of pro-Liberate tweets, the remaining BTM topics were mostly against the Liberate Protests, with 7 out of 10 topics comprised of at least 80% of tweets in its cluster that expressed negative reactions and opinions to the Liberate movement. Echo scores for topics with at least 80% of tweets that expressed negative sentiment were also much lower compared to pro-Liberate topics as seen with Topic 5 which has the highest Echo of 10.6 in contrast to pro-Liberate Topic 7 that has an Echo over 10x greater in magnitude at 119.06. The higher number of topic clusters together with the lower Echo scores suggests that discourse among users that expressed negative stances towards the Liberate protests was smaller in overall volume, more diverse and not as widely disseminated compared to pro-Liberate discussions.

Analysis of the URLs associated with tweets exhibited a wide spread of sentiment and reporting across topics; however, the majority of topics still expressed a predominately negative stance towards the protests. The exceptions continue to be Topics 10 and 7 (*Liberate America*), where both have the highest percentage of URLs associated with each tweet (100% and 94% respectively), with the highest percentage of these associated links expressing positive sentiment towards the protests, as shown in Table 4. Topics with lower percentages of URLs indicate that there are less tweets that are replying to a retweet or article from an external site, which could signify a higher degree of original tweets user-generated expressions within that topic. This is illustrated in Topic 8 (*Backlash Against Protesters)*, which has the lowest Echo score across all topics while also having the lowest percentage of associated URLs. Additionally, Topics 10 and 7 both have very low percentages of URLs from media outlets (0% and 3%), which indicates that the topics that show the highest levels of support for the protests are not directly influenced or reference media sources.

3.2. User level comparisons between protest supporters and non-supporters

Analyzing the URLs associated with the sub-category of user-identified tweets shows evidence that *Protest Supporters* are more likely to retweet opinions of other Twitter users while having less interaction with sources outside their network. Based on *t*-test results of mean comparisons between the two groups (as seen in Table 5), Protest Supporters were more likely than non-supporters to include a URL with their tweet, though both groups had high usage of URLs (98.5% vs 88.2% of Non-Supporter, $p < 0.05$). Within the subset of users who

included a URL, URLs from *Protest Supporters* were more likely to originate from another Twitter message (89.3% vs 75.6%, $p < 0.05$). Importantly, *Non-Supporters* were significantly more likely than *Supporters* to include a link to an outside media outlet (20.2% vs <1% of Protest Supporters) as well as to produce a unique tweet (24.7% vs 4.1%). In tandem, these salient differences between *Supporters* and *Non-Supporters,* all of which were statistically significant, suggest notable differences in communication behaviors across the two sides of this political, social and public health divide in public opinion. Evidence suggests that in their tweets, *Supporters* were more likely to refer to third-party content and to content that did not come from a media outlet, and significantly less likely to produce a unique message. In other words, Protest Supporters were more likely than Non-Supporters to retweet the opinions and expressions of other similarly grouped Twitter users without adding additional commentary or new content.

3.3. Social network analysis of users based on retweets

Social Network Analysis (SNA) was also conducted on the user networks based on the relation and interaction of users through retweets to characterize the information transmission of messages throughout the network. While the analyses from the Topic Level section emphasized how the content of messages are replicated throughout the overall Twitter discourse, SNA is able to reveal how users interact with one another through their retweet behaviors. In this model, each node is a Twitter user where the source node is the user who produced the original tweet while the target is the user who retweeted. Of the 15,295 total users, 11,429 (74.7%) either retweeted or produced a tweet that was retweeted and were therefore used as nodes in the network analysis. The total number of edges within the network (i.e., retweets) was 11,767. As seen in Fig. 2, the network is visualized to show the full network of Protest Supporters and Non-Supporters, as well as Protest Supporter and Non-Supporter-only networks to illustrate differences in network structures across the two groups. Red nodes represent Protest Supporters while blue represents Non-Supporters. Retweets are represented by an arrow (i.e., an "edge") pointing from the source node to the target node which retweeted the original message. The size of the node depends on the weighted sum of the edge connections (i.e., larger node equates to a higher number of retweets). Total number of nodes and degree distribution for the total network as well as Protest Supporter and Non-Supporter networks are reported in Table 6.

When visually comparing retweet networks between Fig. 2B and C, the Protester Supporter network has a more centralized structure, with one prominent node in the center from which a large portion of the total messages are transmitted. By contrast, the Non-Supporter network shows a larger number of smaller and more evenly-sized nodes. This is also supported in Table 7a, which compares retweet frequencies (i.e., out-degree distributions) between nodes from both networks that had been retweeted at least 1 time. While the Non-Supporter network has a higher number of nodes that were retweeted at least once (105 users vs 15 Protest Supporters), users from the Protest Supporter network received a higher number of Max retweets (6057 vs 1208 of Non-Supporters) as well as higher frequencies of retweets across percentiles.

Additionally, user accounts of influential nodes were coded for affiliations to media and political organizations based on the information available on their Twitter profile. Users were classified as a member of the media if they identified as a journalist or author, or stated affiliation with a news show or media outlet. As seen in Table 7b, there is a higher level of media involvement among influential nodes in the Non-Supporter network compared to Protest Supporters with 43.8% of nodes having a media affiliation compared to 20.0% of Protest Supporters. Political organizations were defined as an association or non-profit that declares explicit affiliation to a political ideology or purpose. Among the influential nodes, only one user was affiliated with a political organization. However, this one user is the president of a political organization called *Judicial Watch*, which is well known for conservative views, support of President Trump, and repeatedly suing the US State Department to release Hillary Clinton's emails [30]. This single Twitter user is the source of 89.4% of the retweets within the Protest Supporter network, as shown in Table 7c. Within the Non-Supporter network, 3 political organizations were identified (Media Matters, The Democratic Coalition, and Duty To Warn). However, despite having a higher number of organizations compared to the Protest Supporter network, only 5.1% of retweets were sourced to these organizations. This indicates that political organizations have a much more prominent influence within the Protest Supporter network compared to Non-Supporters. While Non-Supporters were less likely to retweet political organizations, Table 7c shows higher influence from media personalities with 43.4% of retweets coming from a media source compared to 3.9% of Protest Supporters. These results show that influential nodes associated with political organizations are very prominent within the Protest Supporter discourse with little influence from members of the media. In contrast, discourse within the Non-Supporter network is driven more by media figures with little influence exhibited by political organizations.

In order to determine whether the structural differences observed between *Protest Supporter* and *Non-Supporter* retweet networks are statistically significant, ERGM was used to analyze the full network. As shown in Table 8, Geometrically Weighted Out-Degree (GWO) was used to compare the distributions of outgoing ties (i.e., number of times retweeted) between Protest Supporters and Non-Supporters while *edges* measures the likelihood that a tie will form within the network, which was included in the model to control for network density. Both groups show negative coefficients that are statistically significant ($p < 0.001$), indicating that the distributions of out-degree for both groups are more uneven (i.e., larger amount of nodes with low degree and high degree instead of middle values) compared to a random network. Additionally, *Protest Supporters* have a more negative coefficient (−11.18 log odds) compared to Non-Supporters (−9.13 log odds), which provides further evidence of the more centralized character of information transmission within the Protest Supporter network due to the greater level of uneven distribution of out-degree.

4. Discussion

Our analyses, although limited to a specific time window and to tweeting behavior, show statistically significant differences between the online topics and network structure between Liberate Protest *Supporters* and *Non-Supporters*. Thematically, *Supporters*' tweets were more concentrated into fewer and larger topic clusters, which themselves were characterized by significantly higher echo (retweet) scores as well as by a high probability of including a URL and of that URL linking to another tweet rather than to an external media source. Tweets by *Non-Supporters*, by contrast, were thematically clustered into a greater number of smaller topics with much lower retweet rates, less links to URLs, and a much higher probability of linking to content from a media outlet. At the level of users we observed the following pattern: *Non-Supporters* were much more likely to produce a unique tweet (24.7%), while less than 5% of *Protest Supporters* did so. The degree of many of these differences is worth noting; for example, 20.2% of tweets by *Non-*

Table 6
Network statistics.

	Total network	Protest supporter	Non-supporter
Nodes	11,429	6020	5409
Edges	11,767	5995	4940
Mean Edge	2.06	2.13	1.98
SD Edge	58.60	78.19	21.26

Table 7a
Influential nodes - retweet comparisons between protest supporter vs non-supporter.

		Protest supporter	Non-supporter
Number of times Retweeted (out-degree)	*Number of Influential Nodes*	15	105
	Mean	451.5	47.6
	Max	6057	1208
	Median	13	7
	60th percentile	21	9
	70th percentile	83	15.6
	80th percentile	136.6	25.2
	90th percentile	213.8	80
	95th percentile	1999.8	246.4

***Note*:** Table is filtered for nodes that have at least 1 out-degree (i.e., been retweeted by other user at least once). 10,940 out of 11,429 (95.72%) of the total nodes have a degree of 1, which means that they either retweeted another user or were retweeted themselves only once.

Table 7b
Influential nodes – analysis of users associated with media.

	Protest supporter	Non-supporter
Number of influential nodes	15	105
Journalist	2	15
News Show	0	7
Media outlet	0	13
Author	1	11
Total count	3	46
% of users from media	20.0%	43.8%

Table 7c
Influential nodes – retweet analysis.

	Protest supporter	Non-supporter
% of retweets from Media Node	3.9	43.4
% of retweets from Political Org Node	89.4	5.1

Supporters linked to an external media outlet compared to less than 1% of tweets by *Supporters*, and the three topic clusters with over 30% of pro-protest tweets had echo scores at least five times greater than the next largest one.

Finally, the retweet network structure assessed by SNA further confirms these communication differences, with the Protest Supporter network being more centralized based on result from our ERGM analysis. Together, these findings show convergent evidence for important differences in communication dynamics between the two groups, the first being that the structure of *Supporters*' tweeting behavior is significantly more consistent with the notion of an "echo chamber" environment [32]; that is, more shielded from external media, more focused on a narrow set of issues, and more likely to retransmit those same issues as non-unique messages. In contrast, *Non-Supporter* tweets and retweet behavior is consistent with a larger number of diverse topics at lower volume of tweets, lower echo (a higher frequency of original expressions on the Liberate topic from users), higher use of external media sources to support opinions, and overall a more decentralized online community and Liberate discourse. These results are reinforced by an in-depth analysis of influential nodes between both networks which reveals that while the *Protest Supporter* network had fewer number of nodes that were retweeted at least once, the number of times they were retweeted greatly exceed retweet counts among influential *Non-Supporters*. Higher influence from political organizations among *Protest Supporters* and higher media involvement among *Non-Supporters* also have implications for what type of information is shared within these discourses.

Table 8
Exponential Random Graph Model (ERGM): Out-degree by protest status.

	Estimate	Std. Error	z value	Pr(>|z|)
edges	−3.49	0.008	−413.5	<0.001
GWO Degree - Protest Supporter	−11.18	0.185	−60.4	<0.001
GWO Degree - Non-Supporter	−9.13	0.068	−133.4	<0.001

Network Stats: *Total Nodes:* 11,429, *Total Edges*: 11,751 (loop edges removed for ERGM).
Model Stats: *AIC*: 128,942, *BIC*: 128,992, *Sample Size per Chain*: 10,000, *Thinning Interval*: 10,000.
***Note*:** Geometrically Weighted Out-Degree (GWO) with a decay of 2.5 was used for this model. Decay value was determined by comparing models with different values. The model with the decay value that produced the lowest BIC was chosen for analysis. Both AIC and BIC within the context of an ERGM measure deviance based on Log-Likelihood, which is calculated by summing the differences between predicted probabilities and observed values. Since ERGMs are unable to model loops [31], loop edges were removed for analysis.

A full characterization of how information is shared by groups across existing political silos and rifts running through contemporary U.S. society requires integrating historical, sociological, and anthropological approaches. However, the identification of characteristics highlighting the differences in tweet-based network structure, user dynamics, and message content between Supporters and Non-Supporters nevertheless provides early clues in how these disparate online social network communities approach mobilization, advocacy and create political and public health discourse in the midst of a pandemic. Based on tweeting behavior, non-supporters show greater openness toward issues and sources, a finding consistent with social media studies which have found that liberals (who were more likely to have opposed the Liberate protests encouraged by Republican President Trump) are more likely to engage in cross-ideological dissemination compared to conservatives [33]. Supporters, in other words, have a significantly higher degree of insularity in what they write about, the information sources they access and share, and the audience that listens to them, than Non-Supporters. This insularity is of concern given that Liberate Protest Supporters were politically influential and directly challenged public health measures designed to slow down the pandemic. The markedly different manner in which these groups produce and share information online helps to answer the question of how a politically influential segment of the population has their knowledge, perception and behaviors influenced by social and cultural dynamics that directly contravene needed public health measures. In order to better contextualize this behavior, it is worth briefly examining where these social and cultural dynamics may have originated from.

The political culture of the United States has for a long time been embedded with a strain of anti-intellectualism [34], a view which in recent years found a foothold within the populist movement led by President Trump, but which has also been observed in other domains

such as the Anti-Vaxxer movement which cultivates suspicion towards public health expertise, scientific evidence on the efficacy of vaccines, and promotes misinformation [35]. These cultural movements are united by their systematic distrust of scientific authorities which they accuse of being cosmopolitan, elitist, and thus culturally and morally corrupt, and have portrayed themselves as a political alternative to intellectual elites recently buoyed by a surge in populist politics [36,37]. Policies within public health, a domain in which measures tend to be created by highly educated experts and disseminated through centralized public health institutions, have shown to be prime targets of this growing political current's grievances. By emphasizing the defense of individual and states' rights versus compliance with allegedly oppressive federal and public health policies and by reframing public health measures as an assault on individual liberties, these political groups draw from well-established American cultural veins to undermine trust in and adherence to potentially life-saving public health measures. Ironically, the hyper-individualistic and anti-authority values espoused by Liberate Protest Supporters are inconsistent with what social media shows us about their behavior surrounding the spread of political information.

Our results show that among protest supporters, messaging is more unitary, topics are fewer and more consistent, sharing of information is more centralized, and communication networks are more tightknit. Moreover, they are less likely to be unique, original, or diverge from the norm of the group, which is inconsistent with values of hyper-individualistic freedom from centralized authorities. The network of users who opposed the protests, on the other hand, was significantly more heterogeneous and decentralized. Whether this may be extrapolated to broader behavioral characteristics of contemporary American political constituencies requires further interdisciplinary research, but if confirmed would indicate that those who subscribe to hyper-individualistic populist political agendas are more likely to engage in social interactions that give rise to a significantly less individualistic social and informational milieu than those of their political opponents. A more worrying aspect of the differences in online dialogue and networks shown by this study is that, by virtue of its greater centralization, hierarchization, and insularity-driven thematic consistency, the online social dynamics of Liberate Protest Supporters provide anti-public health voices a platform with a highly effective mode of coordinated action. As previous work on communication networks have shown, groups with more centralized structures outperform decentralized structures in both speed and accuracy for solving problems [38] which could potentially generalize to political mobilization contexts.

If true, this finding has significant implications for future progress towards controlling the COVID-19 pandemic in the United States. In fact, it is likely that the mobilization of these social dynamics in the April Liberate movement were merely a prelude to sustained opposition from Protest Supporter-associated groups. Additional anti-science and anti-public health intervention movements have already materialized, including social media trending of hashtags including "firefauci" (supporting the firing of Dr. Anthony Fauci who is a member of the Coronavirus taskforce and Director of the National Institute of Allergy and Infectious Diseases) [39] and an increase in confrontations across the US in reaction to mask-wearing mandates in public spaces [40]. After the Liberate movement, many states have also relaxed their stay at home orders and social distancing guidelines, which has led to a resurgence of COVID-19 cases and threatens reopening plans for businesses, schools and other sectors of the economy in many states [41,42]. Many conservative leaders also do not publicly support the use of masks to prevent spread, leadings to higher risk of transmission and further exacerbating the spread of the disease [43]. Similarly situated movements and discourse may also be taking place in other countries, such as Brazil, where similar anti-science sentiment has come from the Jair Bolsonaro administrative, with equally poor public health outcomes and rising case counts [44]. Hence, the stakes for disseminating a narrow but focused message of contrary to and resisting public health interventions has dangerous consequences now and far into the future for this pandemic.

5. Related works

The results presented in this article align with findings from previous work demonstrating political partisanship among Twitter users [33,45] since the vast majority of users were classified as *Protest Supporters* (44.1%) or against them (53.0%). This suggests that Twitter might be a favorable platform for political bases to convene and share information within their own party. Future work could investigate if there are online platforms that show bipartisan behavior within political discourse, or what features of a platform might encourage heighted politicization of important social topics or conversely encourage a cross exchange of ideas.

Previous social media research shows that while a majority of user behavior is passive and mostly involves simply browsing through content [46,47], hyperactive users on social media have agenda-setting effects on political discourse and shape public opinion [48]. These findings are reflected in the communication dynamics reviewed in this study: both *Protest Supporter* and *Non-Supporter* networks have thousands of users, however only a few nodes within either network are retweeted more than once. This suggests that online political discourse (and social media conversations more generally) follow a pattern where small groups of active users express their opinions frequently which are then transmitted throughout the larger network of less active users. Other work has shown that journalists on Twitter tend to interact more often and are generally more active compared to other users [49], and that measures such as higher follower counts are able to identify users who are politicians or in the media [50]. The analysis of influential nodes within the Liberate discourse supports these previous findings since the users who received the highest number of retweets were very likely to be associated with either the media or political organizations. As indicated in past research that shows that highly active users are directly and indirectly more likely to try to persuade others within their networks [51], it is not surprising that users who are involved in media or politics, two professions that prioritize the ability to persuade others, are more likely to engage in online behavior that is shown to exert influence over public opinion.

6. Limitations

The total number of tweets collected for this study (34,672) may be considered small for a national discussion on a popular social media platform such as Twitter. This relatively small volume was likely due to the data collection methodology which involved collected prospective data from the Twitter public API stream filtered for both coronavirus-related key words and the term "Liberate". While the authors intentionally added the COVID-19-related keyword filter to increase the likelihood that tweets collected for this study were related to the Liberate Protests (and not just using the word "Liberate" that can be used colloquially for a host of different topics unrelated to COVID-19), it is likely that this approach also excluded a certain volume of relevant tweets about this movement. Other factors such as a faster news cycle and a smaller window for when the Liberate protests were salient in

public discourse also contributed to the smaller sample size of tweets and also resulted in few relevant tweets detected in the period prior to President Trump's tweet in support of the Liberate movement (though this period was beyond the scope of this study). Additionally, while the most frequently used terms associated with each topic were evaluated to filter out topics consisting primarily of media reporting and discussions of viral videos, it is possible that this approach could exclude tweets relevant to analysis from user-generated content that did not cluster as salient topics. Finally, while the results of this study show the proportion of Protest Supporters and Non-Supporters within the discussion, it is important to note that this only represents the proportion of Twitter users that engaged in the Liberate protest discourse for data we collected and is not intended to reflect the proportion of supporters for the overall US population. Hence, results of this study are not generalizable to the full scope of discourse and network structures of the Liberate movement. Future studies should develop more long-term and comprehensive approaches to collect data (e.g. including using the Twitter REST API and SEARCH API functions and more targeted data collection on a larger variety of specific hashtags) from these social media communities. Additionally, studies should examine data both pre and post events that can lead to higher politicization (e.g. a tweet from a President) that can change the course of online narratives and user interaction with such information. [52]

7. Conclusion

Effective and well-coordinated communication behavior and accurate evidence-based information are essential for the proper functioning of any democratic social system and especially to support the coordinated public health action. In fact, relatively simple public health interventions, such as mask wearing, social distancing, and stay at home requirements, have proven to be effective in other countries. These public health measures are the foundation of local, national, and global public health responses to infectious disease outbreaks, such as the COVID-19 pandemic, particularly important when a vaccine or other effective pharmaceutical intervention is not available. Salient differences in transmissibility, morbidity, and mortality rates across societies with similar per-capita income levels have shown that the human factors that drive social behavior are key factors in supporting the efficacy of public health measures. In other words, a key epidemiological variable is human behavior, which is driven by culture and individual knowledge, perceptions and attitudes, and thus highly sensitive to how information is generated and disseminated. In the case of continued growth of epidemic curves, even minor cultural differences are likely amplified into important differences in infection rates and other major public health outcomes via behavioral variables. COVID-19, with its relatively large share of asymptomatic transmissibility and its longer incubation period, is a case in point. Human factors have thus become the determinant factor for the efficacy of public health measures and the diminution of detrimental social and economic consequences.

In simplest terms, epidemic control requires a population to become highly organized so as to coordinate behavior in a manner that reduces the risk of transmissibility or increases herd immunity. For this to happen, the population needs to be well organized in order to collectively act in a coordinated manner and have the right information to motivate a collective behavioral configuration that minimizes transmission. Rather than collective behavior being motivated by an efficient and trusted flow of evidence-based information, however, the Liberate protests highlight how segments of the population may have their knowledge, perception and behaviors influenced by social and cultural dynamics that directly contravene needed public health measures. This study showed important differences between Protest Supporters and Non-Supporters which suggest that because pro messages are more consistent, unitary, and resilient to external and internal perturbations, the protest supporter network is well positioned to produce a more direct, clearer, and reproduceable message that users can understand. Hence, we see evidence for a case in which anti-scientific social stances are more likely to have a powerful effect on social behavior and political reality in comparison to the less organized and focused opposition movement. Better organized anti-science movements may very well have a structurally-justified higher chance of triumphing politically (or at least "hitting well above their weight") against the less organized attempts at communicating evidence-based public health policy, a worrying phenomenon during a global pandemic and amidst the global rise of both populist social movements and a once in a century pandemic event.

Author contributions

Michael Robert Haupt: Conceptualization, Methodology, Formal analysis, Writing - Original Draft **Alex Jinich-Diamant:** Writing - Review & Editing **Jiawei Li:** Software, Formal analysis, Data Curation **Matthew Nali:** Writing - Review & Editing **Tim K. Mackey:** Writing - Review & Editing, Supervision

Declarations

Availability of Data and Materials: Data collected on social media platforms is available on request from authors subject to appropriate de-identification.

Ethics Approval and Consent to Participate: Not applicable/Not required for this study. All information collected from this study was from the public domain and the study did not involve any interaction with users. User indefinable information was removed from the study results.

Consent to Publish: Not applicable.

Competing Interests: JL, MN, and TKM are employees of the startup company S-3 Research LLC. S-3 Research is a startup funded and currently supported by the National Institutes of Health – National Institute on Drug Abuse through a Small Business Innovation and Research contract for opioid-related social media research and technology commercialization. Author reports no other conflict of interest associated with this manuscript.

Funding: None reported

Author Contributions. JL collected the data, all authors designed the study, conducted the data analyses, wrote the manuscript and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Fig. A1 and Table A1.

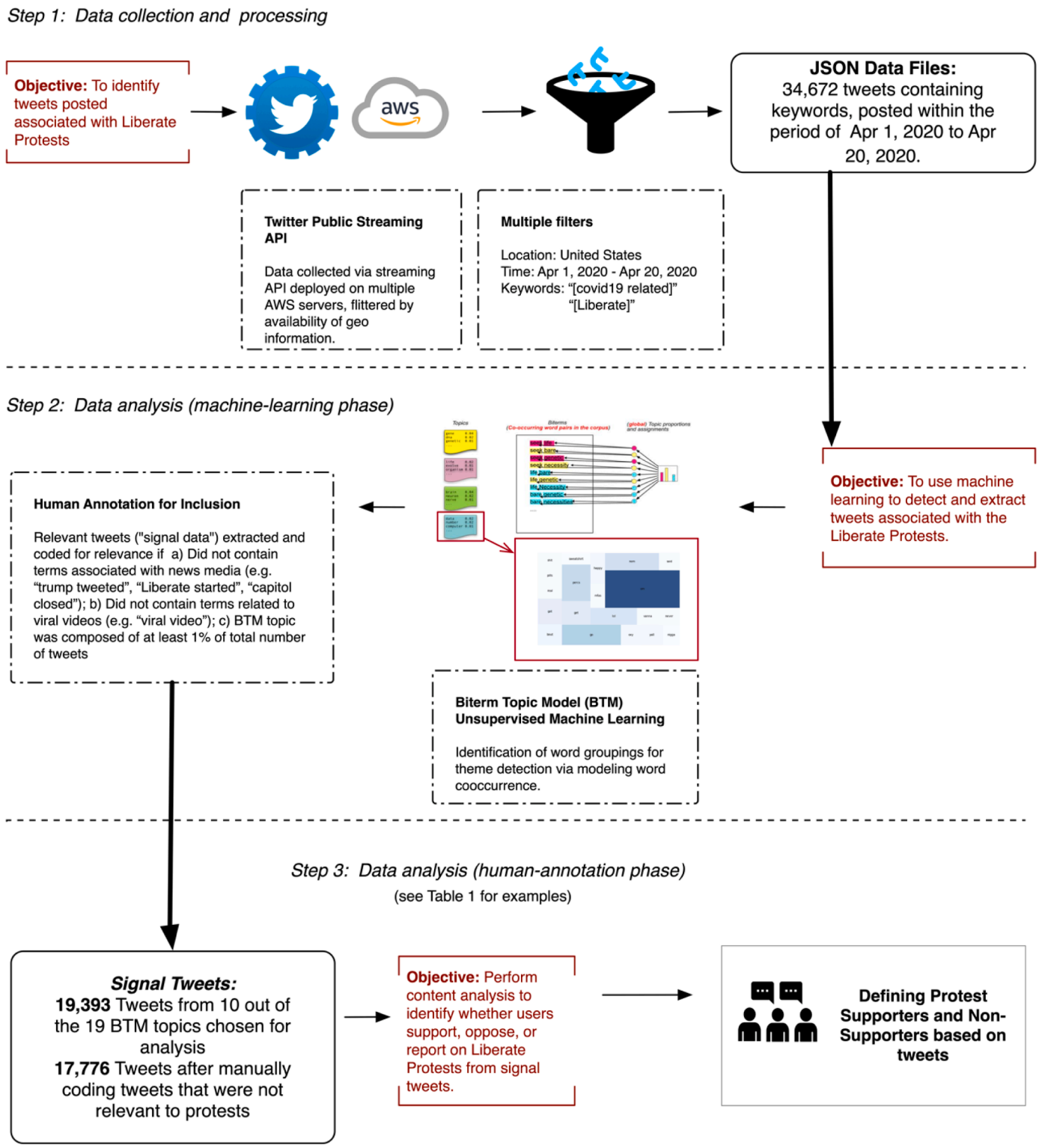
Step 1: Data collection and processing
Objective: To identify tweets posted associated with Liberate Protests
aws
JSON Data Files:
34,672 tweets containing keywords, posted within the period of Apr 1, 2020 to Apr 20, 2020.
Twitter Public Streaming API
Data collected via streaming API deployed on multiple AWS servers, flittered by availability of geo information.
Multiple filters
Location: United States
Time: Apr 1, 2020 - Apr 20, 2020
Keywords: "[covid19 related]"
"[Liberate]"
Step 2: Data analysis (machine-learning phase)
Objective: To use machine learning to detect and extract tweets associated with the Liberate Protests.
Human Annotation for Inclusion
Relevant tweets ("signal data") extracted and coded for relevance if a) Did not contain terms associated with news media (e.g. "trump tweeted", "Liberate started", "capitol closed"); b) Did not contain terms related to viral videos (e.g. "viral video"); c) BTM topic was composed of at least 1% of total number of tweets
Biterm Topic Model (BTM)
Unsupervised Machine Learning
Identification of word groupings for theme detection via modeling word cooccurrence.
Step 3: Data analysis (human-annotation phase)
(see Table 1 for examples)
Signal Tweets:
19,393 Tweets from 10 out of the 19 BTM topics chosen for analysis
17,776 Tweets after manually coding tweets that were not relevant to protests
Objective: Perform content analysis to identify whether users support, oppose, or report on Liberate Protests from signal tweets.
Defining Protest Supporters and Non-Supporters based on tweets

Fig. A1. .

Table A1
Unfiltered Tweets by topic stats.

Topic	Total tweets	Unique tweets	% Total	% Support protest	% Against Protest	% report	% Unrelated/ noise
1	1377	120	7	9	78	1	12
2	951	138	5	14	68	4	14
3	630	106	3	7	68	0	25
4	868	100	4	11	71	4	14
5	849	88	4	8	76	5	11
6	795	121	4	2	92	0	6
7	4323	38	22	76	11	3	11
8	3954	3011	20	7	73	3	17
9	1847	32	10	36	64	0	0
10	3800	76	20	83	13	0	4

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