Categorizing geocoded anti-vaccination tweets in urban areas using Latent Dirichlet Allocation (LDA) and dictionary-based modeling

Jaime Lara Levin

Abstract

The anti-vaccination movement, involving an expansion of vaccine hesitancy and vaccine refusal among parents and guardians, poses a severe public health threat by increasing the possible spread of contagious and preventable diseases, including measles, mumps, and pertussis. In recent years, social media platforms such as Twitter have provided a channel for the dissemination of vaccine misinformation. Echo-chambers of like-minded users enable those against vaccinations to share and validate their opinions. The threat Twitter poses in allowing the spread of anti-vaccination attitudes has led researchers to examine the geographic distribution of anti-vaccination user profiles and commonalities among their arguments against vaccines. However, geographic correlates of particular anti-vaccination arguments are unknown.

This study aimed to identify the differences in anti-vaccination rhetoric expressed in Twitter posts within urban cities on opposite coasts of the United States. Using novel streamed Twitter data from the summer of 2019, this study identified the most prominent topics of anti-vaccination Twitter arguments in northern and southern urban areas in California (San Francisco and Los Angeles) and New York (New York City and Rochester), by creating a topic model with Latent Dirichlet Allocation (LDA). The LDA model pinpointed four distinct reasons as to why users are against vaccinations in the Twitter data studied, each with a unique set of keywords. Using topical key word frequencies, I created a novel measurement (Topic Density Proportion) to find the density of the four topics in each geographic region analyzed. These values indicated that anti-vaccination Twitter users in the Los Angeles area were most concerned about the physical safety of vaccinations, anti-vaccination tweets in the San Francisco and New York areas most often referred to government conspiracy regarding vaccinations, and anti-vaccination tweets in the Rochester area often referenced the First Amendment and the Constitution. Residual chi-squared tests revealed that there was a significant difference between the topics of anti-vaccination tweets expressed in the four geographic locations. The results of this study found that anti-vaccination Twitter users in different urban areas in the United States have distinct concerns regarding vaccinations, ranging from the potential physical dangers of vaccinations to concerns about government conspiracy. The ability to pinpoint the most prevalent anti-vaccination arguments in these areas is immensely impactful, enabling public health officials and policy makers to design tailored interventions to combat specific vaccine misinformation and prevent mass outbreaks.

1. Introduction

Since the mid-20th century, vaccinations have helped curb the spread of deadly, contagious diseases and infections, such as measles, mumps, and pertussis. Many vaccinations for these diseases are readily designed for children under the age of 12 and are only given to a child with a parent or guardian's approval (Terranella et al., 2016; Zerbo et al., 2019; CDC, 2019). Global outbreaks are more probable if pockets of parents and guardians decide not to vaccinate their children and teenagers. Recently, a highly feminized anti-vaccination movement circling around the belief that vaccinations are ineffective, dangerous, and/or solely for the benefit of pharmaceutical companies and the government has increased in prevalence on social media platforms, especially Twitter (Larson et al., 2014; Chen & DeStefano, 1998; Chen & Hibbs, 1998; Smailbegovic et al., 2003). The connection between this movement and a rise in vaccine hesitancy, or purposeful delay or refusal of vaccinations, among mothers with active social media presences has already led to outbreaks of previously preventable illnesses (Freed et al., 2010, Smith et al., 2010; Song, 2014; Smith & Graham, 2017).

The anti-vaccination movement is fueled by postings and content on Twitter, where "tweeting" is used to discuss anti-vaccination rhetoric with family, friends, and other Twitter users and viewers (Scanfield et al., 2010). Twitter's features, including the ability to "retweet" like-minded messages, contribute to ideological overlap on the platform and the creation of online echo chambers, which lead to an amplification and reinforcement of similar vaccine misinformation (Witteman & Zikmund-Fisher, 2012; Eady et al., 2019). Thus, anti-vaxxers (parents or guardians who believe vaccinations are harmful and who choose not to vaccinate their children) tend to be exposed to opinions similar to their own on Twitter, contributing to their negative attitudes towards vaccination, thus allowing for agreement. Proliferation of anti-vaccination content on Twitter results in increased vaccine hesitancy and wavering confidence in the efficacy of vaccinations (Smith & Marshall, 2010).

The implications of this anti-vaccination rhetoric on Twitter are vast. First, children exempt from vaccines are 30 times more likely to contract measles and pertussis compared to vaccinated children (Phadke et al., 2016). Previous research also suggests that United States counties with high rates of exemption could pose risk of disease contraction even to vaccinated children (Omer et al., 2008; Feikin et al., 2000). The anti-vaccination movement poses an enormous public health threat to urban communities where population densities are greater than 1,000 people per square mile, allowing for contraction and rapid spread of contagious diseases. The more populous, urban counties in the United States tend to contain a greater proportion of vaccine-hesitant parents and guardians, as well as a greater proportion of vaccine-exempt children, than less populous counties, making urban regions more susceptible to the contraction and spreading of harmful illnesses (Freed et al., 2010). For example, in 2019, large measles outbreaks took place in New York City and Los Angeles, both cities with population densities above 5,000 people per square mile (California Department of Public Health, 2019; NYC Department of Health, 2019). Researchers trace these outbreaks back to several large pockets of unvaccinated children, whose parents or guardians may have been swayed by anti-vaccination rhetoric, resulting in vaccine refusal (Terranella et al., 2016; Zerbo et al., 2019; CDC, 2019). If not addressed, the rampant anti-vaccination movement on social media platforms will continue to influence the mindset of those choosing whether or not to vaccinate their children, which can lead to further outbreaks in the United States and across the globe.

The influx of vaccination-related echo chambers on Twitter and recent disease outbreaks have led researchers to study the content and origin of vaccine-related tweets (Dubé et al., 2014; Jolley & Douglas, 2014). Several studies grouped vaccine-related tweets by their sentiment, ranging from negative tweets towards vaccination to positive tweets towards vaccination (Salathé et al., 2011). Others discussed the most frequent words that appear in the context of pro or anti-vaccination discourse on Twitter (Radzikowski et al., 2016). More recent studies focused on methods to categorize and cluster anti-vaccination-related tweets in order to qualify and differentiate anti-vaccination arguments on Twitter and gauge general sentiment. Countering specific anti-vaccine sentiment could prevent the contraction and spreading of contagious diseases in highly populous areas (Garay et al., 2019).

Researchers have also analyzed anti-vaccination tweets to investigate the geographic location of Twitter users who are anti-vaccination proponents (Brooks, 2014; Lieu et al., 2015). In order to combat the spread of diseases, it is important to know geographically where people strongly oppose vaccinating their children. Geo-tagged Twitter data (available data that provides a latitude and longitude coordinate of a Twitter user posting an anti-vaccination tweet) enables researchers to study where anti-vaccination ideology may be most prevalent. Prior research analyzing geographic correlates of anti-vaccination tweets suggests that these tweets disproportionately arise from five states, California, Pennsylvania, Connecticut, Massachusetts, and New York, all of which contain highly urbanized areas susceptible to the spread of contagious diseases (Tomeny et al., 2017).

While both content analysis and geographic clustering have been studied separately among anti-vaccination users on Twitter, the geographic base of each subcategory of anti-vaccination tweets and retweets is unknown; the reasons for anti-vaccination as expressed on Twitter in distinct geographic regions of the United States are unclear. This study aims to test whether there is a significant difference in Twitter users' arguments against vaccination in different geographic regions of the United States. The study intends to analyze users' arguments against vaccination in urban areas on opposite coasts, in particular, where there is a high prevalence of anti-vaccine rhetoric. To do so, I first utilized methods of Latent Dirichlet Allocation (LDA) to create categories or "topics" for different types of anti-vaccination tweets in both California and New York. I then created a topic density proportion to measure the relative density of particular arguments against vaccination within cities in these two states. Understanding where anti-vaccination sentiment is most prevalent and what the sentiment discusses is crucial to combating the outbreak and spreading of deadly diseases across the country.

2. Data Collection

2.1 Rtweet Package

To obtain recently posted anti-vaccination-related tweets by Twitter users in New York and California that could be analyzed by content, I utilized the R programming language (https://www.r-project.org) rtweet package (https://rtweet.info). Rtweet is designed to collect and organize Twitter data via Twitter's REST and STREAM Application Program Interfaces (API). Rtweet demands an authorization token and Twitter account to connect to Twitter’s API platform. Unlike other Twitter streamers (tweepy, radian6), rtweet is able to filter tweets by their key words and location simultaneously. Multiple key words can be queried in rtweet, as long as they do not exceed 500 characters, and rtweet will filter tweets that only contain the desired queried words. The geocode argument in rtweet’s package is a geographical limiter of the template “latitude, longitude, radius” (ex: geocode = “37.78,-122.40,1 km”), and filters tweets made within a desired circular radius. Both the key word and geocode parameters of rtweet were used to filter tweets in this study.

2.2 Term Query Methodology

Because this study solely analyzed the anti-vaccination movement on Twitter, it was necessary to ensure that the data culled from rtweet contained only tweets from anti-vaxxers. Past research has indicated that trigrams (combination of consecutive words) and hashtags (metadata tags for tweets) are prominent cues of a tweet’s stance towards vaccination (Mitra et al., 2016; Faasse et al., 2016; Radzikowski et al., 2016; Smith et al., 2010; Kata et al., 2009; Madden et al., 2011; Keelan et al., 2009; Guidry et al., 2015; Briones et al., 2011; Lotan, 2017). Words and hashtags including “#vaccineinjured” or “#VaccineInducedAutism” are indicative of the tweet’s sentiment being against vaccination (Mitra et al., 2016; Faasse et al., 2016; Radzikowski et al., 2016; Smith et al., 2010; Kata et al., 2009; Madden et al., 2011; Keelan et al., 2009; Guidry et al., 2015; Briones et al., 2011; Lotan, 2017). Thus, within every geographic location from which data was streamed, I made an initial query with the same broad anti-vaxx key terms. This initially filtered tweets in the desired radius that were deemed as expressing anti-vaccination sentiment. These terms were generated based on those suggested by previous researchers and descriptions used by journalists covering the anti-vaccination movement on Twitter (Mitra et al., 2016; Faasse et al., 2016; Radzikowski et al., 2016; Smith et al., 2010; Kata et al., 2009; Madden et al., 2011; Keelan et al., 2009; Guidry et al., 2015; Briones et al., 2011; Lotan, 2017). 95 anti-vaccination related key words were used to initially filter anti-vaccination tweets in each geographic location chosen for this study.

2.3 Geocoding Choice and Methodology

This study aimed to compare subcategories of anti-vaccination tweets in urban cities in New York and California, two highly populated states on opposite coasts known to be the source of a high density of tweets against vaccination. For sample uniformity, I pulled data from urban areas in the northern and southern regions of both states, in or near cities that are some of the most populous in the state. I sought to study tweets in populous regions of each state that were geographically spaced from one another in the north-south direction. This would allow for a comparison of anti-vaccination sentiment on Twitter inside individual states and across the two United States coasts. In New York, I created a geographical radius of 50 kilometers around northern Rochester and a geographical radius of 115 kilometers around the southern New York City metropolitan area, and queried for tweets inside these radii. In California, I used the same methodology to create a 200 kilometer radius around northern San Francisco and 150 kilometers around southern Los Angeles (Figure 1). I chose the radius sizes to optimize the geographic regions covered in which population density was greater than 5,000 people per square mile. In each geocoded location, I utilized rtweet to search for tweets including the anti-vaxx related key words mentioned previously.

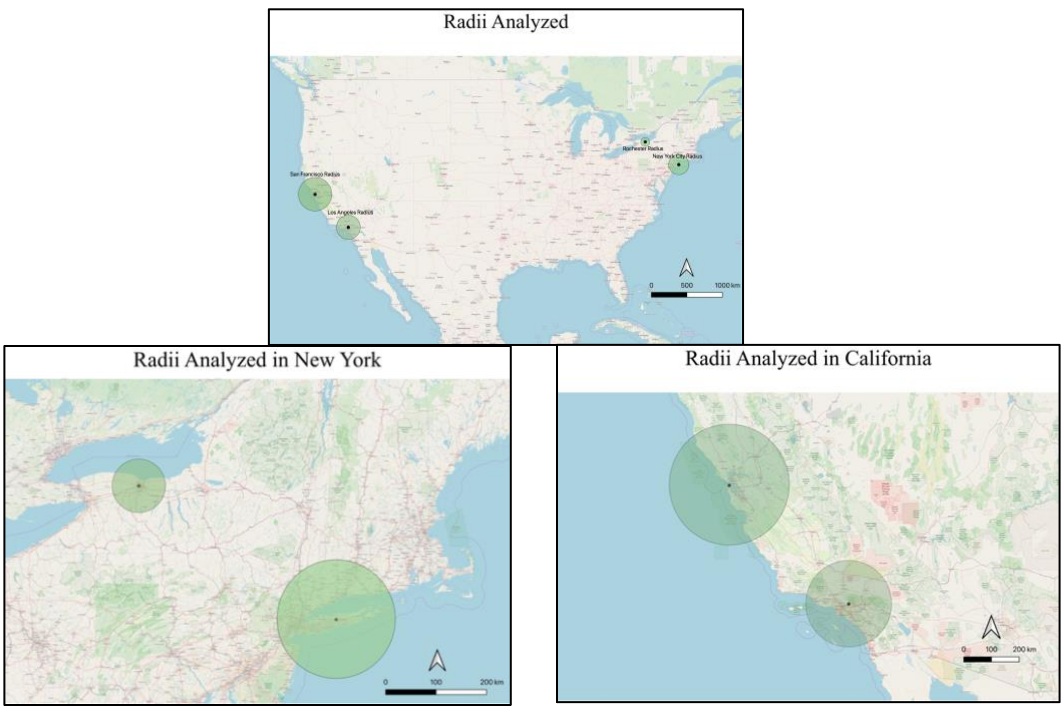


Figure 1. All radii in green utilized to query for anti-vaccination tweets in cities in northern and southern New York and California. The radii utilized for the New York City metropolitan area (New York), Rochester metropolitan area (New York), San Francisco Bay area (California), and Los Angeles metropolitan area (California) were determined to maximize the area covered in which population density exceeds 5,000 people per square mile. Maps created with QGIS Software.

2.4 Data Characteristics

A total of 3,961 tweets (including retweets) from 06/30/2019 to 07/11/2019 were returned from rtweet with the given geographic location and key word parameters discussed above. The greatest number of tweets originated from the Los Angeles radial area (N=1878), followed by the New York City metro radial area (N=1268), the San Francisco radial area (N=696), and the Rochester radial area (N=119). Table 1 illustrates descriptive information for the tweets collected.

	LA Rad.	SF Rad.	NYC Rad.	Rochester Rad.
Tweet Count (N)	1878	696	1268	119
Proportion Re-tweets	.75	.17	.07	.39
Mean Re-tweet count	797.2	10.9	0	4.17
Verified User	14	0	12	7
Mean follower count	3,384.10	1,806.70	824.60	3,646.60

Table 1. Demographic/descriptive table for the collected tweets. “Proportion re-tweets” indicates that certain collected tweets were not authentic to the user, but rather were retweeted. “Mean re-tweet count” describes the number of collected tweets that were retweeted, or reposted, by many other Twitter users. Within the New York metropolitan radial group of tweets, the mean retweet count was 0, indicating that few Twitter posts were “viral” or were reposted by other Twitter users.

3. Methodology

3.1 Creation of an LDA Topic Model

In order to ascertain if there was a difference in Twitter users’ arguments against vaccination among cities in New York and California (i.e. determine if there were distinctly different subcategories of anti-vaccination rhetoric across each of the four cities), I first ran the machine learning Latent Dirichlet Allocation (LDA) algorithm on the tweets’ contents to determine if there were any subcategories within the 3,961 anti-vaccination related tweets and what those subcategories were (Blei et al., 2003). LDA is an unsupervised form of topic modeling in machine learning which makes the assumption that each topic in a textual dataset is associated with a distinct subset of words. It can be represented by the below equation which specifies that within a document (sequence of words that could be related to various topics), every word is conditioned on a particular topic.

$$p(w|\alpha,\beta) = \int p(\theta|\alpha)\left(\prod_{n=1}^{N}\sum_{zn} p(zn|\theta)p(wn|zn,\beta)\right)d\theta$$

where w denotes a document and $p\ (wn|zn,\beta)$ is the likelihood that a particular word wn falls within the zn topic. As indicated by these variables, the model generates an allocation of the words in a document to topics (Blei et al., 2003).

LDA models have the following abilities with textual datasets:

1. Determine the ideal number of categories/topics for the textual data;
2. Create and label these categories for the textual data;
3. Output several characteristic key words from each category.

I sought to use LDA to determine an ideal number of categories of anti-vaccination sentiment found in the 3,961 tweets, create labels for each of these categories, and output several ideal phrases found in tweets associated with the category.

Before creating the LDA model, I preprocessed the text from each tweet to maximize informative topic creation. This involved first removing "stop words" in the tweets, such as "the," "and," and "of," which would not contribute to the creation of topics. To allow the LDA model to focus solely on the content of the tweets, rather than user mentions within a given tweet, the character "@" was deemed a "stop word" and was removed. All remaining words were converted to lowercase, and I then stemmed and tokenized the words within my corpus (i.e. "govern"/ "governance", "vaccination"/ "vaccine") (Denny & Spirling, 2017).

In the case of the collected anti-vaccination tweets, I utilized an LDA model that contained one document (AVS). This document can be described by topics, or distinguishable arguments against vaccination (Z). Within each topic is a probability distribution of specific words, following a "bag of words" approach (Figure 2).

3.2 Topic Model Word Output

An ideal LDA model was constructed by varying the number of topics between 2 and 10. The optimal number of topics was chosen by analyzing which model contained the least word redundancy.

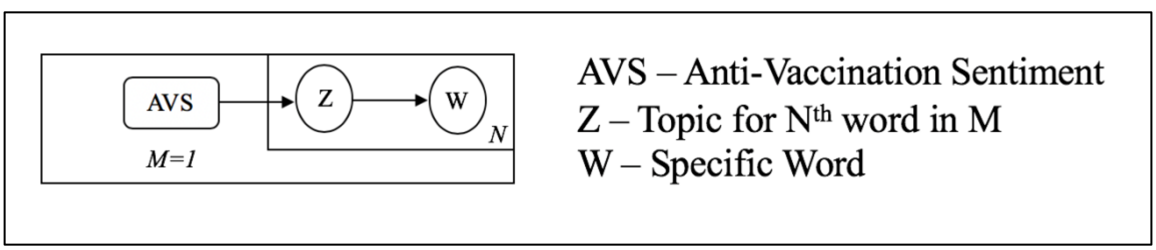


Figure 2. A simplified graphical representation of the LDA model applied.

The least overlap of words between topics occurred with a model that contained 4 topics. R documentation additionally suggests the use of 4 topics for a single document of text data. While several words were repeated throughout each topic, distinct words within each topic enabled differentiation. This suggests that the LDA model determined that within the dataset, there were optimally 4 distinct topics of anti-vaccination sentiment expressed (Figure 3).

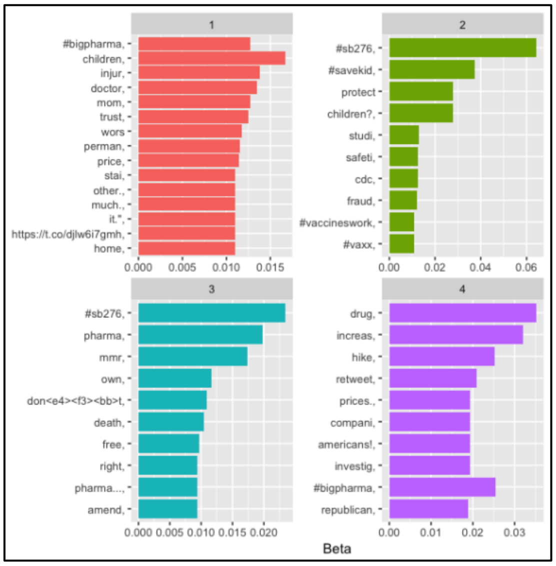


Figure 3. The 4 distinct categories of anti-vaccination tweets LDA created for the 3,961 tweets in the dataset and the associated key words of each category.

The first topic (Topic 1) included words common among anti-vaxxers who distrust government health messages, the Centers for Disease Control and Prevention (CDC), and doctors or other health professionals. This was the only topic that contained the word "trust," in addition to the word stems "doctor," "mom," and "stai." Many people against vaccination who distrust government organizations argue that the government is promoting unsustainable practices, hence the "stai" word stem.

The second topic (Topic 2) captured a large number of tweets from users who described vaccines as physically dangerous and harmful. Common distinct word stems cited in this topic included "savekid," "protect," "safety," and "children."

In the third topic (Topic 3), words related to liberty, independence, and freedom were common. Anti-vaccination users within this category tended to utilize the word stems "own," "free," "right," and "amend-" within their language.

The fourth topic (Topic 4) contained words common among users who choose not to vaccinate for economic reasons. These users cite word stems such as "increase-," "hike," "prices," "company," and "bigpharma" to argue that vaccinations are ineffective and solely benefit pharmaceutical companies financially.

Sample tweets in each topic are given in Table 2.

3.3 Dictionary Formation Using Suggested Key Words

I added onto the list of LDA-model generated key words for each topic to create a broader, more extensive dictionary of key terms associated with each category of anti-vaccination tweets (Table 3). I formed these dictionaries by analyzing commonly occurring entities, including hashtags, words, and phrases around the stems of the LDA-model generated key words. For example, within the "Free Choice/Constitutional Rights" topic, I created the dictionary by mining for the most frequent terms surrounding the LDA stems, "amend-," "free," "own," and "right." The resulting "Free Choice/Constitutional Rights" dictionary not only included the most frequent words found by the LDA model, but also contained common surrounding entities, such as "mychildmychoice," "informed consent," "vaccine exemption," "let parents choose," and "medical freedom."

Anti-vaccine Topic	Sample Tweet
Topic 1: Distrust of Government, CDC, Medical Professionals	“I have 2 vaccine injured children because I trusted the doctors too much. One is worse off than the other. I am now a permanent stay at home mom because of it.”
Topic 2: Vaccines are Dangerous	“If it's just rhetorical (doctors have to claim these diseases are dangerous to sell the vaccines) - no. Children died. Not every child, or even most, but they died. Or they became disabled. And they made others ill.”
Topic 3: Free Choice/Constitutional Rights	“Fighting for disabled adult son's health/human rights like a Mom does ;^) I was pregnant downwind of coal-fired paper mill. My son was born w/Asperger's.#VAXXED”
Topic 4: Vaccines Allow Companies to Make Profit	“Our latest brief by Fellow @katy_milani explores how #BigPharma has become increasingly extractive at the cost of patients.”

Table 2. Sample tweets in each of the four LDA-determined categories. Note: Twitter usernames responsible for each tweet are not included to maintain anonymity. Each tweet’s content is included within the quotation marks.

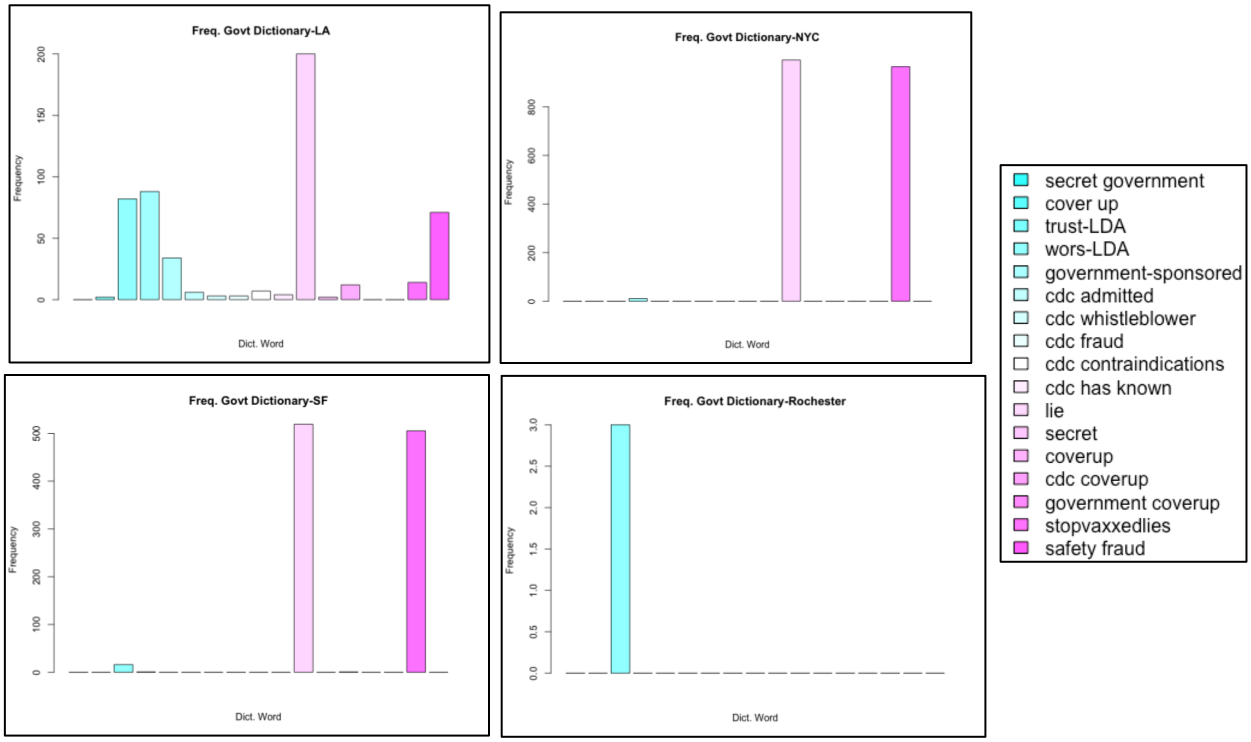
3.4 Geographic Analysis by Topic

By creating a dictionary for each topic containing a broad list of key terms, I was able to analyze the contents of tweets from each region and ascertain which topic the tweets from each region most agree with. I did so by calculating the density of each topic for tweets in each of the four regions. Prior to calculating each topic’s density among the selected cities in California and New York, I obtained the exact frequency of each dictionary term mentioned in tweets within each city. To do so, I employed R’s stringr package, which provides the precise count of numerous word vectors given a specific location. In the case of my data, I counted the frequencies of all dictionary terms in each topic among the four radial locations chosen (Figure 4). A complete frequency table of each topic’s dictionary terms by location is pictured (Figure 4). The use of term frequency analysis aided in understanding trending or prominent terms in each topic by region. Within the Free Choice/Constitutional Rights topic, the dictionary terms “free,” “right,” and “exemption” appeared to be trending in all four cities analyzed, for instance. While term frequency modeling was useful in gauging relative dictionary word counts in each topic, uneven sample sizes from each city could have created a biased distribution of trending words per category. For example, Twitter data collected from the Los Angeles radial group contained many more tweets than the Twitter data collected from the Rochester radial group. Given the large number of tweets obtained from the Los Angeles radial group, it was no surprise that the dictionary word frequencies in each topic were the highest. To account for variations in size among Twitter data collected from the four locations, a uniform measurement was needed to compare the density of words in each topic among the selected cities. Fair comparison of topics between Twitter corpora was enabled with a location-quotient based method.

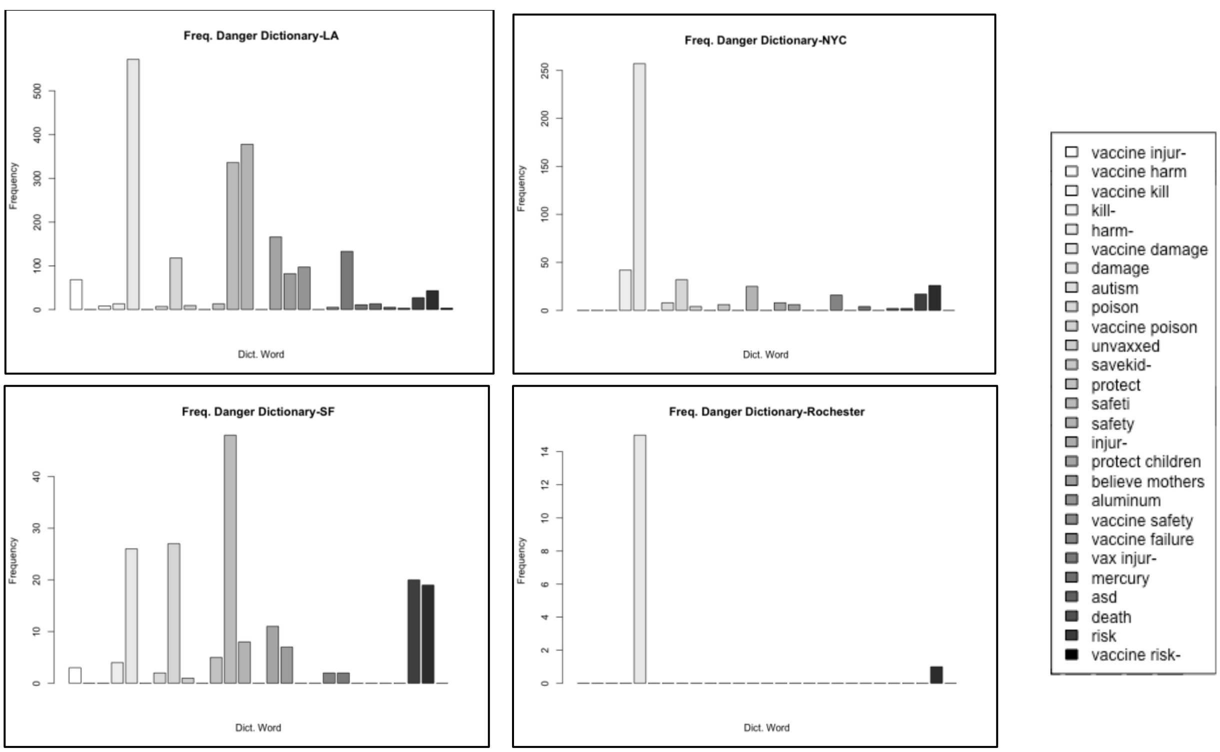
Topic	Key LDA-generated words and stems	Surrounding dictionary words and stems	
Topic 1: Distrust of Government, CDC, Medical Professionals	doctor trust wors- stai-	secret government cover up trust government sponsored cdc admitted cdc whistleblower	cdc fraud cdc contraindications cdc has known lie secret coverup cdc coverup government coverup stopvaxxedlies safety fraud
Topic 2: Vaccines are Dangerous	savekid protect safeti- vaxx	vaccines injure vaccine injured vaccines injured vaccines harm vaccines kill kill harm vaccine damage autism poison vaccines poison	unvaxxed injur- protect children believe mothers aluminum vaccine safety vaccine failure vax injury vax injured mercury asd death risk vaccine risk
Topic 3: Free Choice/Constitutional Rights	#sb276 own free right pharma amend-	religious freedom free choice mychildmychoice informedconsent vaccine exemption letparentschoose health freedom medical freedom vaccination choice medical rights	nomandates first amendment constitution government control exemptions
Topic 4: Vaccines Allow Companies to Make Profit	increas- hike prices compani- bigpharma	pharmaceutical companies cash profits company	

Table 3. LDA-generated words and stems for each topic of anti-vaccination tweets and the added extensive full dictionary of words associated with each category. The complete dictionaries utilized contained both LDA word stems and surrounding word entities.

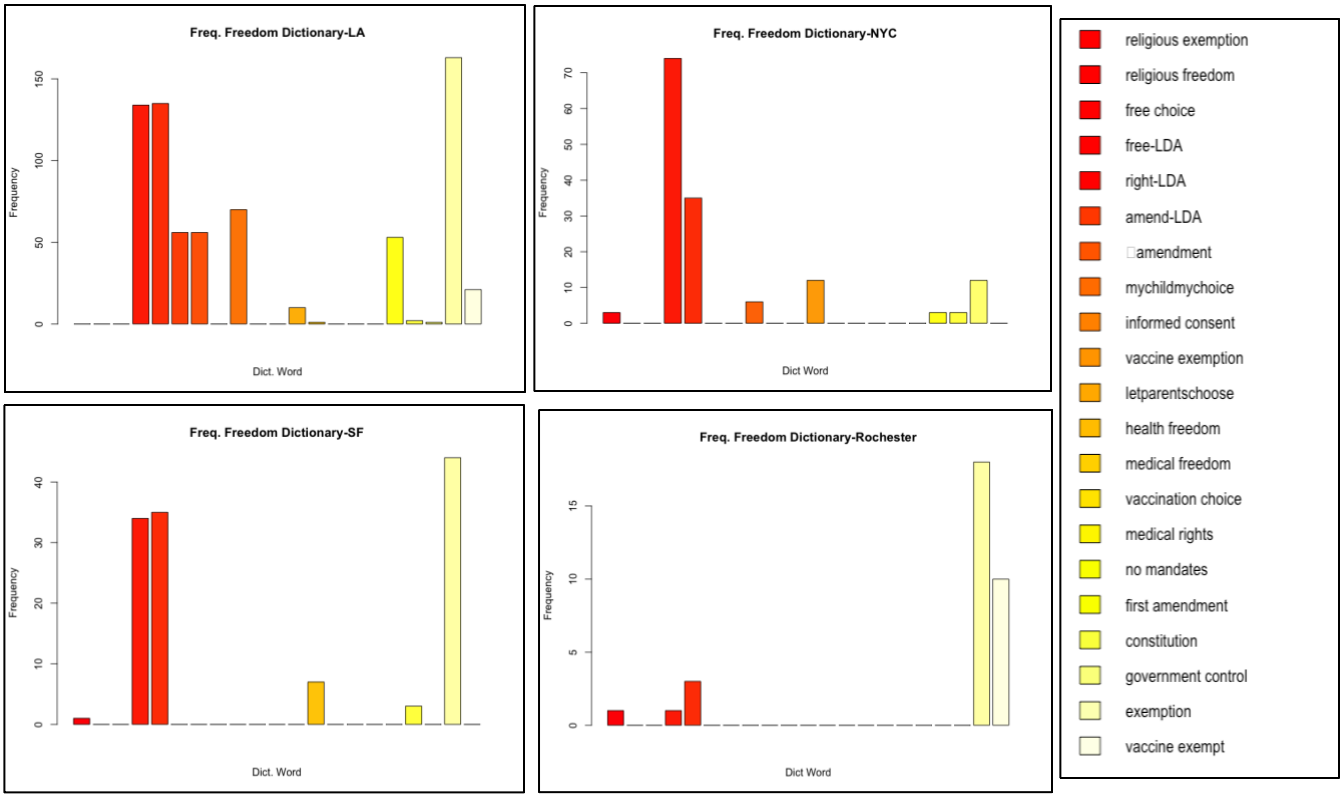
(a) Topic 1: Distrust of Government, CDC, Medical Professionals



(b) Topic 2: Vaccines are Dangerous



(c) Topic 3: Free Choice/Constitutional Rights



(d) Topic 4: Vaccines Allow Companies to Make Profit

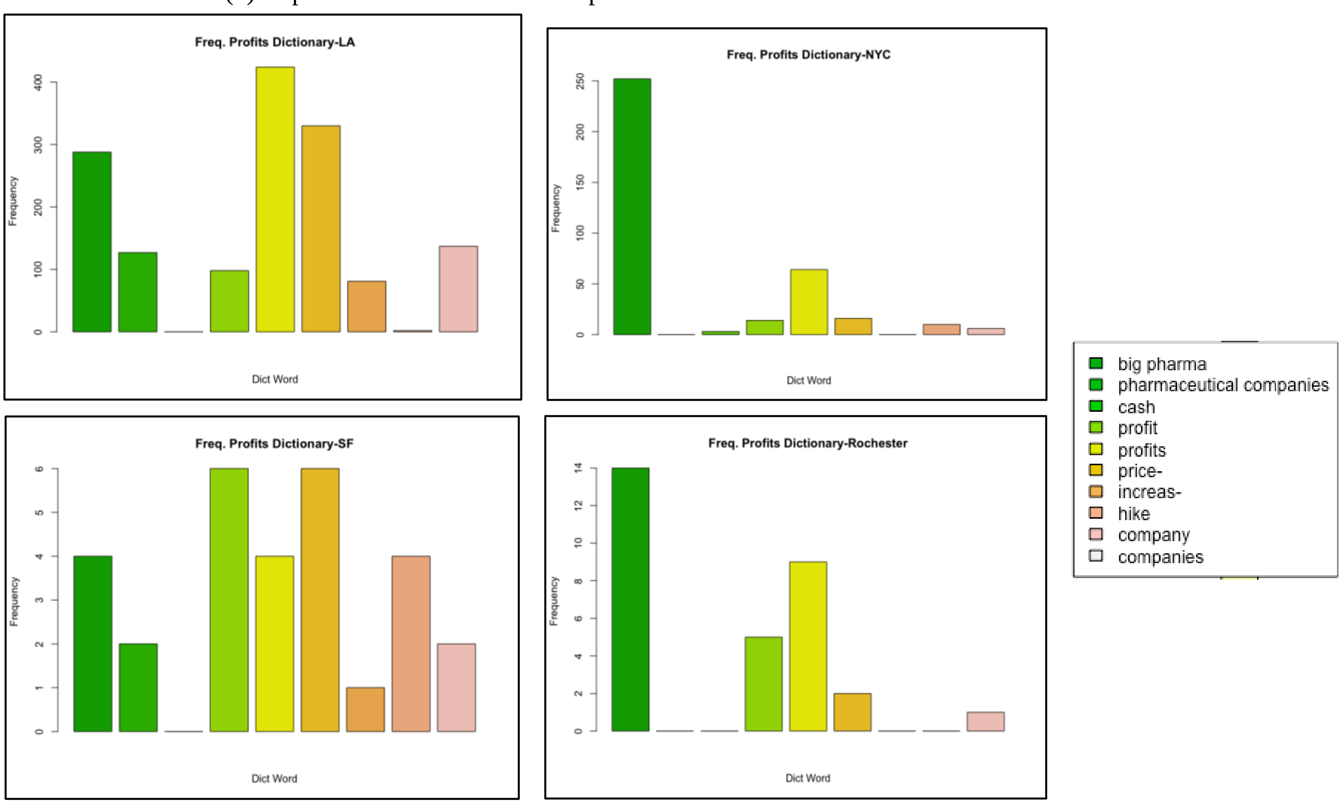


Figure 4. Frequencies of all dictionary and LDA terms in (a) Topic 1, (b) Topic 2, (c) Topic 3, and (d) Topic 4. Graphs of frequencies in California cities are in the left column, while graphs of cities in New York are in the right column.

To calculate the density of tweet topics in each of the four geographic locations and determine the prevalence of each anti-vaccination tweet topic in each region, I propose a novel methodology using dictionary word frequencies and the total number of tweets in the region. Prior studies have employed location quotients (LQ) to compare tweet topic densities in particular states or neighborhoods to that of an entire country. A formula introduced by Anselin and Williams (2016) utilized a LQ to compare the density of geolocated tweets in a particular block of a community to the population density of the same block. Another LQ formula proposed by Lansley compared the density of tweets within “residential,” “non-domenstic buildings,” or “public green spaces” to the density of tweets in all of these areas combined. While location quotients are useful in comparing the density of tweets of a certain topic within a small region to that of an entire nation, they do not allow a word-specific approach in identifying topic density in specific regions (Lansley & Longley, 2016; Arthur & Williams, 2019; Dong, 2018) .

I created two topic density proportions (TDP) to quantify the concentration of each dictionary word by geographic region and to quantify the concentration of all possible dictionary words within each LDA topic by geographic region. The proportion is a uniform measurement that attempts to calculate the abundance of each type of anti-vaccination discourse in tweets among the four cities studied. To calculate the topic density proportion for each dictionary word in each geographic region, I divided the frequency of the word mentioned in tweets in the geographic region by the total number of anti-vaccination tweets made in that location:

$$TDP = \frac{nzi}{Ei}$$

where TDP is the topic density proportion for a particular dictionary word in one of the four categories. n_{zi} represents the frequency of word n stated in topic z, located in the i radius. Ei represents the total number of tweets made within the i radius. The TDP was calculated for each dictionary word in every anti-vaccination topic dictionary, for all 4 radial locations.

An additional TDP value was assigned to represent the overall density of each anti-vaccination topic mentioned in tweets made within each geographic region. I calculated this value by dividing the total frequency any word in a particular topic dictionary was mentioned in a tweet in a particular region by the total number of anti-vaccination tweets made within the region. This was represented by:

$$TDPtotal = \frac{\sum nzi}{Ei}$$

where the TDP_{total} represents the overall density of each anti-vaccination topic made within each geographic region. $\sum nzi$ represents the total frequency of words mentioned in tweets within a particular geographic region having to do with the particular topic and Ei represents the total number of anti-vaccination tweets made within the region. I calculated the *TDPtotal* for each of the four topics in each of the four geographic regions.

The relative *TDPtotal* value range was between 0 and 3. Values closer to 3 indicated a high density of anti-vaccination tweets related to a particular topic, while values closer to 0 indicated a low density of anti-vaccination tweets within the topic for the given region.

Indication of the relative TDPtotal Value Range

0 ⟷ 3

Low Density — High Density

3.5 Residual Chi-squared Test

Using calculated word frequency values for each topic group, a residual chi-square test was performed to assess if there was a significant difference between the tweet topic density among the four cities. Chi-squared tests were calculated using the overall frequencies of topics mentioned for all cities analyzed, and they were also performed to analyze the comparison of topic density between combinations of two cities.

4. Results

4.1 Results for Topic 1: Distrust of Government, CDC, Medical Professionals

TDPtotal values indicated that the New York metropolitan radial group had the highest density of anti-vaccination tweets in Topic 1 (*TDPtotal*=2.313). The San Francisco radial group also showed a high representation of anti-vaccination tweets within Topic 1, with a *TDPtotal* value close to that of the New York radial group (*TDPtotal* =2.240).

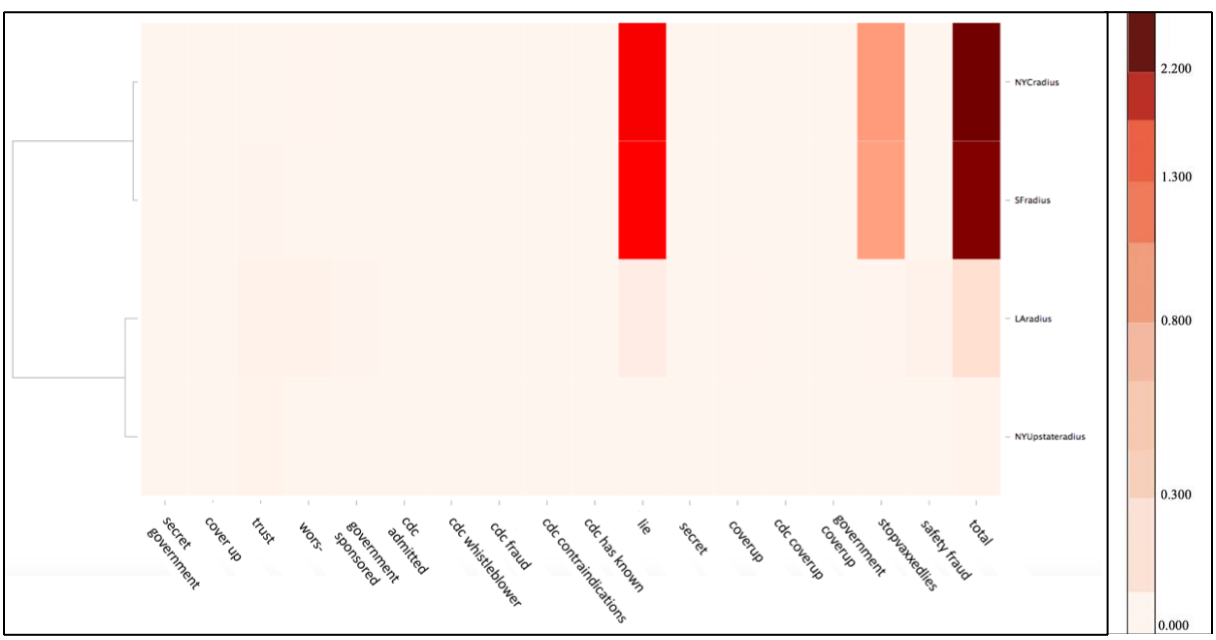


Figure 5. Heat map for *TDP* values of Topic 1. The Rochester radial group is referred to as “NYupstateradius.”

TDP values (Figure 5) show a much greater prevalence in Topic 1 tweets in the New York City metropolitan area radius and the San Francisco radius than the other two urban locations, especially with the elevated density of dictionary and LDA keywords "lie" and "stopvaxxedlies."

The low *TDP* and TDP_{total} values for "Government Conspiracy" tweets within the Rochester and Los Angeles radial groups indicates that anti-vaccination tweets generated in these areas less frequently include discourse regarding lies spread by the CDC and government organizations. Instead, these users' vaccine hesitancy may be attributed to one of the remaining three topics.

4.2 Results for Topic 2: Vaccines are Dangerous

The maximum TDP_{total} value in the "Vaccines are Dangerous" topic was found in the Los Angeles radial group of tweets. Tweets spatially distributed within this radius often cited that vaccines can injure, harm, or kill children (e.g. "vaccine injured," "vaccines harm," "vaccines kill"). The *TDP* values (Figure 6) also suggested that many user profiles in this region linked preservatives in vaccines to autism spectrum disorder (ASD).

The radial groups encircling metropolitan New York and San Francisco possessed similar TDP_{total} values within Topic 2. The New York metropolitan radial group contained higher *TDP* values regarding mercury and aluminum in vaccines compared to the San Francisco radial group. The *TDP* values in both of these locations indicated that word content in tweets often associated vaccination and ASD.

The TDP_{total} value in this category was lowest within the Rochester radial group. Words that had prominent *TDP* values in this area were "death" and "harm," whereas citations of ASD and chemicals did not appear in tweets.

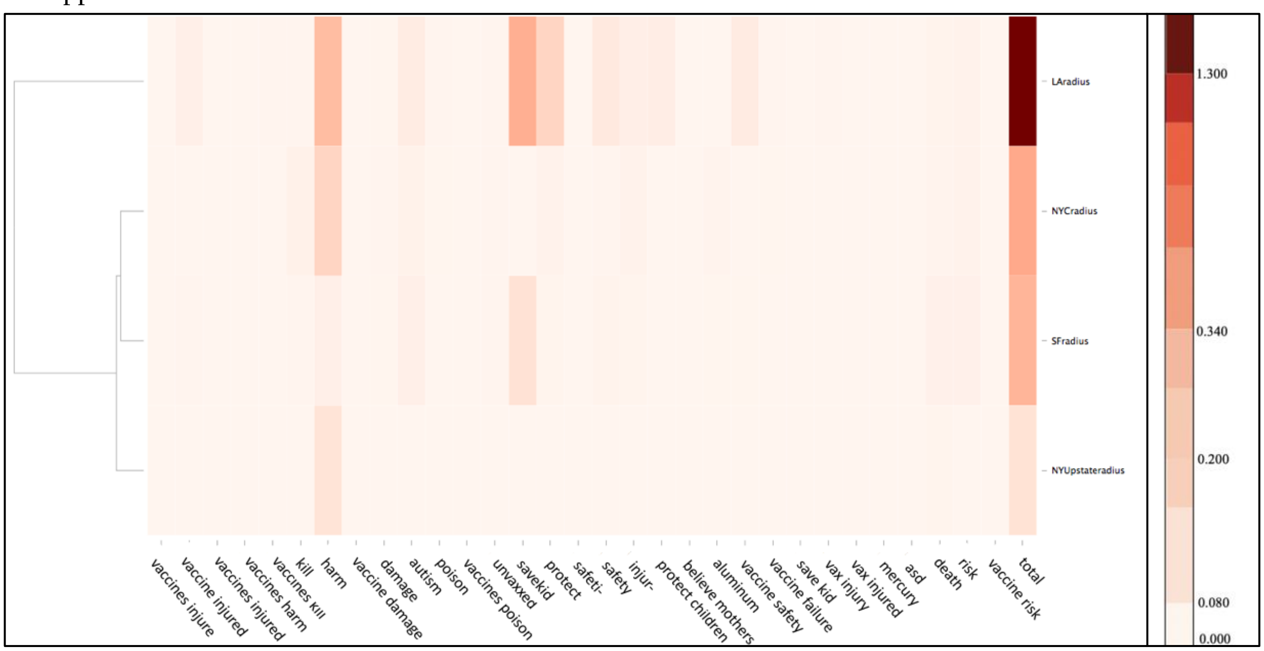


Figure 6. Heat map for *TDP* values of Topic 2. The Rochester radial group is referred to as "NYupstateradius."

4.3 Results for Topic 3: Free Choice/Constitutional Rights

Anti-vaccine tweets in Topic 3 appeared disproportionally in the Los Angeles radial grouping. This is indicated by a high TDP_{total} value, compared to the TDP_{total} values of the remaining three cities studied. Within the Los Angeles radial group, anti-vaccination tweets in the “Freedom of Choice” category tended to contain the most diverse array of keywords in this topic. 11 out of the 18 dictionary words found in this topic were represented in tweets located in this radial grouping.

According to the *TDP* values (Figure 7), the radius surrounding the New York metropolitan area contained the lowest density of anti-vaccination tweets with content related to this category. The Rochester radial group and the San Francisco radial group had TDP_{total} values between the TDP_{total} values of the Los Angeles radial group and the New York metropolitan radial group, respectively.

Assessing tweet topic density by general TDP_{total} values could fail to capture words in that category that might arise disproportionally in a certain city. Although the New York metropolitan radial group had a low total proportion within Topic 3, *TDP* values for certain words in this category were prominent within this spatial region. For instance, the LDA-based words “free” and “right” had a high *TDP* value in the New York metropolitan radius. Other dictionary-based words, “informed consent,” “health freedom,” “constitution,” “government control,” and “exemptions” also appeared in topical tweets in this area.

TDP values of certain words within the Rochester radial group and the San Francisco radial group should also be noted. While the total proportion of Topic 3 words in these loci was not as high as that of the Los Angeles radial group, the San Francisco radial group had the highest *TDP* value for the search term “medical freedom” and the Rochester radial group contained the highest *TDP* value for the search term “health freedom.”

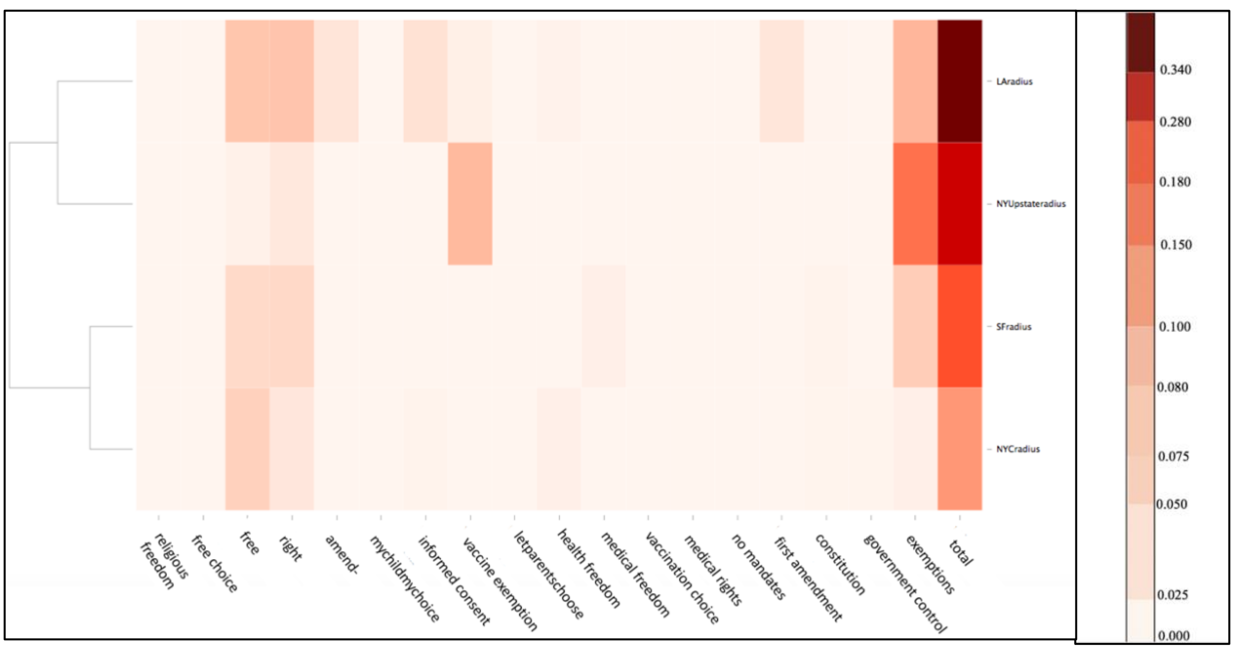


Figure 7. Heat map for *TDP* values of Topic 3. The Rochester radial group is referred to as “NYupstateradius.”

Although the location of anti-vaccination tweets for Topic 3 were not as densely distributed in the Rochester, New York metropolitan, and San Francisco radial groupings, high *TDP* values for certain dictionary and LDA words in this category indicate that anti-vaccination Twitter users in these areas still discuss anti-vaccination motives related to freedom of choice in their tweets.

4.4 Results for Topic 4: Vaccines Allow Companies to Make Profit

Anti-vaccination tweets related to Topic 4 were most densely located within the Los Angeles radial group. *TDP* values (Figure 8) in this location indicated that the word stems "increas-," "big pharma," and "pharmaceutical companies" contributed most to the final TDP_{total} count.

The New York metropolitan and Rochester radial groups had similar TDP_{total} values for this topic. Dictionary words such as "price" and "profit" had higher *TDP* values in the Rochester radial group compared to the New York metropolitan radial group. Conversely, the *TDP* value for the key search term "big pharma" was greater in the New York metropolitan radial group compared to the Rochester radial group.

The low TDP_{total} value within the San Francisco radial group indicated that few Twitter user profiles in this area cite economics or company profits as a reason for vaccine hesitancy in their tweets. The *TDP* values for dictionary words in this topic contributed relatively equally to the total proportion value.

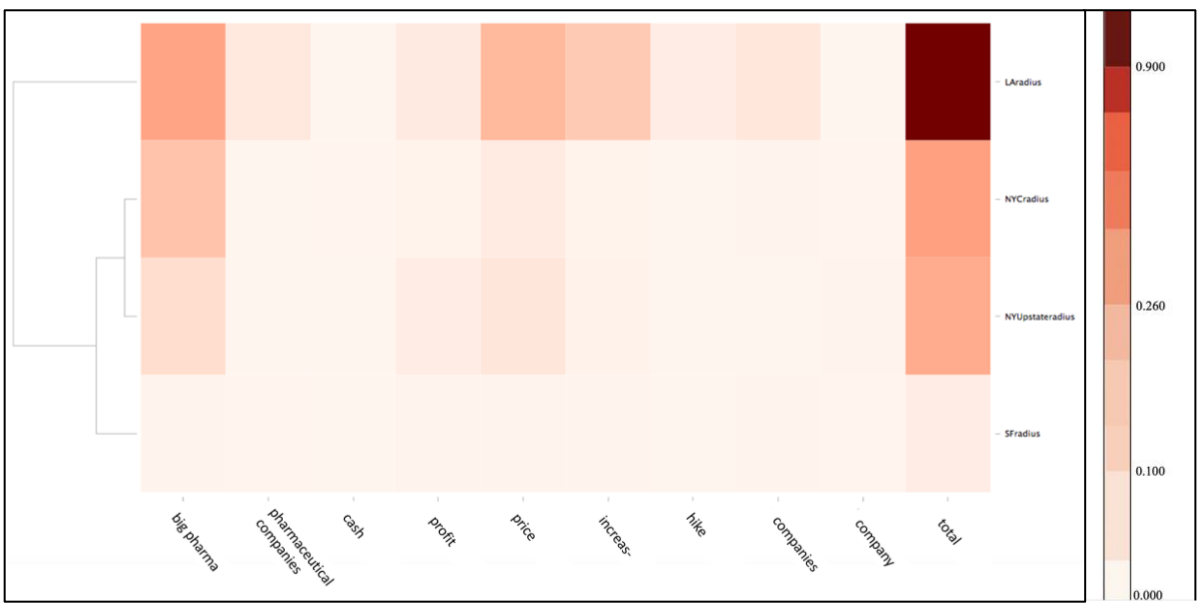


Figure 8. Heat map for *TDP* values of Topic 4. The Rochester radial group is referred to as "NYupstateradius."

4.5 Comparison of TDP_{total} Values Among Locations

Using TDP_{total} values, I compared tweet topic densities among the four location groups analyzed (Figures 5-8). As previously stated, the Los Angeles radial group of anti-vaccination tweets tended to have the highest TDP_{total} value within Topics 2, 3, and 4. The New York metropolitan area contained the highest TDP_{total} value within Topic 1. Certain word densities were consistent in the four topic groups in each city, as represented by the *TDP* values (Figures 5-8).

Analysis of tweet topic density specific to each city was possible using the calculated TDP_{total} values. Comparing TDP_{total} in the same city for all four topics reveals the most prominent topic in that particular location. The table below illustrates a comparison of TDP_{total} values among topics in the same city (Table 4).

The proportion values reveal that in the Los Angeles radial group, the most common anti-vaccine tweet topic is Topic 2: Vaccines are Dangerous. Topic 4 anti-vaxx tweets are also common within this location. Topics 1 and 3 are least prevalent in the Los Angeles radial group of tweets, indicated by a TDP_{total} value lower than that of the first two categories. In the San Francisco radial group, Topic 1: Distrust of Government, CDC, Medical Professionals has the greatest TDP_{total} value, shown with a value over 2. Topic 2 emerged as the next most dominant topic, followed by Topics 3 and 4. Topic 1 was densest in the New York metropolitan radial group as well, represented by a TDP_{total} value greater than 2. Unlike the San Francisco radial group, the NY metropolitan area's Topic 1 was followed by high TDP_{total} values in Topics 2 and 4. The lowest TDP_{total} value in the New York metropolitan radial group occurred for Topic 3. The anti-vaccination tweets within the Rochester radial group fell most commonly under Topic 3. Topic 4 had a considerably high TDP_{total} value in this area, just below that of Topic 3. TDP_{total} values within Topics 1 and 2 were lowest in this radial group. Overall, the most common topic across the four radial groups was "Government Conspiracy" as indicated in the San Francisco and New York metropolitan radial group TDP_{totals}.

	Free Choice (Topic 3)	**Gov't (Topic 1)**	**Danger (Topic 2)**	**Vaccines Profit (Topic 4)**
LA Radius	.344	.281	1.302	.915
SF Radius	.178	2.240	.335	.042
NYC Radius	.117	2.313	.378	.288
NY Upper Radius	.277	.025	.134	.261

Table 4. TDP_{total} values for all four topics in all four geographic regions. Assessing TDP_{total} specific to each region reveals the most prominent topics of anti-vaccination messages there.

4.6 Residual Chi Square Test Results

Contingency tables comparing topical word frequencies revealed that there was a significant difference in the topics of anti-vaccination tweets represented in each city (Table 5).

Contribution to the significant *p-value* score can be represented by the balloon plot (Figure 9). According to the diagram, the relative contribution of each cell to the significant *p-value* and total chi-squared score for frequency of tweets in each category (number of instances tweets in each geographic region mentioned one of the dictionary terms for each topic) indicates the nature of the dependency between the rows and columns of the table. In the right illustration, a darker blue shade reveals a high contribution to the total chi-squared score. Thus, the most contributing cells are LA radius/Topic 1 (27%), SF radius/Topic 1 (8.31%), NYC radius/Topic 1 (16.43%), LA radius/Topic 4 (11.02%), and LA radius/Topic 2 (13.72%). A higher contribution to the *p-value* and Chi-squared score translates to a strong association between variables.

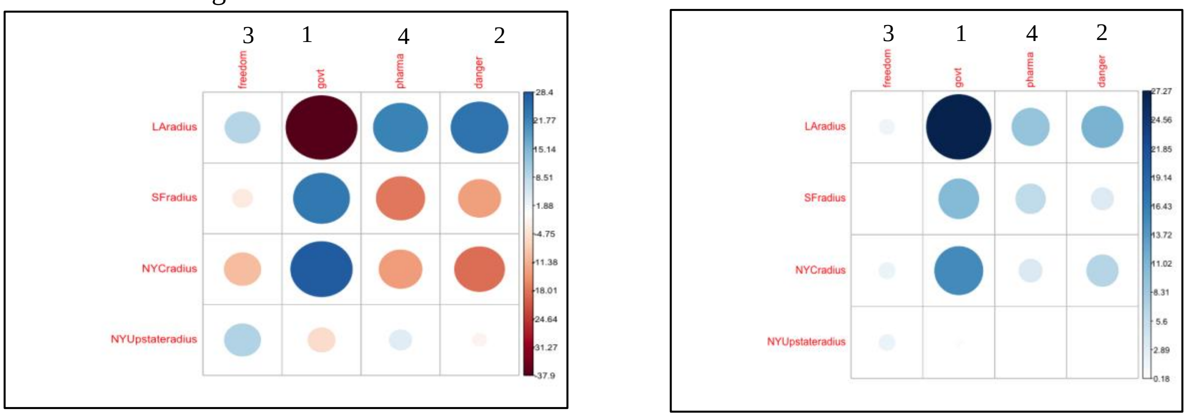


Figure 9. Balloon plots illustrating the nature of association between radial groups and LDA topics examined.

In the left illustration, positive residuals, or positive associations between rows and columns, are represented by blue while negative residuals, or negative associations between rows and columns, are in red. Within the Los Angeles radial group of anti-vaccination tweets, the chi-squared values show a positive correlation between the location and the Topics 2-4 and a strong negative correlation between this location and Topic 1. The group of anti-vaccination tweets in San Francisco was strongly associated with Topic 1, and negatively correlated with Topic 4. Tweets in the New York metropolitan area were negatively associated with Topic 2 and positively associated with Topic 1. No strong correlations were observed within the Rochester radial group of anti-vaccine tweets. The residuals indicated a slight positive association between this location of tweets and Topic 3, and a negative correlation with Topic 1.

Location Groups Compared	**Topic 1**	**Topic 2**	**Topic 3**	**Topic 4**	**P-Value**
All Groups					<0.001
LA/SF Groups	LA<SF	LA>SF	LA>SF	LA>SF	<0.001
LA/NYC Groups	LA<NYC	LA>NYC	LA>NYC	LA>NYC	<0.001
LA/Rochester Groups	LA>Roch.	LA>Roch.	LA>Roch.	LA>Roch.	<0.001
SF/NYC Groups	SF<NYC	SF<NYC	SF>NYC	SF<NYC	<0.001
SF/Rochester Groups	SF>Roch.	SF>Roch.	SF<Roch.	SF<Roch.	<0.001
Rochester/NYC Groups	NYC>Roch.	NYC>Roch.	NYC<Roch.	NYC>Roch.	<0.001

Table 5. Topic comparisons between combinations of radial groups studied. Statistically significant differences are based on residual chi square tests.

5.1 Discussion

This study demonstrated that there is a significant difference in the anti-vaccination rhetoric disseminated on Twitter by individuals in different cities on opposite U.S. coasts. The four distinct topics of anti-vaccination tweets found by the LDA model arose disproportionately in some cities over others. For example, the Los Angeles radial group of anti-vaccine tweets had a higher density of tweets related to "Freedom of Choice," "Vaccines Profit," and "Vaccines are Dangerous" Topics compared to the other locations. The New York City metropolitan radial group and the San Francisco radial group possessed the highest density of anti-vaccine messages in the "Government Conspiracy" Topic. The Rochester radial group of tweets seemed to have lower topic density values in comparison to the other locations analyzed.

Even so, topic creation enabled region specific analysis of the common anti-vaccination topics. Topic Density Proportion values indicated that the Los Angeles radial group of tweets were most often within the "Vaccines are Dangerous" Topic, San Francisco and NY Metro radial tweets were most often in the "Government Conspiracy" Topic, and Rochester radial tweets were most often in the "Freedom of Choice" Topic. The high *TDP* value for tweets for the "Vaccines are Dangerous" category in Los Angeles could potentially be explained by popular social media influencers in this area, who overstate vaccine risks and their potential to induce death or autism. During the period of data collection, Californians (particularly those within the Bay Area) were fiercely debating the passage of the law SB 276, which aims to close loopholes in vaccine exemptions. A common argument against the passage of this bill was the fear of government influence and power, which could explain the high density of tweets within the "Government Conspiracy" topic in the San Francisco radial group. This topic was also commonly expressed in the New York metropolitan radial group, where Brooklyn residents were exposed to a "vaccine safety handbook" that likened the US government's promotion of vaccines to the medical atrocities of Nazi Germany. A probable cause of the high "Freedom of Choice" density in Rochester could be the ongoing debate over religious and medical exemptions in Monroe County over the summer months. Many schools' decisions to deny medical exemptions to students sparked conversation over liberty granted by the Constitution.

The *TDP* proportion values also showed which topics of anti-vaccination tweets did not seem to be a concern in certain cities. In the Los Angeles radial group, the "Government Conspiracy" Topic had the lowest density, in the San Francisco radial group the "Vaccines Profit" Topic had the lowest density, in the New York metropolitan radial group the "Free Choice" Topic had the lowest density, and in the Rochester radial group the "Government Conspiracy" Topic had the lowest density. The strong correlation between specific anti-vaccination tweet topics and particular locations has implications in designing and implementing real-time online interventions to combat vaccine misinformation.

This study is novel in its ability to target the qualitative variation in anti-vaccination tweets by geographic region on opposing coasts. By tracking the most common topics of anti-vaccination tweets in different cities, it is possible for public health officials to design fine-tuned targeted approaches to address misinformation head on. For example, this study revealed that the nature of anti-vaccination tweets in the Los Angeles area is most often related to concerns about vaccine safety. With this information, specific health interventions related to vaccine effectiveness can be designed in the area to combat these ideas. Given that localized geographic clusters of anti-vaccine beliefs and refusal of vaccines compromise herd immunity, targeted interventions against prominent anti-vaccine topics could be beneficial in preventing future outbreaks. A fundamental limitation of this study involves the restrictions of the rtweet package, which only enables the streaming of tweets from approximately a one-week time frame. Additionally, the increased debate over vaccine exemption laws and summer camp vaccination requirements over the summer could potentially have influenced the arguments shown in my data. Potentially informative non-geolocated tweets were excluded from the data. More extensive demographic information describing Twitter user profiles could be helpful when targeting specific arguments against vaccines. However, Twitter's privacy settings do not allow for the access of user-specific socioeconomic and racial data.

Further, to collect tweets, I was as thorough as possible in choosing search phrases related to the anti-vaccination movement. However, new anti-vaccination related key terms that might have recently surfaced were not included in the dataset I gathered, resulting in possible missed information. Another limitation of qualitative social media data is the inability to imply causal relationships. It is impossible to explain "why" the densities I observed occurred. With access to socioeconomic and demographic data for Twitter user profiles, it could be possible to explain why anti-vaccine Twitter users' arguments might be within the "Vaccines are Dangerous" in Los Angeles and the "Government Conspiracy" topic in the New York metropolitan area. This was the first study to examine the spatial distribution of anti-vaccination arguments on social media; the sole social media source used to obtain this information was Twitter. Future work could conduct identical content-based analysis using other social media platforms, such as Reddit or Facebook, and with these platforms, I hope to study more tweets in other urban regions.

The methodology I employed can be used on a broader geographic scale. By creating a topic density proportion, it is possible to visualize dominant anti-vaccination topics that arise in different U.S. regions or globally. Especially in a time when social media has enabled the spread of misinformation, the ability to pinpoint prominent arguments against vaccines is necessary for public health officials to promote accurate scientific information.

References

Arthur, R. & Williams, H. T. P. The human geography of Twitter: Quantifying regional identity and inter-region communication in England and Wales. *Plos One* **14,** (2019).

Blei DM, Ng AY, Jordan MI. Latent Dirichlet Allocation. Journal of Machine Learning Research. 2003;3:993–1022.

Briones, R., Nan, X., Madden, K. & Waks, L. When Vaccines Go Viral: An Analysis of HPV Vaccine Coverage on YouTube. *Health Communication* **27,** 478–485 (2012).

Brooks, B. Using Twitter data to identify geographic clustering of anti-vaccination sentiments (2014). Accessed at https://digital.lib.washington.edu/researchworks/bitstream/handle/1773/26187/Brooks_washington_0250O_13777.pdf?sequence=1&isAllowed=y

California Department of Public Health. Measles. *Measles* Available at: https://www.cdph.ca.gov/Programs/CID/DCDC/Pages/Immunization/measles.aspx.

Chen, R. T. & Destefano, F. Vaccine adverse events: causal or coincidental? *The Lancet* **351,** 611–612 (1998).

Chen, R. T. & Hibbs, B. Vaccine Safety: Current and Future Challenges. *Pediatric Annals* **27,** 445–455 (1998).

Dong, Wenfei. Combining Earth Observation and Social Media Data for Informal Settlements Identification in Dar es Salaam, Tanzania (2018).

Denny, M. J. & Spirling, A. Text Preprocessing For Unsupervised Learning: Why It Matters, When It Misleads, And What To Do About It. *SSRN Electronic Journal* (2017). Doi:10.2139/ssrn.2849145.

Dube, E., Vivion, M. & Macdonald, N.E. Vaccine hesitancy, vaccine refusal and the anti-vaccine movement: influence, impact and implications. *Expert Review of Vaccines* **14**, 99-117 (2014).

Eady, G., Nagler, J., Guess, A., Zilinsky, J. & Tucker, J. A. How Many People Live in Political Bubbles on Social Media? Evidence From Linked Survey and Twitter Data. *SAGE Open* **9,** 215824401983270 (2019).

Faasse, K., Chatman, C. J. & Martin, L. R. A comparison of language use in pro- and anti-vaccination comments in response to a high profile Facebook post. *Vaccine* **34,** 5808–5814 (2016).

Feikin, D. R. Individual and Community Risks of Measles and Pertussis Associated With Personal Exemptions to Immunization. *Jama* **284,** 3145 (2000).

Freed, G. L., Clark, S. J., Butchart, A. T., Singer, D. C. & Davis, M. M. Parental Vaccine Safety Concerns in 2009. *Pediatrics* **125,** 654–659 (2010).

Garay, J., Yap, R. & Sabellano, M.J. An analysis on the insights of the anti-vaccine movement from social media posts using k-means clustering algorithm and VADER sentiment analyzer. *IOP Conference Series: Materials Science and Engineering* **482**, 012043 (2019).

Guidry, J. P., Carlyle, K., Messner, M. & Jin, Y. On pins and needles: How vaccines are portrayed on Pinterest. *Vaccine* **33,** 5051–5056 (2015).

Jolley, D. & Douglas, K. M. The Effects of Anti-Vaccine Conspiracy Theories on Vaccination Intentions. *PLoS ONE* **9,** (2014).

Kata, A. A postmodern Pandoras box: Anti-vaccination misinformation on the Internet. *Vaccine* **28,** 1709–1716 (2010).

Keelan, J., Pavri, V., Balakrishnan, R. & Wilson, K. An analysis of the Human Papilloma Virus vaccine debate on MySpace blogs. *Vaccine* **28,** 1535–1540 (2010).

Lansley, G. & Longley, P. A. The geography of Twitter topics in London. *Computers, Environment and Urban Systems* **58,** 85–96 (2016).

Larson, H. J., Jarrett, C., Eckersberger, E., Smith, D. M. & Paterson, P. Understanding vaccine hesitancy around vaccines and vaccination from a global perspective: A systematic review of published literature, 2007–2012. *Vaccine* **32,** 2150–2159 (2014).

Lotan, R. D. R. and G. Anti-Vaxxers Are Using Twitter to Manipulate a Vaccine Bill. *Wired* (2017). Available at: https://www.wired.com/2015/06/antivaxxers-influencing-legislation/.

Madden, K., Nan, X., Briones, R. & Waks, L. Sorting through search results: A content analysis of HPV vaccine information online. *Vaccine* **30,** 3741–3746 (2012).

Manning, M. L. & Davis, J. Journal Club: Twitter as a source of vaccination information: Content drivers and what theyre saying. *American Journal of Infection Control* **41,** 571–572 (2013).

Measles Cases and Outbreaks | CDC. *Centers for Disease Control and Prevention* Available at: https://www.cdc.gov/measles/cases-outbreaks.html.

Mitra, T, Counts, S, Pennebaker, J. Understanding Anti-Vaccination Attitudes in Social Media (2016).

NYC Department of Health. Measles. *Measles - NYC Health* Available at: https://www1.nyc.gov/site/doh/health/health-topics/measles.page.

Omer, SB, Enger, KS, Moulton, LH, Halsey, NA, Stokley, S, Salmon, DA. Geographic Clustering of Nonmedical Exemptions to School Immunization Requirements and Associations With Geographic Clustering of Pertussis. *American Journal of Epidemiology* **168,** 1389–1396 (2008).

Outbreaks of Vaccine-Preventable Diseases. *Vaccinate Your Family* Available at: https://www.vaccinateyourfamily.org/questions-about-vaccines/outbreaks-of-vaccine-preventable-diseases/.

Phadke, V. K., Bednarczyk, R. A., Salmon, D. A. & Omer, S. B. Association Between Vaccine Refusal and Vaccine-Preventable Diseases in the United States. *Jama* **315,** 1149 (2016).

Radzikowski, J, Stefenidis, A, Jacobsen, KH, Croitoru, A, Crooks, A, Delamater, PL. The Measles Vaccination Narrative in Twitter: A Quantitative Analysis. *JMIR Public Health and Surveillance* **2** (2016).

Salathé, M. & Khandelwal, S. Assessing Vaccination Sentiments with Online Social Media: Implications for Infectious Disease Dynamics and Control. *PLoS Computational Biology* **7** (2011).

Scanfeld, D., Scanfeld, V. & Larson, E. L. Dissemination of health information through social networks: Twitter and antibiotics. *American Journal of Infection Control* **38,** 182–188 (2010).

Smailbegovic, M. S., Laing, G. J. & Bedford, H. Why do parents decide against immunization? The effect of health beliefs and health professionals. *Child: Care, Health and Development* **29,** 303–311 (2003).

Smith, M. J. & Marshall, G. S. Navigating Parental Vaccine Hesitancy. *Pediatric Annals* **39,** 476–482 (2010).

Smith, N. & Graham, T. Mapping the anti-vaccination movement on Facebook. *Information, Communication & Society* **22**, 1310-1327 (2017).

Smith, P. J., Humiston, S. G., Parnell, T., Vannice, K. S. & Salmon, D. A. The Association between Intentional Delay of Vaccine Administration and Timely Childhood Vaccination Coverage. *Public Health Reports* **125,** 534–541 (2010).

Song, G. Understanding Public Perceptions of Benefits and Risks of Childhood Vaccinations in the United States. *Risk Analysis* **34,** 541–555 (2013).

Terranella, A, Rea, V, Griffith, M, Manning, S, Sears, S, Farmer, A, Martin, S, Patel, M. Vaccine effectiveness of tetanus toxoid, reduced diptheria toxoid, and acellular pertussis vaccine during a pertussis outbreak in Maine. *Vaccine* **34**, 2496-2500 (2016).

Tomeny, T.S., Vargo, C.J. & El-Toukhy, S. Geographic and demographic correlates of autism-related anti-vaccine beliefs on Twitter, 2019-15. *Social Science & Medicine* **191**, 168-175 (2017).

Witteman, H. O. & Zikmund-Fisher, B. J. The defining characteristics of Web 2.0 and their potential influence in the online vaccination debate. *Vaccine* **30,** 3734–3740 (2012).

Zerbo, O, Bartlett, J, Goddard, K, Fireman, B, Lewis, E, Klein, N. Acellular Pertussis Vaccine Effectiveness Over Time. *Pediatrics* **144** (2019).

Source Code and R Packages Used:

LDA model source code available: https://www.kaggle.com/rtatman/nlp-in-r-topic-modelling
QGIS Software: http://qgis.osgeo.org
R ‘rtweet’ package: https://cran.r-project.org/web/packages/rtweet/rtweet.pdf
R ‘Topic Models’ package: https://cran.r-project.org/web/packages/topicmodels/topicmodels.pdf
R ‘Text Mining’ (‘tm’) package: https://cran.r-project.org/web/packages/tm/tm.pdf
R ‘SnowballC’ package: https://cran.r-project.org/web/packages/SnowballC/SnowballC.pdf
R ‘tidyverse’ package: https://cran.r-project.org/web/packages/tidyverse/tidyverse.pdf
R ‘tidytext’ package: https://cran.r-project.org/web/packages/tidytext/tidytext.pdf
R ‘stringr’ package: https://cran.r-project.org/web/packages/stringr/stringr.pdf
R ‘d3heatmap’ package: https://cran.r-project.org/web/packages/d3heatmap/d3heatmap.pdf
R ‘corrplot’ package: https://cran.r-project.org/web/packages/corrplot/corrplot.pdf
R ‘gplots’ package: https://cran.r-project.org/web/packages/gplots/gplots.pdf