Quantifying language changes surrounding COVID-19 Vaccine Discourse on Twitter

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Abstract

Dedication

***

All my thanks to my advisors, lab, partner, and family, I hope to return all of the help and kindness I have received.

Acknowledgements

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Chapter 1

Introduction

1.0.1 Vaccine Discourse on Twitter

Global pandemics including the 2019 novel Coronavirus pandemic (COVID-19) endangered populations worldwide. Rates of rapid transmission and mortality incited 3 a global response to curb transmission, specifically through the development of several vaccines [2] [3]. The introduction of widespread vaccine distribution and in certain cases vaccine mandates, incite varied responses, yet little is known around how people have responded to these mandates [4]. Conversations on a specific word events occur within diverse subsamples of people, and subsequently this discourse can exhibit common words used in statements [5]. Similarly, we can see common adjacent words and phrases to these keywords. Common groups of words associated with a world event can increase and decrease over time. Increase and decrease of a set of common words describe the popularity of people discussing a topic, and further with a notable rise and fall of discourse align with specific smaller events [6].

Social media platforms offer an opportunity to understand how populations discuss contemporary events and issues [7] [8] [?]. Many people use social media platforms to express thoughts and opinions on world events. Responses vary from short, a single word or line to extensive paragraphs. Individual social media users may also respond to comments, copy and paste others posts or links to sources to their own page [6]. Such examples demonstrate the instantaneous nature of conversations on these platforms unique to previous modes of communication such as newspapers, or published journals for example. Twitter is a particularly widely used social media platform which provides unique insight into topic discussion and the spread of social movements [9]. The platform proves to encourage response to events experienced by humanity and allow for fast paced, otherwise referred to as high-resolution records of conversation. Twitter provides a sufficient sub sample of discourse from people with little to none or extensive 25 academically rigorous knowledge of a world event of subtopic.

This study seeks to achieve identify, specifically on Twitter, the set of words which are used to talk about vaccines within the context of the COVID-19 pandemic. An unbiased lexicon is important for further studying who what when and where people are talking about COVID-19 vaccines [4]. Previous investigation on vaccination sentiment has been performed for the events which define news events defining the 2019-2021 Coronavirus (COVID-19) pandemic. However, such analyses negate the importance of choosing a non-biased organically emerging selection of terms most used when tweeting about coronavirus [10] [11] [12] Twitter in particular is cited as a leading source of information and misinformation about vaccines [13] [3]. It is observed through the process of searching for a naturally occurring keyword lexicon, evidence can be found of patterns of discourse surrounding important events during the COVID-19 pandemic.

In this study the anti-vaccination movement is examined through the lens of episodic events occurring in a single day to long term events evolving over several days or weeks. Previous research seeking similar information, or collective responses to world events employ Natural Language processing tools. Using information theoretic tools patterns of discourse surrounding the word 'vaccine' appear [14] [13]. An emergent lexicon of keywords linked to 'vaccine' correlate well with short term and long term events defining the COVID-19 timeline of and indicate continued increases in discourse as COVID-19 responses are implemented. Using natural language processing tools to find a small lexicon describing 'vaccine' during COVID-19, it is observed that 'vaccine' embedded in tweets showss patters of increased vaccine discourse in two categories 1)surrounding political figure or medical 49 National Institute of health announcements and 2) steady increase in vaccine discourse with distribution of vaccines. Rank divergence and ambient sentiment approaches investigate these episodic spikes in vaccine discourse, and further we examine the entropy of such discourse using comparative rank divergence techniques, or the extent to which discourse is sustained over the long term.

Examining a COVID-19 'vaccine' specific lexicon and subsequent distinct discourse patterns aims to address the following questions: 1)How are vaccination sentiments characterized on social media? This project focuses on the Coronavirus pandemic in the United States with context provided from adjacent events such as measles, mumps, and rubella MMR. 2)Is it possible to identify the traction and sustained resilience of long-term or episodic 59 patterns of vaccination information spreading and group organizing? Similarly, can different anticipatory and reactionary patterns on

Twitter be identified surrounding 61 different types of pandemics?

1.0.2 Related Works

Abundant research exists focusing on using social media platforms to explore and understand dynamics of public discourse [7] Furthermore, discourse on preventative medical care, such as vaccines, in general is well studied [4]. Specifically,information spreading studies have been conducted to aid in disseminating information about preventative health protocols surrounding worldwide pandemics [4]. A number of reviews exist evaluating methods for evaluating the nature of discussion about the COVID-19 pandemic.

In this study we contend that social media platforms constitute as a highly viable and informative platform for various of audiences to discuss the associated acute and preventative vaccine protocols for the COVID-19 pandemic [14]. Audiences on twitter have been examined for the COVID-19 pandemic recently across twenty four languages as well as across social political and demographic axis [15] [9].

Discourse surrounding the COVID-19 pandemic focuses on characterizing the ways people discuss vaccines [4]. Vaccine hesitancy is a well studied area of research [16] [17]. Maglione et al. looked at vaccine hesitancy with clinical data and reported that Twitter users associated with hesitancy towards vaccines show lower vaccination rates [18] Other researchers have performed vaccine sentiment studies on other social media platforms related to detecting relief efforts with the onset of community disasters [19]. Analysis of text-based vaccine conversations during medical appointments found actionable strategies associated effective dissemination of scientifically supported vaccine information, such as vaccine efficacy, side effects and collective participation in vaccines to combat spreading worldwide [20].

Developments in tracking and predicting vaccine sentiment provide an opportunity for early detection and prevention of spread, however they come with several concerns, such as incorrect predictions, positivity bias [7],and potential biases [5]. In the instance of COVID-19 there existed a shift in overall social media participation [21] [22]. Lastly, despite the temporal shifts towards vaccine discourse the populations of twitter users stayed relatively similar to previous years, which may not capture communities emerging with firm anti-vaccination sentiments [23].

Groups of social media users also hold negative attitudes towards the concept of interventions through regulated vaccine mandates by expressing concerns about long term health impacts, government control and lack of freedom [10]. Anti-vaccination communities often believe vaccines and mandates are invasive, medically threatening, and a loss of their freedom [24] [9] [25].

Several other studies have more directly examined attitudes towards those with anti-vaccination sentiment related to previous pandemics such as the Swine Flu, or H1N1 in 2008. Also notable events on the historical vaccine discourse timeline include a Mumps, Measles and Rubella outbreak in 2015 leading to the Senate Bill 277 mandating elementary school children must be vaccinated [26] [27]. These studies sought to investigate vaccine sentiment and the entropy of discourse over the longterm associated with vaccine hesitancy [wake field]. Events which lead to public school vaccine mandates increased traction for several prominent antivaccine communities [28] [29]

Several groups sought to investigate the extent of these individuals and their communities using a qualitative approach [30] [31]. These tweets were coded based on the attitude they indicated (stigmatizing, personal experience, supportive, neutral, or anti-stigma) and on their content (awareness promotion,research findings, resources, advertising, news media, or personal opinion). A study conducted in 2022 finds evidence epistemic echo chambers occur when users are exposed to highly dissimilar sources of vaccine information [32]. This group employs machine learning techniques to show the probability a group displays anti-vaccination sentiment based on a collection of fifteen words, and their adjacency to hashtags also using the collection of words with the root 'vaccin*'. In our study we emphasize the importance of allowing words to organically occur surrounding a single anchor prefix 'vaccin*'. Also stance detection only suggests the prescence and abscense of groups tagged by phrases or words common to a specific statement of anti-vacccination sentiment. Increasingly more difficult, is the task of quantifying the volume and presence such groups since differentiating those discussing Furthermore, depending the vaccination stance of their contacts, a network of misinformation forms. One group hones in on stance detection by showing that groups of anti-vaccination interests are often politically charged [9].

The goal of the current study is to contribute to a contemporary examination of pandemic, specifically COVID-19 focused work by implementing a data-driven approach spanning a five year period. Using messages from Twitter, conversations around vaccines are examined in two primary ways. First, the growth of public attention,second the divergence of language from general messages and last the associated happiness shifts, and the rise of ambient words or phrases.

Chapter 2

Methods

2.1 Data and Methods

2.1.1 General Twitter

Social media platforms offer an opportunity to understand how populations discuss contemporary events and issues [1]. Many people use social media platforms to express thoughts and opinions on world events. Responses vary from short, a single word or line to extensive paragraphs. Individual social media users may also respond to comments, copy and paste others posts or links to sources to their own page. Such examples demonstrate the instantaneous nature of conversations on these platforms unique to previous modes of communication such as newspapers, or published journals for example. Twitter is a particularly widely used social media platform which provides unique insight into topic discussion and the spread of social movements.The platform proves to encourage response to events experienced by humanity and allow for fast paced, otherwise referred to as high-resolution records of conversation. Twitter provides a sufficient sub sample of discourse from people with little to none or extensive academically rigorous knowledge of a world event of subtopic. However, there are several considerations including a base of users that are typically in the fifteen to twenty five year old bracket, and further left leaning [21], therefore an important consideration in examining vaccine discourse is to consider anti-vaccination groups often seek non-traditional platforms to disseminate their propaganda, perhaps due to opposition from major media outlets [25]. These alternative platforms include independent blogs, Twitter, Instagram, and Facebook. However, in 2019 Facebook announced that the platform will now screen-for and eliminate deceptive posts. Given these practices of suppressing anti-vaccination propaganda, members of such groups are often less willing to self-identify on social media platforms [33] [34].

The source of data for the present study is Twitterâs Decahose API, filtered for English messages, from which we collect a 10% random sample of all public tweets between January 2019 and January 2022. This collection is separated into three corpora consisting of (a) all tweets, (b) tweets containing the phrase âvaccineâ, and (c) tweets containing a small set of phrases related to vaccine. Statistics and timeseries comparisons between corpora are made as follows.

2.2 Twitter

2.2.1 N-grams

In gaining insight into vaccine discourse, tweets are parsed containing 1-, 2- and 3-grams. A 1-gram is a one-word phrase, 2-gram is a two-word phrase. The data set used comes from tweets parsed by Storywrangler [35].

At the fifteen minute, day level resolution the number of times each unique n-gram appears is counted. Relative frequency and counts can be found. Rank is given by descending order of count. Specifically the n-grams with a low rank value appear often, whereas those with a high rank value appear infrequently. The 1-gram âandâ has a median rank of 1 [17]. Add rank and count plot here.

2.2.2 Vaccine Tweet Samples

To demonstrate vaccine related language, a collection of n-grams is selected from the the ten and one hundred percent sample of the decahose tweet database. Messages selected are those that contain 'vaccin*', which includes words such as 'vaccine' 'vaccination' 'vaccinated'. Using these datasets, we examine the counts of this one-gram and surrounding words in all tweets. We analyze changes in the conversation surrounding COVID-19 vaccines through time. We focus primarily on 'vaccin' or 'vaccine' as a representative example of phrases related to covid vaccines.

Chapter 3

Collective Attention

3.1 Vaccine Discourse

To examine the relative "positivity" of this conversation ambient happiness scores were calculated for each day using messages mentioning the phrase vaccine using a ten percent sample of the twitter decahose 36. Ambient happiness scores are computed by averaging the scores of each word that appear in a message containing vaccine, using the labMT dictionary [16]. As the rank of this 1-gram has decreased over the past decade, meaning âvaccinâ appears more frequently, it can be inferred that the ambient happiness of these messages has not changed alongside these dates. By examining the daily behavior of these timeseries, several dates emerge where either the rank or ambient happiness deviate from their baseline behavior. For instance, key events associated with large spikes or drops in the timeseries are observed in March and November 2020. The significance of these events are described below.

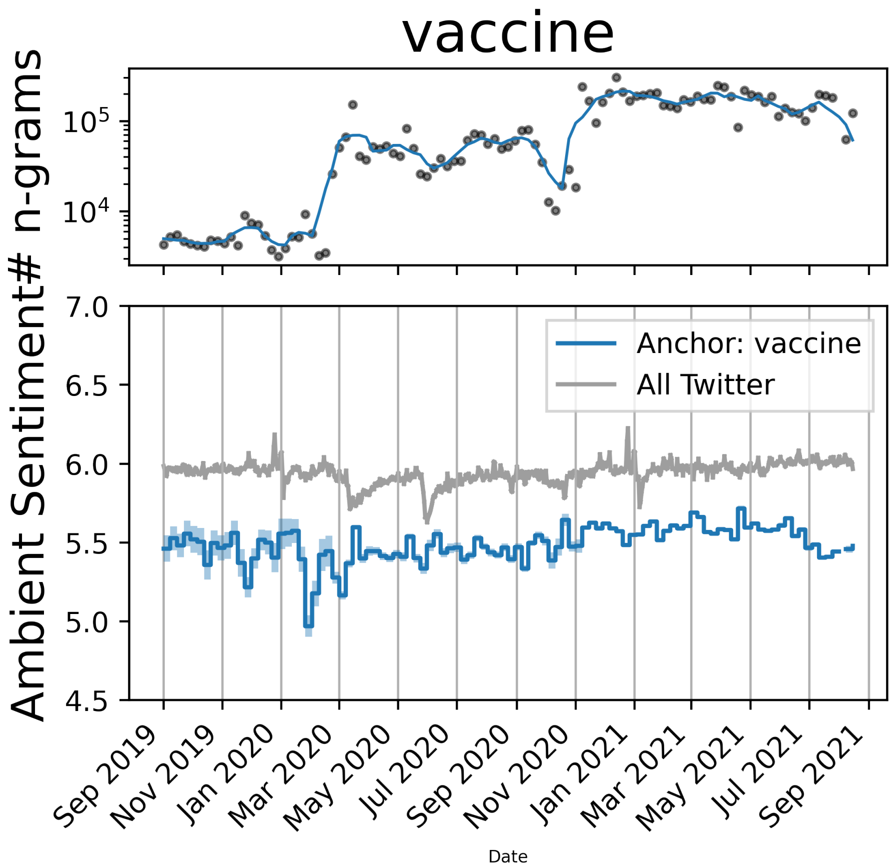

Figure 3.1: Timeline of vaccine discourse on Twitter. The top panel shows the rank time-series of the 1-gram "vaccinâ over the period of September 2019-September 2021 on a logarithmic axis. Rank is determined by ordering 1-grams in descending order of counts for each day, and plotted on an inverted axis. The bottom panel shows the 'ambient happiness' of all messages containing the 1-gram âvaccinâ for each day over the same time period. Ambient happiness remained roughly constant during the period of increasing volume.

The lowest rank days within all tweets containing 'vaccin' for the 1gram 'vaccine' show two distinct decreases in rank on March 15th and November 9th, 2020. Within the dataset of January 1st 2019 and October 2021 we observe several distinct changes, occurring overnight from the previous day on each date respectively.

The first date, March 15th corresponds to the Center for Disease control and presidential announcement about the coronavirus pandemic (COVID-19). The rank is 497, a twelve-fold decrease from the previous 30 day average.

The magnitude of discourse stays the same between the March and November 2020 increases. This behavior is also represented by average counts staying the same. A ten-fold change in lowered rank occurs on after November 9th. We see the second lowest rank on November 9th, with a rank of 182. The second peak is within two days within the week after November 9th, the rank drops ten times the average rank for the past month.

The total counts of 'vaccin' with respect to the average counts for the previous thirty days, support periods of increased vaccine discourse related to two primary events, namely the announcement of COVID-19 in March 2020, followed by the announcement of a viable vaccine in November 2020. When looking at ambient sentiment, in March 2020 the World Health Organization declares COVID-19 as a pandemic. At this time discourse picked up around what is characterized as speculated implementation of a vaccine. It is also important to note ambient sentiment is skewed by events leading to negative sentiment, for example, by the death of Kobe Bryant on January 26th, 2020

In November 2020 we observe increased discourse associated with the announcement of vaccine efficacy, specifically from the Pfeizer and Moderna vaccines. Against the backdrop of the presidential announcement, the language predominantly focused on momentum supporting vaccines, as well as concern about health and societal impacts of a vaccine, for example, freedom in response to possible vaccination requirements for travel or other activities. November 20th is the lowest rank day for the word 'vaccin'. Additionally, November 21st is the second highest day with respect to total counts for 'vaccin', however, ambient happiness shows no deviation from the baseline behavior relative to the following average for 2020.

3.2 Word Shift

Insight into increasing and decreasing ambient happiness for a time series can be observed at a higher resolution by searching for words heavily contributing to word shift plots. Messages containing vaccine are selected within a one week period surrounding a peak day of interest. Each word appearing within this timeframe are weighted with a positive (yellow) or negative (blue) score [35]. The depth of color indicates word frequency, those with less tone show terms which fade away in use. Words lowering an average score appear on the left and positive weighted words appear on the right side. Phi at the top of the plot represent the average ambient sentiment (ci). Rank from highest to lowest appears in the vertical axis

Word shifts are included for the top three days with the lowest rank, highest counts and lowest sentiment. On these days several patterns occurred. The lowest rank days with the greatest change from the previous month average occurred on March 15th and November 9th. The lowest rank days occurred on December 18th. For the word shifts we examine on these two days for words appearing in the ten percent sample of the decahose and score positivity and negativity with the lab MT database within the period of January 1st 2020 through October 30th 2021. The value of the average happiness for each period is displayed at the top of the plot, here we see the following.

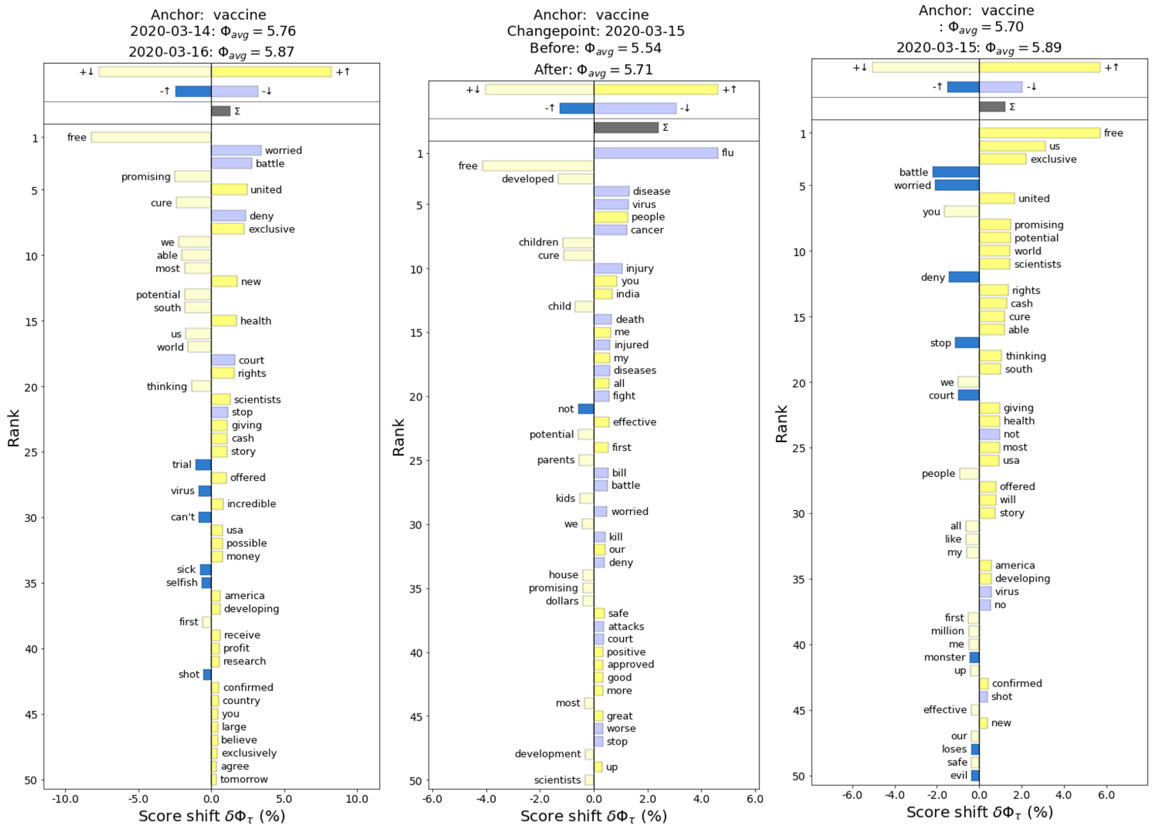

Figure 3.2: March 15th, 2020 Happiness word shift graphs. In each of the three panels from left (a),(b),(c), we show 1-grams that contribute most to the shift in ambient happiness on key dates shown in Fig. 4.1, relatively to the prior week. The sample of tweets contains the months of January 2019-November 2021. On the left hand pannel, (a) represents the comparison of two dates, (b) contains the period before and then the defined date at the top of the plot (c) contains a comparison of the first date to the full sample. The words shown in blue are ones that have been labeled as relatively negative, and the ones shown in yellow have been labeled as relatively positive [21]. For example, the top four positive words in (b) âfreeââpromisingâ and âcureâ, the relatively positive words such as 'trial' 'thanksgiving and 'well' appear less often. The darker shade of these colors tells us where there is an increase in these words, while the lighter shade represents a decrease in usage. The happiness score shift is shown on the horizontal axis, representing how positive or negative the language on these days becomes, and the happiness rank of the 1-gram in this subset is shown on the vertical axis. Average ambient happiness scores for the day of the event, as well as a week before the event, are also noted at the top of each subplot.

The word shift for this day has an average happiness score of ϕ_{avg}5.87, and two days prior has a happiness average of $\boldsymbol{\phi_{avg}}$5.76. On March 14th the shift is dominated by the top four positive words 'free' 'promising' and 'cure'. The date of March 16th contains both positive and negative words contributing most to the score which include 'worried' 'battle', negative, and positive words 'united' 'exclusive' 'new' an 'health'.

The changpoint word shift for the period from January 1st 2020 to March 15th has an average happiness score of $\boldsymbol{\phi_{avg}}$5.34 and in the period from March 16th to October 31st 2021 $\boldsymbol{\phi_{avg}}$5.71. The words in the first period contributing most to the shift include 'free' 'developed' 'children' and 'cure'.

In the second period, dominant negative words include âfluâ 'disease' 'virus' and positive words observed include 'people; 'me' 'you' and 'effective'.

WS Highest Count November 9th Second Lowest Rank It is also important to consider the November 9th comparison between the period of time prior to the Center for Disease Controll (CDC) and the presidential announcement of COVID-19. During the subsequent month following the November 9th peak, it is observed the words contributing to the negative shift include 'infection' 'ambulance'.

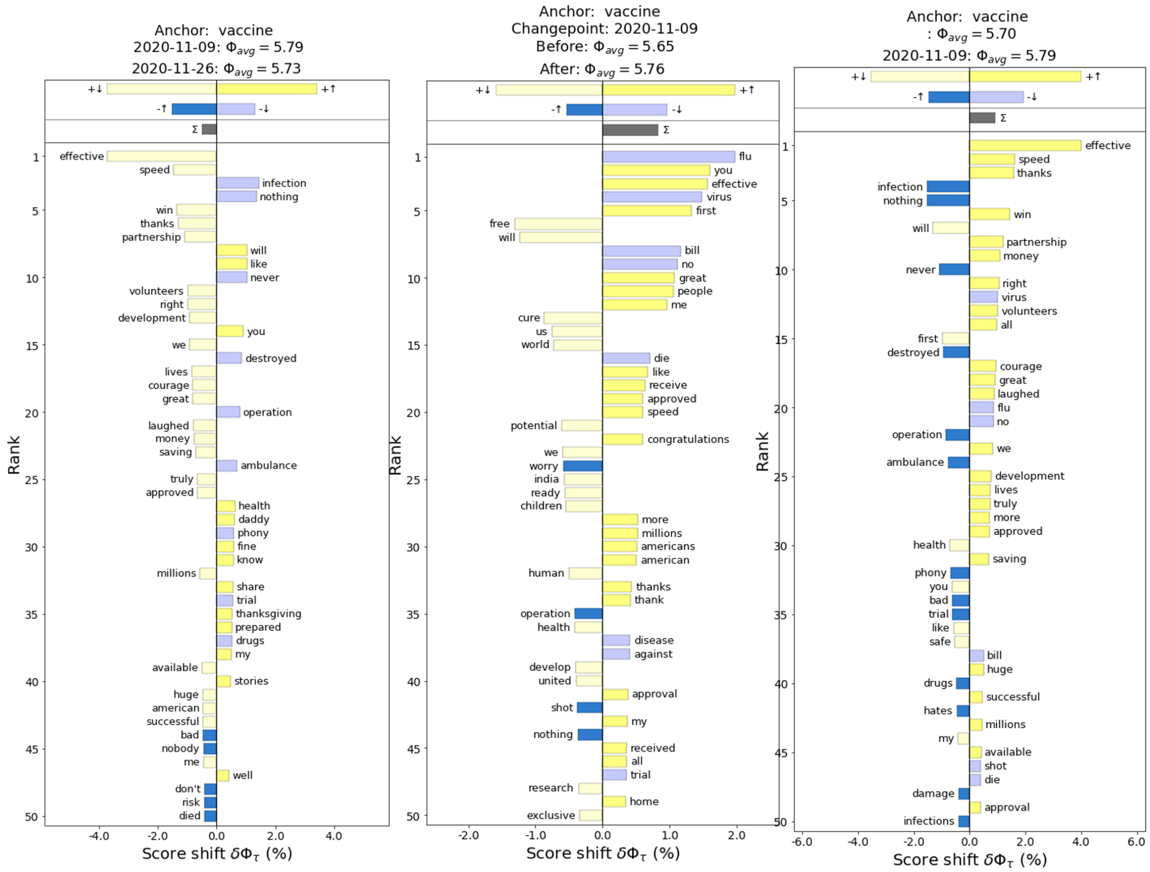

Figure 3.3: November 9th, Ten fold overnight increase in discourse. 2020 Happiness word shift graphs. In each of the three panels, we show 1-grams that contribute most to the shift in ambient happiness on key dates shown in Fig. 4.1, relatively to the prior week. In each of the three panels from left (a),(b),(c), we show 1-grams that contribute most to the shift in ambient happiness on key dates shown in Fig. 4.1, relatively to the prior week. The sample of tweets contains the months of January 2019-November 2021. On the left hand panel, (a) represents the comparison of two dates, (b) contains the period before and then the defined date at the top of the plot (c) contains a comparison of the first date to the full sample. The words shown in blue are ones that have been labeled as relatively negative, and the ones shown in yellow have been labeled as relatively positive [21]. For example, the top four positive words 'free' 'promising' and 'cure', the relatively positive words (Example) appear less often. The darker shade of these colors tells us where there is an increase in these words, while the lighter shade represents a decrease in usage. The happiness score shift is shown on the horizontal axis, representing how positive or negative the language on these days becomes, and the happiness rank of the 1-gram in this subset is shown on the vertical axis. Average ambient happiness scores for the day of the event, as well as a week before the event, are also noted at the top of each subplot.

We perform a comparison between November 9th 2020 to two weeks after on November 26th 2020. On November 9th the average happiness score is $\boldsymbol{\phi_{avg}}$5.79 and on November 26th $\boldsymbol{\phi_{avg}}$5.73. On November 9th, 'effective' 'speed' and development dominate the shift contrasted against 'infection' and 'nothing' 'destroyed' and 'operation' a collection of dominant words.

Changepoint: Comparing the period prior to and after December 9th, the average happiness score is $\boldsymbol{\phi_{avg}}$5.65 in the first period and $\boldsymbol{\phi_{avg}}$5.76 in the second period. The first period is dominated by words with a positive score including 'free' 'will'; and 'cure' dominating the shift. Within the second period, âfluâ 'effective' and 'virus' contribute to a dominantly to negativity.

Single Day Versus Whole January 1, 2020- October 30th 2021: In comparing a single day November 9th to the total period, the average happiness score is $\boldsymbol{\phi_{avg}}$5.79. The words contributing to the single day November 9th include dominant words including 'infection' 'nothing' 'never' and 'destroyed', weighted as negative. In the total period, positive words contributin to the shift include 'effective' 'speed' 'thanks'; and 'partnership'.

The Lowest Rank occurs on December 18th.

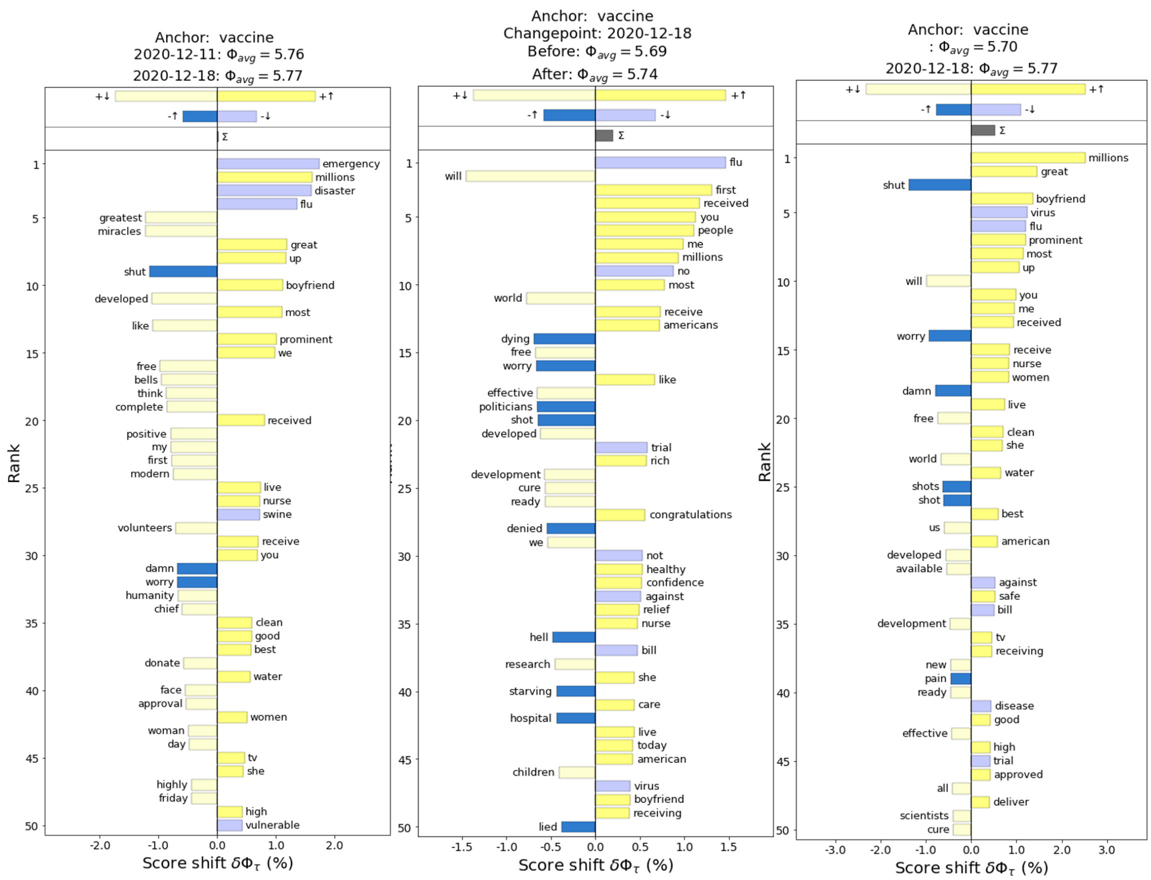

Figure 3.4: December 18th, 2020, Lowest Rank day. Happiness word shift graphs. In each of the three panels, we show 1-grams that contribute most to the shift in ambient happiness on key dates shown in Fig. 4.1, relatively to the prior week. In each of the three panels from left (a),(b),(c), we show 1-grams that contribute most to the shift in ambient happiness on key dates shown in Fig. 4.1, relatively to the prior week. The sample of tweets contains the months of January 2019-November 2021. On the left hand panel, (a) represents the comparison of two dates, (b) contains the period before and then the defined date at the top of the plot (c) contains a comparison of the first date to the full sample. TThe words shown in blue are ones that have been labeled as relatively negative, and the ones shown in yellow have been labeled as relatively positive [21]. For example, 'swine' and 'flu', the relatively positive words 'millions or 'approved' appear less often. The darker shade of these colors tells us where there is an increase in these words, while the lighter shade represents a decrease in usage. The happiness score shift is shown on the horizontal axis, representing how positive or negative the language on these days becomes, and the happiness rank of the 1-gram in this subset is shown on the vertical axis. Average ambient happiness scores for the day of the event, as well as a week before the event, are also noted at the top of each subplot.

During December vaccine research announcements occur. On December 18th the average happiness score is $\boldsymbol{\phi_{avg}}$5.77. The word 'developed' appears often within tweets containing 'vaccine' A week beyond the December 18th increase we see words appear indicating institutional memory of other vaccines including 'swine' and 'flu'. During this time Pfizer, Biotech are reported as effective

When comparing the period Jan 2020-October 2021 before and after on December 9th, the average happiness score before December 18th is 5.69, and after, $\boldsymbol{\phi_{avg}}$5.74. We see the word 'shot' appear and then this does not appear again in the subsequent part of the period.

After December 2020, we observe the word 'received', 'millions' as positively weighted collections of words which indicate the upswing in discourse about the potential vaccine after December 9th.

On December 18th the average happiness score is $\boldsymbol{\phi_{avg}}$5.77 and the total period from January 2020 to November 2021. We see again, shot and shots appear and worry dominating the single day collection of 'vaccine' tweets. 'worry' also contributes to the shift.

Chapter 4

Narrative, Social Amplifications

4.1 Rank Turbulence Divergence

Throughout the timeline of the COVID-19 pandemic assessed here January 2019 through September 2021, appearance of the 1-gram 'vaccin' increases over time. To identify the corpus associated with vaccine discourse, we employed n-grams and the relative frequency and rank values for each day. We then compared the word usage in this corpus to a subset to an adjacent month. Within a specified timeframe surrounding a single day, differences in language usage is established using rank-turbulence divergence [0]. Using this method, the result is a shift in language between two sets of tweets. To achieve this, tweets containing 'vaccin' are aggregated n-gram counts. Additionally, counts for phrases containing 'vaccin' are aggregated over 30 days and repeated for each month between several pairings of years. We perform smaller aggregations of tweets in two week increments surrounding days with the lowest rank, highest frequency as well as top and bottom sentiment. Each of these plots use the full ten percent decahose sample. As a result, rank divergence is emerged in the comparison of the two subsets of messages. Appearing in figure 5.1 is a histogram containing relative ranks for the 1-gram 'vaccin'. The right hand side contain 1-grams as well. The threshold α occuring in the right hand plot is set to 1/4. The spine of the plot appear words with similar rank in both subsets. Further down the spine indicates words appearing in both corpses, however do not co-occur often.

Studies this year have shown that at the onset of the pandemic, "vaccine" Google searches increased initially, followed by a sharp increase when rollouts were announced. It has also been recorded that in the time between March and July 2020, average phone screen time doubled to 5 hours per day and rates of depression increased by 90 percent [22]. While these figures cannot tell us everything about how language differs between subsets of conversation, they do provide a sense of the vaccine topics individuals discussed in 2020.

The one month period comparing January to February 2020 shows the increase in words related to political figures aligning with messages aimed at making the vaccine affordable and accessible.

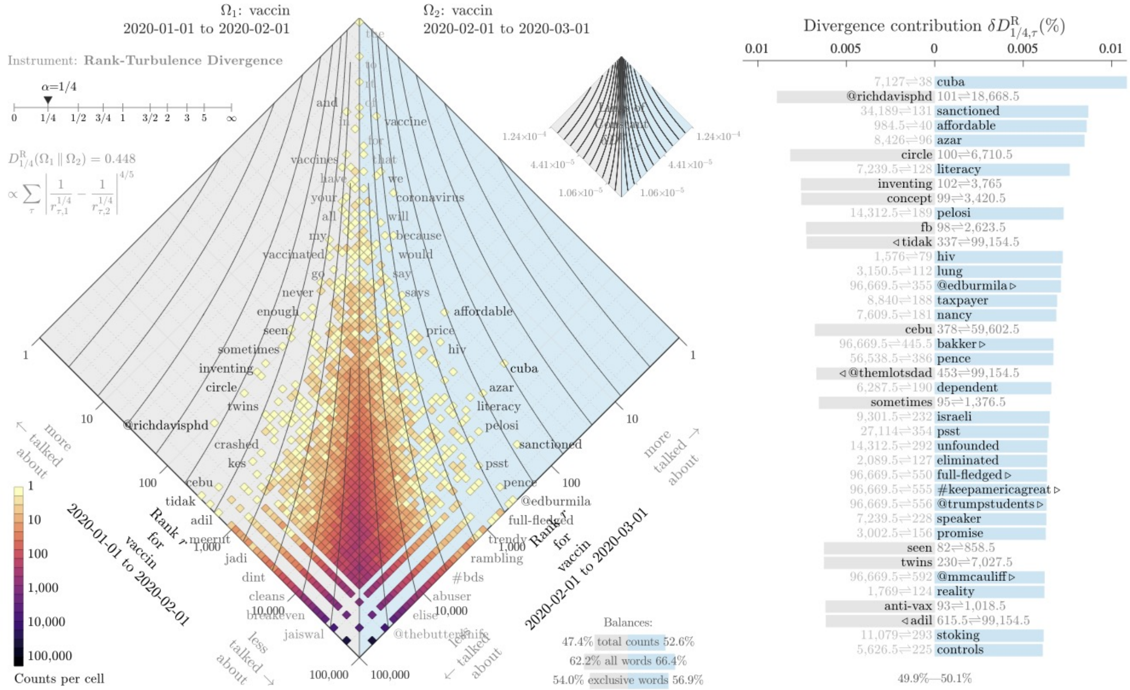

Figure 4.1: January 2020 compared to February 2020: Allotaxonograph using rank-turbulence divergence of 1-grams from tweets two comparative months,containing the anchor phrase âvaccine". In the central 2D rank-rank histogram panel, phrases appearing on the left have higher rank in the vaccine subset than in random tweets, while phrases on the left appeared more frequently in the the sample thirty days after the date of interest. The table to the right shows the words that contribute most to the divergence. For example, the phrase 'affordable' was the 948th most common 1-gram in the subset of tweets posted in January, though in February has a rank of 40. The balance of the words in these two subsets is also noted in the bottom right corner of the histogram, showing the percentage of total counts, all words, and exclusive words in each set. See Dodds et al. [0] for a detailed description of our allotaxonometric instrument.

The Balances for these shifts includes total counts of 47.4 percent and 52.6 percent representing the total counts of 'vaccin' within the collection of all tweets containing âvaccinâ for each month compared. The Balances percentages for âall wordsâ is 62.2 percent and 66.4 percent, which is the percent âvaccinâ appears in the total collection of words for each side of the balance relative to both periods, in this case two different months. The precents of exclusive words in each compared month are 54 percent for

February and 56.9 percent for March. These exceed 100 percent in total since âvaccinâ may appear more than once in each tweet.

Words defining the month of February are dominated by tweets discussing access to a vaccine. A 200 retweet count and 5,000 like count is set as a threshold for specific tweet searches. Tweet searches elucidate that medical circumstances related to inadequate healthcare dominate the vaccine conversation. Political figures notably tweet about the prospect of a covid-vaccine into their medical campaign. For example, the emergence of Nancy Pelosi voicing concern for âbig-pharmaâ and concern for taxpayers receiving an affordable and accessible vaccine .

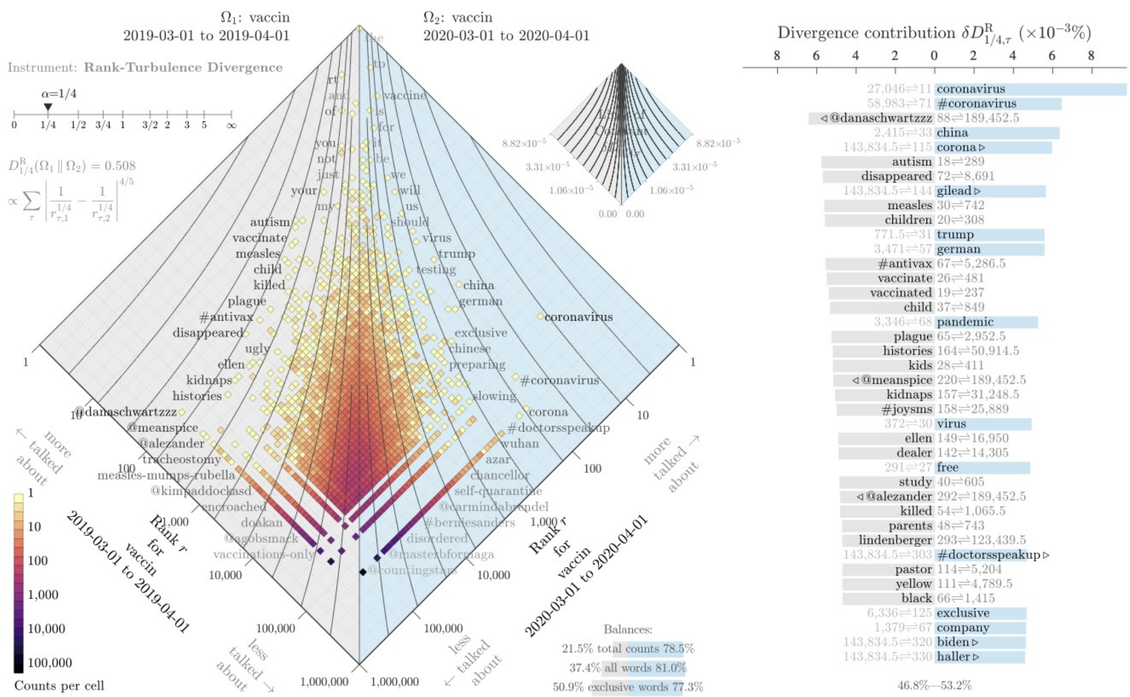

Figure 4.2: March 2019 compared to March 2020: Allotaxonograph using rank-turbulence divergence of 1-grams from tweets in the first thirty days of March 2019, compared to 2020 containing the anchor phrase 'vaccin'. The table to the right shows the words that contribute most to the divergence. For example, the phrase 'coronavirus' went from appearing not at all to appearing frequently. It is notable that COVID-19 does not appear in March 2020, early in the pandemic.

In March 2020, popular twitter users emerge with messages discussing speculative societal and medical implications of a vaccine. The Balances for these shifts includes total counts of 21.5 percent and 78.5 percent representing the total counts of 'vaccin' within the collection of all tweets containing 'vaccin' for each month compared. The Balances percentages for all words is 37.4 percent and 81.0 percent, which is the percent of the time? that 'vaccin' appears in the total collection of words for each side of the balance relative to both periods, in this case two different months. The precents of exclusive words in each compared month are 50.9 percent for March 2019 and 77.3 percent for March 2020. These exceed 100 percent in total since 'vaccin' may appear more than once in a tweet.

As COVID-19 is announced by the Center for Disease Control in March 2020, several words contribute to the divergence in March 2019 include 'autism' 'measles' 'child' 'kids' 'children'. If we make a comparison of these months to 2019 these child focused words associated with vaccine also appear.

In March 2020, One of the notable results is vaccine tweets use the word 'coronavirus' which only in later months changes into 'covid'or 'COVID-19', within the two year period. Codifying language may be simply a matter of convenience. Otherwise it is reasonable to say COVID-19 encompasses more information, the year, and might be a better term for groups including political figures and medical communities to use. (a reach) The other dominant twitter voices during this snapshot include independent voices such as @richdavisphd, a chemist who emerged as a voice admonishing emerging antivaccination misinformation.

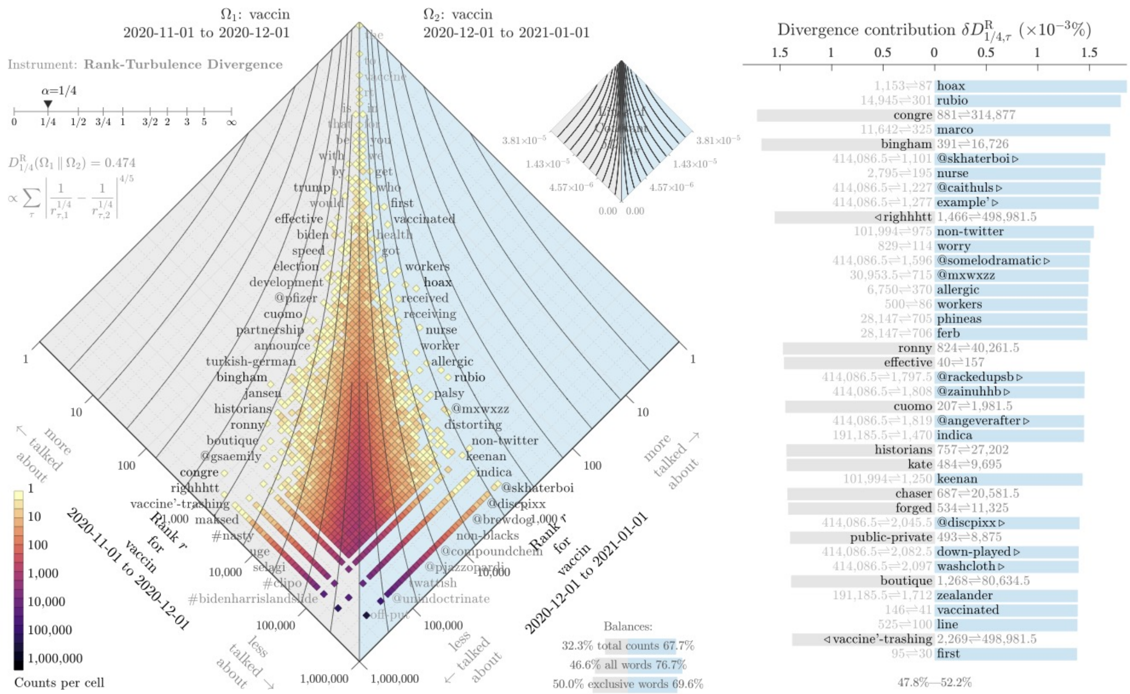

Figure 4.3: November 2020 Compared to December 2020 : Allotaxonograph using rank-turbulence divergence of 1-grams from tweets thirty days surrounding November 9, 2020 containing the anchor phrase 'vaccin'. In the central 2D rank-rank histogram panel, phrases appearing on the left have higher rank in the vaccine subset than in random tweets, while phrases on the left appeared more frequently in the the sample thirty days after the date of interest. The table to the right shows the words that contribute most to the divergence. For example, the phrase 'hoax' was the 1,153rd most common 1-gram in the subset of tweets posted during November 2020, but thirty days into Decebmber 'hoax' is the 87th ranked. See Dodds et al. [0] for a detailed description of our allotaxonometric instrument.

In November 2020 we notice 'rubio' 'bingham' 'allergic' and 'worker' contributing to the divergence measure. Since we set α to $1/4$ we only see 'congre' appear in the shift. Since alpha is tunable, words do not appear with lower rank on the righthand divergence chart with exact rank changes. These do appear on the allotaxonometer plot.

The Balances for these shifts includes total counts of 32.3 percent and 67.7 percent representing the total counts of âvaccinâ within the collection of all tweets containing

’vaccin’ for each month compared. The Balances percentages for ’all words’ is 46.6 percent and 76.7 percent, which is the percent ’vaccin’ appears in the total collection of words for each side of the balance relative to both periods, in this case two different months. The precents of exclusive words in each compared month are 50.0

In November, ’hoax’ ’rubio’ and several independent, non-medical or political accounts appear contributing most to the divergence. Again, political discourse dominates both months, and we contend this political discourse is centered around opinions about the specific responses political figures have.

Also of note, in October 2020 vaccine conversation focuses on the firm which invented the Pfizer vaccine, specifically the Tukish Pfeizer scientists Ozlem Tueci and Uger Sahin.

In March 2020 Covid is declared a pandemic by the Center for disease control. In April the volume of discourse is sustained.

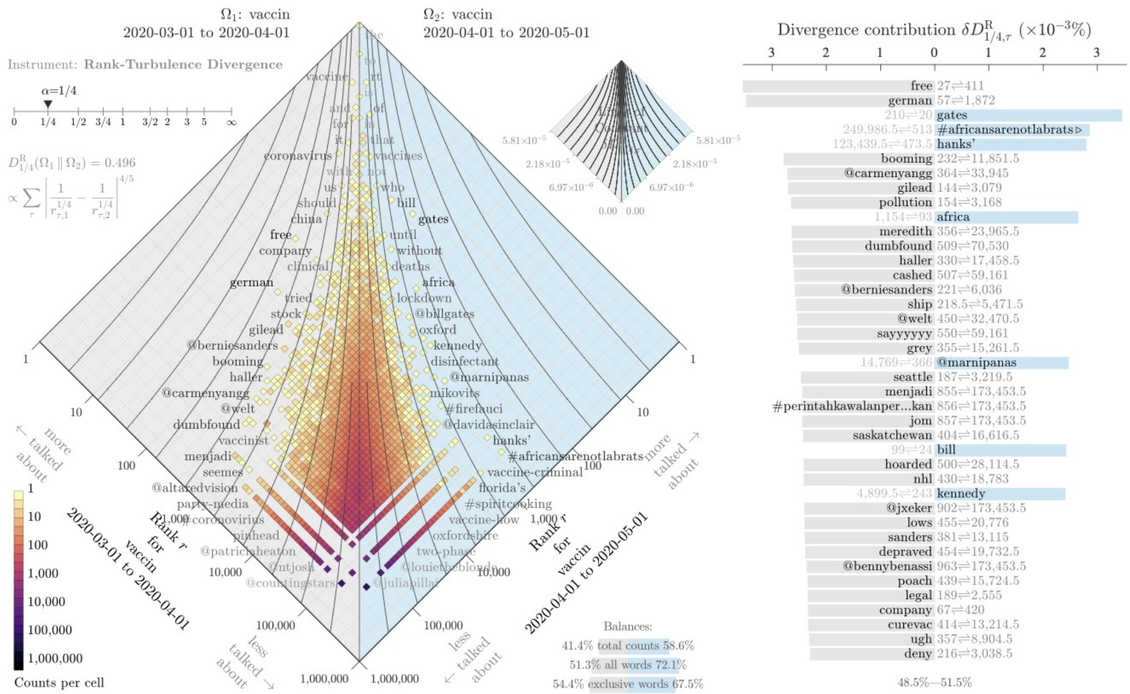

Figure 4.4: March 2020 Compared to April 2020: Allotaxonograph using rank-turbulence divergence of 1-grams from tweets thirty days including March 15th 2020 containing the anchor phrase 'vaccin'. In the central 2D rank-rank histogram panel, phrases appearing on the left have higher rank in the vaccine subset than in random tweets, while phrases on the left appeared more frequently in the the sample thirty days after the date of interest. The table to the right shows the words that contribute most to the divergence. For example, the phrase 'Haller' was common with a rank of 330 though Jennifer Haller, the first person to receive a trial vaccine dies away in April. The balance of the words in these two subsets is also noted in the bottom right corner of the histogram, showing the percentage of total counts, all words, and exclusive words in each set. See Dodds et al. [0] for a detailed description of our allotaxonometric instrument.

Comparing March 1st to April 1st against April 1st to May 1st the Balances for these shifts includes total counts of 41.4 percent and 58.6 percent representing the total counts of 'vaccin' within the collection of all tweets containing 'vaccin' for each month compared. The Balances percentages for 'all words' is 51.3 percent and 72.1 percent, which is the percent 'vaccin' appears in the total collection of words for each side of the balance relative to both periods, in this case two different months. The precents of exclusive words in each compared month are 54.4 percent for February and 67.5 percent for March. These exceed 100 percent in total since 'vaccin' may appear more than once in a tweet.

As with February, during March politicians discuss prospective vaccines. German scientists working on a vaccine are approached by Trump who offered monitary incentive, which causes an uproar in discourse. These events are represented in the words contributing to divergence shift including 'free' 'german' 'gillead' and 'haller'. The first trial vaccine is administered to Jennifer Haller in March of 2020, long before announcements are made about vaccine rollouts occurring in November.

In April, 'gates' 'africa' and 'bill' appear. Notably the spread to poorer countries stimulates vaccine discourse about availability and also the underreporting of deaths. The discourse about Africa also introduces the idea that somce countries may be used as lab rats for potential vaccines. Also in April Bill Gates announces funding vaccine initiatives.

Chapter 5

Concluding Remarks

This investigation seeks to describe discourse surrounding the COVID-19 pandemic vaccines. Using the anchor 'vaccin', we sought to find how overall momentum built as COVID-19 unfolded. The 1-gram 'vaccin' decreased in rank by over ten fold in March and December 2020. Further, it was observed the ambient happiness told a unique story around vaccine hesitancy, though not within the specific March and November windows, though over the two year 2019-2021 timeline of COVID-19.

Compiling a new data set of n-grams found in the subset along with the full sample of tweets mentioning 'vaccine', elucidated the top n-grams related or surrounding COVID-19 vaccine discourse. We noted as vaccine discussion increased it showed a vastly different narrative pattern to the measles discourse surrounding an outbreak in 2015. This indicated a change in the instituional memory where vaccine concern is expressed around concerns of freedom, mandates and accessibility and away from MMR vaccine fears about risks to children. Each pandemic and its relative attention showed a different narrative simply with volume of discourse. Given Twitter data has many limitations, since its user base does not fully represent sample all of the human population, or even major groups discussing vaccines. For example, Dodds [5] , and Baucom find that often illicit or unpopular views people tend to obscure their identities [37]. The age breakdown of users is also skewed, with 38 percent of 18-29 year-olds using Twitter while only 17 percent of 50-64 year-olds use the site. While demographics of race are fairly uniform (21 percent of white adults, 24 percent of black adults, and 25 percent of Hispanic adults), the platform is more often used by individuals with a college degree (32 percent) living in an urban area (26 percent) [33]. It is also important to consider twitter accounts are run by governments institutions, and other organized groups. These accounts, such as '@NIH', would have a pro-vaccine agenda to their posted tweets, and stance detection has its own caveats. Due to these complexities of the Twitter user base, our study to parse out different beliefs or stances on vaccine discourse would be investigated with caution. These limitations could be addressed in future studies by expanding the data sources, e.g., by looking to other available online sites such as Reddit, Instagram, or Facebook, whose user bases differ in some regards.

The work presented here is also limited to the anchor phrase 'vaccin' and may miss similar conversations on the topic. To provide a more robust understanding of vaccine discourse, it would be prudent to expand the existing 'vaccin' dataset to include tweets with additional anchor n-grams, although a method for determining these anchors would be necessary. In this study a story of fast paced response to a global pandemic and collective societal intervention is elucidated. In tandem with the fast paced onset of covid cases and in response to government announcements an mandates a cacophony of discourse arises more than any previous pandemic. Furthermore, the temporal patterns in time series analysis indicate (***) Public health campaigns aiming to reduce vaccine propaganda can leverage success with vaccination rates. As COVID-19 continues to be a dominant narrative on twitter it would be useful to expand on language or events contributing to these shifts.

Overall the volume of discourse corresponds with the presidents March announcements and acknowledgements of the COVID-19 pandemic and second the post-election dissemination of vaccine information.

Discourse surrounding the first and second peaks of total discourse correspond with sentiment including the following list of words during these two periods.

We can see terms which describe vaccine discourse over the entirity of twitter and within this contains a subset of anti-vaccination sentiments. These plots show that comparing year to year between 2019 and 2020 anti vaccination sentiment is maintained amongst these communities however, the corresponding words are different describing speculated symptoms and hesitancy

Looking month to month at 2019 and 2020 it is observed that vaccine speculation occurs during the original announcements and sentiment varies during this time. We contend shift in sentiment surrounding vaccine in tandem with positive and negative words during this time as seen in the word shift above for 30 days surrounding the two spikes in discourse track well with several positive and negative tweets from the president and then the NIH.

Vaccine discourse during the November election and vaccine announcements for a plan to combat COVID-19 aggressively is relatively neutral by comparison. We infer that learning at the broad scale community level is neutral. However, as confirmed by previous studies conducted by Dodds, 2019 and Jiang, 2020 discourse may be polarized by political groupings [6] [9].

Further investigation might include looking closer at a collection of tweets associated with the rise and fall of sentiment over a period of two months, March and April to see if this relative change in sentiment is associated with a group of specific tweets with polarized political op pinions [9]. Last, it is worthwhile to investigate discourse surrounding different states, for example collective hesitancy to covid regulations and adherence in the twitter conversations containing the names of different states.

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