Winds of Change: Impact of COVID-19 on Vaccine-Related Opinions of Twitter Users

Soham Poddar\textsuperscript{1}, Mainack Mondal\textsuperscript{1}, Janardan Misra\textsuperscript{2}, Niloy Ganguly\textsuperscript{1,3}, Saptarshi Ghosh\textsuperscript{1}

\textsuperscript{1} Indian Institute of Technology, Kharagpur, India
\textsuperscript{2} Accenture Labs, Bangalore, India
\textsuperscript{3} Leibniz University of Hannover, Germany
\textsuperscript{*} sohampoddar@kgpian.iitkgp.ac.in

Abstract

Administering COVID-19 vaccines at a societal scale has been deemed as the most appropriate way to defend against the COVID-19 pandemic. This global vaccination drive naturally fueled a possibility of Pro-Vaxxers and Anti-Vaxxers strongly expressing their supports and concerns regarding the vaccines on social media platforms. Understanding this online discourse is crucial for policy makers. This understanding is likely to impact the success of vaccination drives and might even impact the final outcome of our fight against the pandemic. The goal of this work is to improve this understanding using the lens of Twitter-discourse data. We first develop a classifier that categorizes users according to their vaccine-related stance with high precision (97\%). Using this method we detect and investigate specific user-groups who posted about vaccines in pre-COVID and COVID times. Specifically, we identify distinct topics that these users talk about, and investigate how vaccine-related discourse has changed between pre-COVID times and COVID times. Finally, for the first time, we investigate the change of vaccine-related stances in Twitter users and shed light on potential reasons for such changes in stance.

Introduction

The ongoing COVID-19 pandemic has affected close to 500M people till now (April 2022) and caused more than 6M deaths. Since December 2020 / January 2021, multiple pharmaceutical companies (e.g., AstraZeneca, Pfizer, Moderna) have put forward vaccines that are claimed to reduce the chance of COVID infection and fatality.\textsuperscript{1} Naturally, governments across the world have been procuring and administering these vaccines to their citizens since then. However, administering COVID-19 vaccines also has a key societal angle. To make these vaccines effective against COVID-19 at-scale and to eradicate the disease, almost everyone in the society needs to consent to be vaccinated. In other words, only with near societal-scale vaccination, can we achieve the “herd immunity” and eradicate the disease\textsuperscript{2}. As of April 2022, a large portion of the population has already been vaccinated, however a fraction of people have still been hesitant and resisted taking the vaccines, speculating various reasons including that the development of these vaccines might be rushed and propelled by monetary and political reasons (Chou et al. 2020). Their hesitancy persists in spite of Governments giving various incentives towards vaccination.

There exists a long-drawn debate about vaccines since long before the onset of the COVID-19 pandemic. The debate is between \textit{Anti-Vaxxers} who believe that vaccines do more harm than good, and \textit{Pro-Vaxxers} who support and promote the benefits of vaccines. Both the groups are known to actively propagate their views over social media (Mitra et al. 2016; Gunaratne et al. 2019). It is important to know what the present attitude of the Anti-Vaxxer and Pro-Vaxxer communities is towards COVID-19 vaccines, and whether there has been any change in these attitudes in the pandemic times. While there have been a few surveys and manual analyses that have attempted to answer these questions (Funk and Tyson 2020; Bonnevie et al. 2020), to our knowledge, there has not been any prior attempt to devise automatic methods of answering these questions at scale using data from social media. It is important for policy makers to get answers to these questions at multiple stages of the pandemic, e.g., to figure out what the main concerns about vaccines are at different stages, so that they can take intervening steps accordingly.

To our knowledge, this study is the first that (i) devises automated methods over data collected from social media (Twitter) to answer such questions, and (ii) conducts a long-term (over 2 years) analysis of people’s attitudes towards vaccines, both individually and collectively. Specifically, we investigate two key questions – (1) What attitudes towards COVID-vaccines are expressed by Anti-Vaxxers and Pro-Vaxxers on Twitter? Especially, are the anti-vax opinions about COVID-19 vaccines similar to the traditional anti-vax arguments that were prevalent in pre-COVID times?, and (2) Has the vaccine-related stance of some users changed over time due to the pandemic? If so, why?

We make three important contributions in this work. First, we develop a dataset of COVID-vaccine related tweets labelled according to their vaccine stances, as detailed in later sections. Training a classifier on these tweets, we created a method to \textit{categorize Twitter users according to their vaccine-related stance} as expressed through their tweets both in pre-COVID and COVID times, with 97\% precision. We use this method to detect and investigate specific user-
Second, we use topic modeling to identify 12 COVID-vaccine related topics/themes from the tweets of Pro-Vaxxers and Anti-Vaxxers. We further analyze the relative presence of these topics in vaccine-related online discourse in different time periods – pre-COVID, COVID and COVID-vax time periods. Through this analysis, we find that some anti-vax themes such as the vaccine development being rushed and concerns about vaccines being ineffective have become more frequently discussed in COVID times (compared to the pre-COVID times).

Third, we show that there exists a set of users who have changed their prior vaccine-related stance in the COVID times (from Anti- to Pro-Vaxxers, or vice-versa). Understanding this set of users, whom we call stance-changed users, can be important for the authorities attempting to maximize the coverage of vaccines. Though some prior works have shown that people have changed their stances towards COVID-19 vaccines (Funk and Tyson 2020; Bonnevie et al. 2020), no prior work has systematically explored such users and why they changed their stance. In this work, we characterize different sub-groups of stance-changed users and explore possible reasons of such stance-change. To this end, we uncover correlations between the stance-change of a user and life-events (e.g., loss of a close relative) as well as change in stance of the users’ social contacts.

We believe that the insights obtained from this study will help authorities better understand how vaccine-related stances of users are changing in pandemic times, and will help them to formulate effective policies to increase vaccine adoption by the masses. We make our dataset and classifier public to facilitate further research on this topic.3

Related Works

The dichotomy of opinions on vaccines between Anti-vaxxers and Pro-vaxxers on social media has been identified in many prior works (Mitra et al. 2016; Gunaratne et al. 2019). Both these groups have been seen to be quite strong in their stance, each believing the other to indulge in conspiracies (Yuan et al. 2019; Cossard et al. 2020). We briefly survey a few relevant works in this section.

Vaccine-stance detection methods: Several studies have attempted to classify social media posts (e.g., tweets) based on their stance towards vaccines, using hashtag counts (Gunaratne et al. 2019), machine learning models (Mitra et al. 2016; Yuan et al. 2019) and neural models (Müller et al. 2020; Cotfas et al. 2021). Some works have also provided labeled datasets for this classification. Some studies have also tried to classify the stances of users based on percentages of posted tweets of different stances (Mitra et al. 2016) as well as by community detection algorithms (Yuan et al. 2019; Gunaratne et al. 2019).

Social media discourse on COVID-19 vaccines: With the onset of the COVID-19 pandemic, people have naturally resorted to sharing their emotions on social media (Lwin et al. 2020). Tough times give rise to several conspiracy theo-

3https://github.com/sohampoddar26/covid-vax-stance

4https://github.com/twintproject/twint

4
generic keywords such as ‘corona vaccine’ and ‘covid vaccine’ and the names of popular vaccines and their manufacturers, such as ‘astra zeneca’, ‘pfizer’, ‘moderna’, etc. We collected 6.6M English tweets from the COVID period (Jan–Dec 2020) and 6.2M English tweets from the COVID-vax period (Jan–Mar 2021). Evidently, the social media discourse on vaccines has increased manifold in 2021 after the administration of COVID vaccines has started.

Checking for bias in tweets collected by Twint: Since we did not use the official Twitter API to collect tweets, we check if our collected data contains any bias. To this end, we collected the tweets posted during June 2021 using both the Twitter API (fetched in real-time) and the Twint library (fetched in August 2021) using the same set of search-query terms. While the Twitter API collected 4.8M distinct tweets, the Twint library collected 745K distinct tweets during the same period. Thus, Twint collects 15.5% of all tweets collected by the Twitter API. Note that, Twint does not collect retweets; so we have not considered the retweets collected by the Twitter API. Next, we compared the set of tweets collected by the two methods as follow:

- **Representativeness w.r.t. time:** On each of our observed days, the fraction of tweets collected by the Twint library is relatively uniform (close to 15% of what is collected via Twitter API). This gives us confidence that the set of tweets collected by the Twint library is temporally representative.
- **Representativeness w.r.t. tweet popularity:** We measure the popularity of a tweet by its retweet-count that is stated in the tweet object. Among the tweets collected by Twitter API, 93.0% had less than 10 retweets and 99.1% had less than 100 retweets. In comparison, among the tweets collected by Twint, 90.4% had less than 10 retweets and 98.8% had less than 100 retweets. The numbers are quite similar for both and thus, the set of tweets collected by Twint does not have much bias towards more popular tweets.

Thus, though we could fetch only 15% of all the posted tweets, the collected tweets do not have much apparent biases. Also we believe that the stance-detection methods used in this work (described in the next section) are robust towards small variations in data w.r.t time or tweet popularity, due to the conservative thresholds we use in the classifiers.

Since the Twitter API does not allow access to tweets older than ~ 7 days, we needed to use some library like Twint to collect older tweets, as has been done by several prior longitudinal studies (Dutta et al. 2021; Punuru et al. 2020; Nuzhat et al. 2020). Also, many prior studies have been based on the 10% and even the 1% Twitter random sample (provided by Twitter). Hence, we believe that the mostly unbiased 15% tweet sample (that Twint gave us) is sufficient and appropriate for the present study.

### Identifying Users’ Stance towards Vaccines

This section discusses our approach to classify users based on their stance towards vaccines during the three time periods (pre-COVID, COVID, and COVID-vax). Since a user’s stance may have changed over time, we do not attempt to do this classification based on the profile attributes of the user. Instead, we first develop a tweet-classifier to predict the stance of individual tweets, and then use this classifier to identify a user’s stance during a certain time period from the tweets posted during that period.

### Developing a Tweet Classifier

#### Annotating tweets and other datasets:

There exist a few publicly available datasets that have labelled tweets as **Anti-Vax**, **Pro-Vax** or **Neutral** according to their stance towards vaccines. Müller et al. (2019) provided a large set of tweets about vaccines before the onset of the COVID-19 pandemic, while Cotfas et al. (2021) provided a dataset of tweets about COVID-19 vaccines collected during a month between November and December of 2020. We call these two datasets the **Muller** and **Cotfas** datasets respectively.

Since the Cotfast dataset only consists of tweets from one particular month, it might not cover different types of tweets posted over the entire discourse about COVID-19 vaccines. Hence we wanted to extend this dataset with tweets from a broader timeline. To this end, we randomly selected 1,700 tweets posted between January 2020 and March 2021, to be annotated into the three classes. For the annotation, we employed three annotators on the crowdsourcing platform Prolific (https://www.prolific.co/). To ensure reliable annotation, we employed only annotators who are proficient in English and have participated in more than 1000 tasks with 100% acceptance rate on the platform (top 1% annotators).

Among the 1700 annotated tweets, 94 tweets were labelled different by all three annotators, 785 tweets had unanimous agreement, and 821 tweets were labelled the same by two annotators and different by the other. We discarded the tweets where all three annotators disagreed. We create two datasets by merging our annotated tweets with the tweets in the Cotfas dataset – in one dataset, we added the 1,606 tweets having majority agreement to the Cotfas dataset; in the other dataset, we add the 785 tweets having unanimous agreement to the Cotfas dataset. Thus we have four datasets as summarized in Table 1.

#### Table 1: Summary of different datasets used for training and testing of the classifiers, each of them having 3 class labels.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>#tweets</th>
<th>Anti-Vax</th>
<th>Pro-Vax</th>
<th>Neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td>Muller</td>
<td>18.5k</td>
<td>10.5%</td>
<td>40.3%</td>
<td>49.3%</td>
</tr>
<tr>
<td>Cotfas</td>
<td>2,792</td>
<td>28.3%</td>
<td>35.5%</td>
<td>36.2%</td>
</tr>
<tr>
<td>Cotfas + our data (majority)</td>
<td>4,398</td>
<td>24.6%</td>
<td>38.2%</td>
<td>37.2%</td>
</tr>
<tr>
<td>Cotfas + our data (unanimous)</td>
<td>3,577</td>
<td>26.0%</td>
<td>38.7%</td>
<td>35.3%</td>
</tr>
</tbody>
</table>

#### Classifier models:

To classify tweets into the three classes, we used a variety of classification models, including Support Vector Machines (SVM) with TF-IDF feature vectors of tweets, the supervised FastText classifier (Joulin et al. 2016) along with some state-of-the-art BERT-based models. Specifically, we tried out the standard ‘bert-large’ (Devlin et al. 2018), and the ‘covid-twitter-bert-v2’ (Müller et al. 2018), and the ‘covid-twitter-bert-v2’ (Müller}
et al. 2020) model which has been pre-trained specifically on COVID-related tweets (which we refer to as CT-BERT). We used the implementations of these models provided by the HuggingFace library (Wolf et al. 2020). For each of the BERT-based models, we paired them with a classification head to perform three-class classification.

**Evaluation of tweet classification:** We performed stratified 5-fold cross validation on the four datasets, and evaluated the classifiers using the average macro-F1 scores across the 5-folds. Table 2 (first four rows) presents the cross validation performance of the classifiers. On each of the four datasets, ‘covid-twitter-bert-v2’ (CT-BERT) performs the best.

We also performed cross-dataset testing, where we trained the CT-BERT model on one dataset and tested on other datasets. Table 3 shows the macro-F1 scores of CT-BERT in cross-dataset setting. The model does not perform too well when trained and tested on different datasets, possibly because the time-scale of the datasets are very different – the Muller dataset is of pre-Covid times, Cotfas dataset contains tweets during the different time periods. To predict stance of tweets from the pre-Covid times and the Covid-times. To predict stance of tweets from the pre-COVID period, we use the CT-BERT classifier fine-tuned over the Muller dataset (which achieved the best Macro F1-score over the Muller dataset in Table 2). To predict the stance of tweets from the COVID period and the COVID-vax period, we use CT-BERT++ finetuned again over the Cotfas dataset extended with the 785 unanimously labelled tweets in our dataset.

Using these classifiers we predicted the stance of all the tweets we had collected; the distribution of stances is given in Table 4.

**Checking for classifier bias:** We check for any potential biases that the final classifier may have with respect to certain specific words in the data, using the SPCPD bias word detection strategy (Badjatiya et al. 2019). We ran the final classifier (CT-BERT++) on each individual word from the datasets, and checked which words are classified as Anti-Vax or Pro-Vax. Out of 37,127 distinct words in all the datasets combined, as many as 37,011 words are not labeled as Anti-vax/Pro-vax, indicating no bias with respect to 99.7% of the words. Only 116 words were predicted as Anti-Vax or Pro-Vax. From manual observation, we find all these words to be hashtags that are used almost exclusively with the corresponding stances. For example, hashtags such as ‘#refusePoisonVaccines’, ‘#dontTrustVaccines’, and ‘#vaccinesKill’ were labeled as Anti-Vax, whereas hashtags such as ‘#getVaccinated’ and ‘#vaccinesSaveLives’ were labeled as Pro-Vax. We believe these keywords are indeed strongly associated with the corresponding stances. Thus we did not find any unjustified bias in the classifier.

### Identifying Vaccine-Related Leaning of Users

**Identifying Pro-Vaxxers and Anti-Vaxxers:** We use the tweet-classifiers described above to identify the stance of
Change in numbers of Anti-Vaxxers and Pro-Vaxxers:
Table 5 shows the variations in the number of Anti-Vaxxers and Pro-Vaxxers over the three time periods, while Table 4 shows the variations in distribution of Anti-Vax and Pro-Vax tweets. From these tables, it is evident that a lot more users have started discussing about vaccines since 2020, than in the pre-COVID times. Table 5 shows that there was a substantial increase in the number of Anti-Vaxxers in the COVID period (2020), owing to the uncertainty and delay in vaccination during that period. However, once vaccination started in the COVID-vax period, a much larger number of users are seen to post Pro-vax opinions (even after the misclassification of some Pro-Vaxxers as Anti-Vaxxers in the COVID-Vax period, as stated in Table 6).

It can be noted that, in this paper, the set of ‘Anti-Vaxxers’ may include a broader group of users than the traditional group studied in previous works prior to 2020. Anti-Vaxxers traditionally mean people who are against the intake of all vaccines in general. Whereas, in COVID times, people have shown different levels of hesitancy/unwillingness to take the COVID-19 vaccines (or even a particular COVID-19 vaccine) due to various reasons (discussed in the next section), even though they might not be against other vaccines.

**Summary:** We designed a highly precise user-classification method, using which we classified the vaccine-stance of tens of thousands of Twitter users, over the three time periods.

**Discourse Regarding Vaccines on Twitter**
In this section, we identify major themes/topics of discussion on vaccines across the different time-periods, by Anti-Vaxxers and Pro-Vaxxers.

**Method for Identifying Vaccine-Related Topics**
Given a particular set of tweets (e.g., the tweets posted by Anti-Vaxxers), we adopt the topic modeling-based method suggested in (Bozarth et al. 2020). The method involves four steps: (1) identifying candidate topics and topic-words through vanilla LDA, where we estimate the number of topics using topic coherence or perplexity scores (Newman et al. 2010), (2) manually mapping the identified topics and topic-words to a smaller subset of coherent topics and associated seed-words, (3) using Labelled-LDA (Ramage et al. 2009) with these seed-words as input, and finally (4) manually examining the topics generated by Labelled LDA and combining topics that share the same theme and removing topics without coherence. This approach finally produced 8 distinct Anti-vax topics from the tweets posted by Anti-Vaxxers and 4 Pro-vax topics from the tweets of Pro-Vaxxers. Overall, 80% of the tweets posted by Pro-vaxxers and 83% of tweets posted by Anti-vaxxers could be assigned a topic by the above method. We also computed the relative frequency of the topics in the three different time periods.

**Opinions Expressed by Different User-Groups**
**Topics discussed by Anti-Vaxxers:** The topics discussed by the Anti-Vaxxers are shown in Table 7, along with their distribution over the three time periods (considering the tweets that could be assigned topics), and example tweets. We find...
<table>
<thead>
<tr>
<th>Topic 1 [Health Concerns]: Concerns about the ingredients and side effects of vaccines, including deaths caused.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Words: die, people, reaction, kill, receive, safe, effect, health, reaction, danger</td>
</tr>
<tr>
<td>[19.0%] Perhaps we now have the link between vaccination and autism spectrum disorder, the link being the inclusion of an aluminium adjuvant in the vaccine.</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th>Topic 2 [Against Mandatory]: The user is against mandatory vaccination – talks about freedom and choice.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Words: want, force, mandatory, time, body, right, mandate, passport, refuse, court</td>
</tr>
<tr>
<td>[17.6%] Anti-vaxxers are AGAINST government mandates and FOR informed consent and choice.</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
<th>Topic 3 [Big Pharma]: Dissatisfied with the role of pharmaceutical companies – they are tricking people, trying to make money.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Words: pfizer, big, company, ask, pharmacy, immune, moderna, money, drug, manufacture</td>
</tr>
<tr>
<td>[17.4%] Big Pharma lines their pockets, doctors get bonuses for having 63% of their patients vaccinated</td>
</tr>
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<thead>
<tr>
<th>Topic 4 [Political]: The vaccine is political in nature – Governments are promoting their own agenda.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Words: trump, push, govern, lie, world, russian, gates, bill, fda, country</td>
</tr>
<tr>
<td>[9.8%] US politicians unwilling to accept that vaccines cause patient harm WHY?</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
<th>Topic 5 [Ineffective]: Vaccines don’t work – Skeptical about the effectiveness of vaccines</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Words: work, will, get, stop, mask, lockdown, protect, effect, immune, mutate</td>
</tr>
<tr>
<td>[8.6%] Merck scientists are in court over lying about the efficacy of Mumps vaccine.</td>
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</tbody>
</table>

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<tr>
<th>Topic 6 [Rushed]: Vaccine development is being rushed – Not enough testing has been done</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Words: test, experiment, long, year, trial, medic, rush, risk, study, approve</td>
</tr>
<tr>
<td>[8.3%] This vaccine has NOT been tested for CARCINOGENIC potential, or for IMPAIRMENT of FERTILITY.</td>
</tr>
</tbody>
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<tr>
<th>Topic 7 [Shedding]: Virus Shedding – People who take vaccines will transmit the disease to others</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Words: shed, people, flu, vax, live, mrna, fact, spread, cause, sick</td>
</tr>
<tr>
<td>[13.2%] the recently vaccinated with the mmr can shed for up to 21 days through recently vaccinated children.</td>
</tr>
</tbody>
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<tr>
<th>Topic 8 [Deeper Conspiracy]: Disease is a Hoax, Tracking Chips and talks of other conspiracies (other than just money making)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Words: need, people, risk, control, believe, old, vulnerable, death, population, mask</td>
</tr>
<tr>
<td>[6.0%] #Vaccines are for POPULATION CONTROL aka eugenics.</td>
</tr>
</tbody>
</table>

Table 7: Broad topics posted by Anti-Vaxxers, along with the percentage of tweets in that topic posted during a time period (within square brackets) and excerpts from sample tweets from the corresponding time periods.
Especially in the US, the 2020 presidential elections gave rise to a huge debate where the government was blamed for pushing COVID-19 vaccines (reflected by the increased fraction of such tweets in 2020).

Another common Anti-vax topic is that vaccines are [ineffective] against the disease. In the pre-COVID period, users opined that vaccines are ineffective against flu and measles. In the context of COVID-19 vaccines, many Anti-Vaxxers users have expressed concern that these vaccines will be ineffective against the disease (e.g., since the virus can mutate). In the COVID-vax period even more users are concerned about the effectiveness, following reports of people affected by COVID even after getting vaccines. Another major concern is that the vaccines are being rushed by the government and the big pharma, and that not enough testing has been done before releasing the vaccines to the general public (the topic [Rushed] in Table 7). Discussion on this topic has become much more frequent in the COVID times.

Finally, a few Anti-Vaxxers also talk about some more controversial topics. One of them is about [Shedding], which says that vaccinated users transmit the disease to others. In pre-COVID period, this was a very frequent talking point against MMR and Flu vaccines. In the COVID and COVID-vax periods, users also talk about shedding the virus after taking COVID-19 vaccines, but the frequency has reduced as compared to the pre-COVID times. Additionally, some [Deeper Conspiracy] theories are especially being discussed in the COVID times, such as COVID-19 being made up to trick people into buying vaccines, presence of tracking chips in vaccines, population control, etc. These conspiracy theories are talked about a lot more after the onset of COVID (Cinelli et al. 2020).

**Topics discussed by Pro-Vaxxers:** The topics discussed by Pro-Vaxxers are given in Table 8, along with their distribution across the three time-periods and some example tweets. Many users have actively stated that they wish to take (or have taken) vaccines ([Want Vaccines]) and are seen to post information that promotes the adoption of vaccines (the [Promote Vaccines] topic in Table 8). In the COVID-vax period, many Pro-Vaxxers have shared that they have taken the COVID-19 vaccine, stating that the side effects they experienced are mild, Pro-Vaxxers also [Support Authorities] by thanking them for development and distribution of vaccines. However, it is observed that the fraction of people actively talking about getting vaccines ([Want Vaccines]) has reduced since the onset of COVID, which shows some level of vaccine hesitancy among the masses. On the other hand, more Pro-vaxxers have actively expressed their disapproval against Anti-Vaxxers ([Against Anti-Vaxxer]) in the COVID and COVID-vax periods (as also observed in prior works (Yuan et al. 2019; Cossard et al. 2020)).

**Summary:** We identified broad topics discussed by Anti-Vaxxers and Pro-Vaxxers across different time periods. Our identified topics match with those identified by prior works (Mitra et al. 2016; Jamison et al. 2020). But to our knowledge, no prior work analyzed how Anti-vax / Pro-vax discussions have varied in pre-COVID times and COVID times. While the broad topics being discussed are similar in pre-COVID and COVID times, we observe differences in their relative frequencies, e.g., lot more complaints about vaccines being rushed/ineffective and deeper conspiracy theories in COVID times, compared to the pre-COVID times.

**Change in Vaccine-Stances of Users**

Recall from earlier sections that we identified large numbers of Pro-Vaxxers and Anti-Vaxxers from the pre-COVID,
Table 9: Statistics of users who changed their vaccine-stance across the different time periods. The number of users who have changed their stance are marked in bold.

<table>
<thead>
<tr>
<th></th>
<th>pre-COVID period</th>
<th></th>
<th>COVID period</th>
<th></th>
<th>COVID-vax period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Anti-Vaxxer</td>
<td>Pro-Vaxxer</td>
<td>Anti-Vaxxer</td>
<td>Pro-Vaxxer</td>
<td>Anti-Vaxxer</td>
</tr>
<tr>
<td>Anti-Vaxxer</td>
<td>2791</td>
<td>218</td>
<td>7855</td>
<td>121</td>
<td>329</td>
</tr>
<tr>
<td>Pro-Vaxxer</td>
<td>21</td>
<td>6853</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

COVID and COVID-vax time periods (see Table 5). Many of these users actively posted tweets only during one of the time periods; hence we could detect the stance of a user during multiple time-periods only for a smaller set of users. We now consider those users for whom we could detect vaccine-related stance during at least two different time periods. Table 9 shows how their stances varied across the three periods.

Most users continue to follow the same stance towards vaccines. However, we find 675 users who have changed their stance towards vaccines. We see 218 users who were pro-vaxxer in pre-COVID period (2018-19) have become Anti-Vaxxers in COVID period (2020), which corroborates with the rise of vaccine hesitancy in COVID times (Bonnieve et al. 2020). Interestingly, a small set of 21 users did just the opposite – they turned from Anti-Vaxxers in pre-COVID times to Pro-Vaxxers in 2020. Again, people seem to be gaining back trust in vaccines in 2021, as we see 329 users shifting from Anti-Vaxxers (in 2020) to Pro-Vaxxers (in 2021). However, 121 users who were supporting vaccines in 2020 started showing hesitancy towards vaccines in 2021. In fact, there are 14 users who changed their stance multiple times – from Pro-Vaxxers in 2018-19 to Anti-Vaxxers in 2020 and again to Pro-Vaxxers in 2021.

Checking for bots: Automated bots abound on Twitter (Suyyadharikandeh et al. 2020), and we wanted to ensure that we are focusing on human users. To this end, we used Botometer-v4 (Suyyadharikandeh et al. 2020) which returns a score between 0 (very likely to be a human) and 1 (very likely to be a bot) for a Twitter user. We applied Botometer-v4 over all the 675 users who changed their stance. The tool assigned a score ≥ 0.5 to 68 users, implying that these users are more likely to be bots. Since the automated detection of bots often predicts a lot of false positives (Rauchfleisch and Kaiser 2020), we manually checked these 68 accounts. We found only one of these accounts to be automated, that automatically shares articles from an external personal blog. We ignore this account in subsequent analyses.

In the rest of this section, we focus on the 674 users who have changed their vaccine-related stance. We refer to this set of users as the stance-changed users.

Is the stance change an effect of users posting different opinions about different vaccines? It is possible that an individual user has different opinions about different COVID-19 vaccines. Hence there is a potential concern about the set of stance-changed users – is the observed change in stance an artefact of users posting positive opinions about one vaccine at one point of time, and negative opinions about some other vaccine at some other point of time?

To address this concern, we check for the mentions of different vaccines (with different variations of their names and manufacturers, such as AstraZeneca/Oxford, Pfizer/BioNTech, Moderna, Sputnik, Sinopharm, etc.) in all the tweets posted by the stance-changed users. Out of the 674 distinct stance-changed users, 133 had posted at least one tweet about two different vaccines. Out of these, we found only 13 users (2% of 674) who posted a clear preference towards one vaccine, while rejecting/opposing another vaccine. We have given a few examples of tweets from such users in Table 11 (each row showing two tweets from the same user). We also noted that, all these users also expressed concerns about vaccines in general during one of the time periods, and posted in support of vaccines in general in some other time period. Thus, we conclude that all the 674 users whom we have identified, actually changed their general (not related to specific vaccines) stance towards vaccines at some point of time.

Demonstrating the change for some individual users: Table 10 shows samples of tweets posted by some of the stance-changed users. Each row of this table show two tweets posted by the same user during two different time periods. Some of the tweets seem to indicate potential reasons of why the users changed their stances. For instance, user U1 (who shifted from Anti-Vaxxers in pre-COVID period to Pro-Vaxxers in COVID period) experienced a life-changing event that may have changed his/her stance. Those who changed from Pro-Vaxxers to Anti-Vaxxers (user U3 & U4) during this time were getting skeptical of COVID-19 vaccines in specific due to various reasons, including political factors. Some users were hesitant about the COVID-19 vaccines in 2020; but with the actual rollout of vaccines in 2021, they are willing to get vaccinated (e.g., U5 & U6). Finally some users who were Pro-Vaxxers in 2020 also have turned Anti-Vaxxers in the COVID-vax period (U7 & U8), due to factors such as mistrust in how effective vaccines would be, and opposition to mandatory vaccination.

Representativeness of Stance-Changed Users

In this section, we analyse the stance-changed users to understand how representative they are of the general population of active Twitter users. This question is important to ascertain the practical utility of the insights about these users (as reported later in the paper), for policy-makers.

As stated in earlier sections, we attempted to detect the stance of a user during a certain time-period only if that user posted at least 3 tweets during that period. Thus the stance-changed users have posted at least 3 tweets each in two different time periods. Hence, we compare these users with the population of active Twitter users who posted at least 6 tweets related to vaccines in the entire time period of analysis (Jan 2018 – March 2021). In total, there are ‘340K’ such active users.

Figure 1 compares social network properties (number of
COVID period (2020): Anti-Vaxxers

U1 Thank you, @USER. You know your son. Seizures followed vaccination. Vaccine safety has not been proven. Cases like yours demand further investigation.

COVID period (2020): Pro-Vaxxers

My husband died after becoming ill with corona virus. I am glad a vaccine has been developed in record time. I intend to be vaccinated as soon as possible

U2 Having an autistic child destroyed my family. I took my healthy baby to the doctor that gave the vaccine that caused it.

Pre-COVID period (2018-19): Anti-Vaxxers

A vaccine eradicated smallpox. If the government was trying to kill us by way of a vaccine, we wouldn’t be living longer, and diseases would not be prevented

Pre-COVID period (2018-19): Pro-Vaxxers

Every child should be vaccinated I don’t understand why parents wouldn’t sad endangering others

COVID period (2020): Anti-Vaxxers

I will never take a vaccine for COVID. This whole fiasco w/masks & destroying our economy over a virus w/ 99% survival rates, is ridiculous.

COVID period (2020): Pro-Vaxxers

Honestly this administration caused so much sickness and death I will not trust a vaccine. #LyingTrump

COVID-vax period (2021): Anti-Vaxxers

Today has been a great day. My granddad has told he’s getting the Covid vaccine.

COVID-vax period (2021): Pro-Vaxxers

Pro-Vaxxers have had the vaccine and are doing quite well.

Pre-COVID period (2018-19): Anti-Vaxxers

I’m not paying Big Pharma for a vaccine against something that they invented in order to sell vaccines.

Pre-COVID period (2018-19): Pro-Vaxxers

I’ve had the first shot of the Pfizer vaccine. I’m a school bus driver. I’m in contact with kids daily and several times

Pro-COVID period (2020): Pro-Vaxxers

But even a vaccine won’t stop the spread, so we could see these levels for years.

Pro-COVID period (2020): Anti-Vaxxers

My children are still elderly drivers and I don’t want the vaccine.

Table 10: Samples of tweets (excerpts) from some of the stance-changed users (U1-U8). Each row shows two tweets posted by the same user during two different time periods. We do not state any usernames/identifiers to protect the privacy of the users.

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>U1 Thank you, @USER. You know your son. Seizures followed vaccination. Vaccine safety has not been proven. Cases like yours demand further investigation.</td>
<td>My husband died after becoming ill with corona virus. I am glad a vaccine has been developed in record time. I intend to be vaccinated as soon as possible</td>
</tr>
<tr>
<td>U2 Having an autistic child destroyed my family. I took my healthy baby to the doctor that gave the vaccine that caused it.</td>
<td>@USER Thank you for getting us vaccines in Illinois. As a frontline healthcare worker I thank you.</td>
</tr>
</tbody>
</table>

Next, we compare the tweeting behavior of the two user-groups; Figure 1c and 1d respectively compare the distributions of the fraction of Anti-Vax tweets and fraction of Pro-Vax tweets posted by an individual user (in the entire time period of analysis) in the two user-groups. We see that a large portion of the active user population (37%) did not post any Anti-Vax tweet at all (Figure 1c), while about 12% of the active user population did not post any Pro-Vax tweet at all (Figure 1d); also, only a small fraction of the active users post a large fraction of Anti-Vax tweets. In sharp contrast, the stance-changed users post higher fractions of Anti-vax as well as higher fractions of Pro-vax tweets, compared to the general active Twitter population interested in vaccines (who post a lot more neutral tweets on vaccines).

Thus, the stance-changed users are representative enough of the active Twitter population interested in vaccines in terms of social network properties, but they express their opinions (both Anti-vax and Pro-vax) much more than the general active Twitter population who post about vaccines.

Table 11: Samples of tweets (excerpts) from some of the stance-changed users (U1-U8). Each row shows two tweets posted by the same user during two different time periods. We do not state any usernames/identifiers to protect the privacy of the users.

<table>
<thead>
<tr>
<th>Against a Vaccine</th>
<th>Supporting a vaccine</th>
</tr>
</thead>
<tbody>
<tr>
<td>U1 declining Pfizer vaccine seeing peoples side effects</td>
<td>I’m more likely to trust the Oxford one</td>
</tr>
<tr>
<td>U2 I have concerns about the efficacy of the Astrazeneca vaccine</td>
<td>There’s a shortage of Pfizer vaccines and the Moderna one won’t be out till March</td>
</tr>
<tr>
<td>U3 I don’t want the Pfizer vaccine. Let them have it.</td>
<td>PLEASE use the Moderna vaccine, not the Pfizer</td>
</tr>
<tr>
<td>U4 Pfizer has not been tested, at all, at these intervals.</td>
<td>Oxford vaccine is demonstrating lower transmission.</td>
</tr>
</tbody>
</table>

Table 11: Samples of tweets (excerpts) from some of the stance-changed users (U1-U8). Each row shows two tweets posted by the same user during two different time periods. We do not state any usernames/identifiers to protect the privacy of the users.

Followers and followings) and the tweet composition behaviour of the two user-groups. Figures 1a and 1b show that the followers and followings distributions of the stance-changed users and the active users are very similar.

Figure 1: Comparison of stance-changed users with the general active Twitter population interested in vaccines, in terms of (a) number of followers, (b) number of followings, (c) % of Anti-vax tweets posted, and (d) % of Pro-vax tweets posted.
Characterizing Stance-Changed Users

Now, we analyze the stance-changed users to understand what anti-vax topics they used to discuss before/after their stance change. To this end, we select four groups of stance-changed users – (G1) all the 21 users who changed from Anti-Vaxxer in pre-COVID period to Pro-Vaxxer in COVID period, (G2) 50 randomly selected users from those who changed from Anti-Vaxxer in COVID period to Pro-Vaxxer in the COVID-vax period, (G3) 50 random users from those who changed from Pro-Vaxxer to Anti-Vaxxer between the pre-COVID and COVID periods, and (G4) 50 random users who changed from Pro-Vaxxer in COVID period to Pro-Vaxxer in COVID-vax period. Two authors manually examined the vaccine-related tweets posted by these users from the time period when they were Anti-Vaxxers, to identify which anti-vax topics (from Table 7) they posted about.

Figure 2 compares these groups of users – the anti-vax topics are shown on the X-axis while the fraction of users from each group who posted tweets corresponding to the topics is shown on the Y-axis. Note that we did not see any tweet about deeper conspiracy theories (Topic 8 in Table 7) from any of these groups. Since all these users were/became Pro-Vaxxers at some point, it is likely that they were not staunch Anti-Vaxxers, and conspiracy theories may be an opinion prevalent among staunch Anti-Vaxxers only.

Users who shifted from Anti- to Pro-Vaxxers: We observe an interesting difference in the anti-vax opinions of the two groups of users who changed from Anti- to Pro-Vaxxers (G1 and G2). Most of the users in G1 – who were Anti-Vaxxers in pre-COVID period (2018-19) – opposed vaccines because of the health concerns, mostly in regards to their children being harmed. A fair number among them also were against mandatory vaccination, and against how the Big Pharma are trying to sell vaccines with side effects. However, the users in G1 did not post much about the vaccine development being rushed/untested or the role of politics. On the contrary, users in G2 – Anti-Vaxxers in COVID period (2020) but supporting COVID-19 vaccines (in 2021) – seem to care a lot more about the political nature of the vaccines, the potential ineffectiveness of the vaccines against COVID, and that the vaccine development process was rushed.

Users who shifted from Pro- to Anti-Vaxxers: For the users in G3 – who became Anti-Vaxxers in the COVID period – the main concerns seem to be about the potential side-effects of vaccines (health concerns), and that the big pharma and politicians are exploiting the crisis to their advantage. Their other concerns are about vaccines being rushed into distribution, and that the vaccines would not be effective against the disease. On the other hand, among the users in G4 – who shifted from Pro-vaxxer in 2020 to Anti-Vaxxers in the COVID-vax period – most blamed the governments (more than the big pharma), stating that they will not take vaccines offered by specific governments and political leaders. When vaccinations actually started, these users started to tweet more against mandatory vaccination, and the ineffectiveness of the vaccines amidst rising mutations of the corona-virus. Health concerns about vaccines remains a common theme between both user-groups.

Users who were Anti-Vaxxers in 2020 but Pro-Vaxxers in other time periods: Finally, we compare the two groups G2 and G3 – both these groups were Anti-vaxxers in 2020; however, users in G2 became Pro-vaxxers in 2021, whereas users in G3 were Pro-vaxxers in 2018-19. Users in G3 tweeted more in 2020 about Health concerns and the Political side of vaccines, than the users in G2. In contrast, the users in G2 tweeted (in 2020) more about vaccines being Ineffective and Rushed. These observations signify that even though both groups had the same stance (Anti-Vax) in the COVID period (2020), their concerns were different.

Exploring Correlation of Users’ Stance with Stance of their Neighbours

We explore if the social network has an effect of the changing stance of users. In particular we analyse the influence (if any) of the people whom a user is following at various points of time, on the changing stance of the said user.

Method: Currently, it is not possible on Twitter to know the creation date for social links, or to collect the list of followings of a user (also known as friends of the user) on a past date. Hence, we adopt the following method. For a particular user $u$, we collect all the current followings of $u$. Then we check the tweets posted by each of these followings during a particular time period (e.g., 2018-19, or 2020, or 2021). We compute what fraction of $u$’s followings were Pro-Vaxxers and Anti-Vaxxers during each of the three time periods, based on the vaccine-related tweets that they (the followings) posted in the respective time periods.

Thus, for user $u$, we first compute the fractions of Anti-Vaxxer and Pro-Vaxxer followings of $u$ during a particular time period. Then we see how the fractions of Anti-Vaxxer and Pro-Vaxxer followings of $u$ have changed from one time period to another (e.g., from 2018-19 to 2020, or from 2020 to 2021). Finally, we average this change in fractions of Anti-Vaxxer and Pro-Vaxxer followings of a user, over all users in a group (e.g., the groups G1, G2, G3, G4 introduced in the previous section).

Observations: Table 12 shows these changes. For instance, across all the users in G1 (who changed from Anti-Vaxxer in
2018–19 to Pro-Vaxxer in 2020), the fraction of Pro-Vaxxers in their followings increased in 2020 to 1.06 times the fraction in 2018–19, whereas the fraction of Anti-Vaxxer followings increased to 1.94 times over the same time period. Below each number, we have also added the 95% confidence intervals (within parentheses) to demonstrate that the reported numbers are meaningful, and not skewed because of a few particular users. The first notable observation from Table 12 is that only a few of the changes are close to 1.0. This implies that, for the stance-changed users, the amount of Anti-Vaxxers and Pro-Vaxxers among their followings changed by quite a margin across different time periods.

In most cases, we also see correlation between the change of stance of the users with the change in the fraction of followings of the corresponding stance. Even though the overall number of Anti-Vaxxers increased in 2020, and Pro-Vaxxers in 2021 (as was seen in previous sections), we see a difference in the amount of increase in the fractions between the different user groups. For example, among the users in G3 (who shifted from Pro-Vax in 2018–19 to Anti-Vax in 2020), the fraction of Anti-Vaxxers in their followings increased by 4.43 times in 2020. In contrast, for the users in G1 (who shifted from Anti-Vax in 2018–19 to Pro-Vax in 2020), the increase of Anti-Vaxxers in their followings was only 1.94 times. Similarly, for the users in G4 (who changed from Pro-Vax in 2020 to Anti-Vax in 2021) and vice versa (G2), the increase in Pro-Vaxxers in the followings (from 2020 to 2021) was 1.49 times and 2.25 times respectively. The most interesting observation is for those users who changed their stance from Pro-Vaxxers to Anti-Vaxxers and again back to Pro-Vaxxers – there is an increase of 1.94 times in the fraction of Anti-Vaxxers among their followings between the pre-COVID and COVID periods, whereas the fraction of Pro-Vaxxers among their followings increased by 2.17 times between the COVID and COVID-vax periods.

We also analysed the users who were Pro-Vaxxers or Anti-Vaxxers throughout the three time periods (details omitted for brevity). Even though the amount of Pro-Vaxxers and Anti-Vaxxers in their followings change over the time periods, the fraction of followings with the same stance as the user hugely surpasses the fraction of followings with the opposing stance throughout all time periods. For the users who are Pro-Vaxxers throughout, the fraction of Pro-Vaxxer followings was 80 times that of the fraction of Anti-Vaxxer followings at minimum (COVID period), and 230 times at maximum (pre-COVID period). Similarly, for the users who are Anti-Vaxxers throughout, the fraction of Anti-Vaxxer followings was 4 times the fraction of Pro-Vaxxer followings at minimum (pre-COVID period) and 7 times at maximum (COVID period).

Even though the overall number of users posting about vaccines may have increased during COVID times, the important point to note is that in most cases, there is a much greater increase in the fraction of followings with the same stance as the user, than the increase in followings with the opposite stance. Thus, the vaccine-stance of a user seems to be correlated with the vaccine-stance of his/her social neighborhood. Also, our findings hint that users who change their vaccine-stances have a non-homogeneous neighborhood across pre-COVID and COVID times.

### Table 12: Studying the change of stance among the followings of the stance-changed users – shown (in bold) are the changes in the number of anti-vax and pro-vax followings between different time periods, averaged over all users in a particular group.

<table>
<thead>
<tr>
<th>User-groups who changed their stance</th>
<th>Change from 2018-19 to 2020 in</th>
<th>Change from 2020 to 2021 in</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Pro-followings</td>
<td>#Anti-followings</td>
<td>#Pro-followings</td>
</tr>
<tr>
<td>G1: Anti (2018-19) to Pro (2020)</td>
<td>1.06× (0.82, 1.29) (1.46×)</td>
<td>1.94× (1.03, 2.85)</td>
</tr>
<tr>
<td>G3: Pro (2018-19) to Anti (2020)</td>
<td>1.04× (0.88, 1.20) (0.60×)</td>
<td>4.43× (3.60, 5.27)</td>
</tr>
<tr>
<td>G2: Anti (2020) to Pro (2021)</td>
<td>1.34× (1.20, 1.48) (1.77×)</td>
<td>4.38× (3.43, 5.34)</td>
</tr>
<tr>
<td>G4: Pro (2020) to Anti (2021)</td>
<td>1.38× (1.19, 1.56) (0.75×)</td>
<td>5.89× (4.01, 7.78)</td>
</tr>
<tr>
<td>Pro (2018-19) to Anti (2020) to Pro (2021)</td>
<td>0.72× (0.56, 0.87) (0.47×)</td>
<td>1.94× (1.16, 2.73)</td>
</tr>
</tbody>
</table>

### Conclusion

This work presents a first attempt to systematically analyse how a global event (the COVID-19 pandemic) has changed the vaccine-related stances/opinions of people from pre-COVID to COVID times. Our findings also hint at how the stance-change of a user can be correlated with factors such as major events in his/her life (e.g., death of a close relative) or changes in his/her social neighborhood.

**Implications of the work:** We believe that the present work is useful to the authorities in their quest to ensure large-scale adoption of vaccines, by educating and disseminating specific information to specific people in the society. Essentially, we provide a framework to use social media data to automatically detect the vaccine-stance of users at scale, and understand the primary vaccine-related concerns (if any) of users in different time periods. This framework can help the authorities in the following ways –

(i) **Devising targeted approaches to alleviate people’s vaccine-related concerns:** A policy maker cannot educate people unless they know the reasons/concerns behind their vaccine-related stance. We have seen that the anti-vax concerns are very different, from deep-rooted (e.g., vaccines kill people) to contextual (e.g., concerns regarding COVID-19 vaccines being ineffective and rushed). So, the policy makers need a targeted approach to educate people having different types of concerns.

(ii) **Identifying and reaching out to people who changed their stances:** We showed there is a population who have changed their vaccine-stances. The authorities can identify the people who can potentially move over from anti-vax to...
pro-vax, and better nudge those people towards vaccination. Perhaps, the experiences of some of the users who changed from Anti-vaxxer to Pro-vaxxer, can be used to nudge others in the Anti-vaxxer community towards vaccination. Also, the authorities can investigate why some originally pro-vax users have become hesitant to take COVID-19 vaccines, and which specific concerns need to be clarified for them.

(iii) **Utilizing social media for nudging people towards vaccination:** We found that the social connections can potentially influence the stance of users, which suggests the importance of using popular social media users in promoting more Pro-Vax information. However, the information needs to be carefully designed in accordance to the primary concerns of different target user groups, without which they might just be mistaken as propaganda. Also, policy makers can design targeted friend/content recommendation algorithms to break into today’s Anti-vax echo chambers with pro-vax opinions.

**Future work:** We only explored the effects of the stances of a user’s followings on the stance change of the user. Other forms of interactions such as retweeted or replied to/by can also have an effect on the stance change of users, and can be explored as a future work. Another future work would be to design predictive models that attempt to predict which users are likely to change their stance, e.g., from a user’s posts and the stances of the followings of a user.

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