A revised behavioral analysis of the late 2020 anti-vaccination infodemic on Twitter

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Abstract

Vaccinations are without doubt one of the greatest achievements of modern medicine, and there is hope that they can constitute a solution to halt the ongoing COVID-19 pandemic. However, the anti-vaccination movement is currently on the rise, spreading online misinformation about vaccine safety and causing a worrying reduction in vaccination rates worldwide. In this historical time, it is imperative to understand the reasons of vaccine hesitancy, and to find effective strategies to dismantle the rhetoric of anti-vaccination supporters. For this reason, between September and November 2020, we analyzed the behavior of anti-vaccination supporters on Twitter. In this paper we identify that anti-vaccination supporters, in comparison with pro-vaccination supporters, share conspiracy theories and make use of emotional language. We show that anti-vaccination supporters are more engaged in discussions on Twitter and share their contents from a pull of strong influencers. We show that the movement's success relies on a strong sense of community, based on the contents produced by a small fraction of profiles, with the community at large serving as a sounding board for anti-vaccination discourse to circulate online. Our data also show that Donald Trump, before his profile was suspended on January 8, 2021, and during the time of our analysis, had been the main influencer in the anti-vaccine community on Twitter. Based on our results, we welcome policies that aim at halting the circulation of false information about vaccines by targeting the anti-vaccination community on Twitter. We also propose solutions to improve the communication strategy of health organizations and build a community of engaged influencers that support the dissemination of scientific insights, including issues related to vaccines and their safety.

An important disclaimer

In order for readers to understand the research presented below, a brief history of this paper is necessary. We first published the paper as a preprint in MedRxiv on December 8, 2020 [1]. The paper was then submitted to PLOS ONE on December 8, 2020. It was sent for revision on February 2, 2021, and formally accepted, after being peer reviewed by two independent reviewers, on February 15, 2021; a minor revision was requested. It was published online on March 3, 2021 [2]. On June 17, 2022, we received a notice by email from a staff editor at PLOS ONE, stating that “some concerns have been raised […] with respect to some clarity in the reporting and methodology”. Although all the editorial concerns were addressed, the editors decided to retract the paper on October 4, 2022, stating that “retraction is warranted due to concerns about the robustness of the experiments and analyses described in this study, as well as the conclusions presented in the article. […] the article does not adhere to the journal’s publication criteria #3 and #4.” This decision was followed by an appeal by the authors, which was rejected following an independent subject expert review, and a final editorial decision to retract the paper on November 18, 2022. The retraction notice, which contains a few technical comments from the editors of PLOS ONE and the authors, can be found here [3]. In the supplementary materials of this paper, we provide a detailed technical overview of the methodological concerns raised by the editors, with an explanation of our take on such issues, and why we stand by our methodological approach and findings. As we are quite concerned by how the retraction process was conducted and what it may mean for academic freedom, and since we still consider our work valid, we are taking this opportunity to publish a revised, post-retraction version of our paper, to establish a transparent discussion about the results of our paper, and about the handling of the retraction process by PLOS ONE. This version of the manuscript takes into consideration the feedback from the editors, the independent review expert recruited by PLOS ONE during the retraction process, as well as colleagues and friends; and the lessons learned in the two years passed between the analysis of the data, the publication, and the publication of this revised version of the paper. It is important to note that our results and discussion were originally published on March 3, 2021, and thus are to be judged and evaluated considering the specific timeframe in which the analysis was conducted and the results published. Time proved most of our considerations to be correct; our paper, at the time of writing, has been cited 216 times [4], and several papers support our findings; for example, Saini et al. find that anti-vaccine tweets are, on average retweeted more than pro-vaccine tweets [5]; Schlette et al., in line with our results, report that, in the Dutch anti-vaccine community, a minority of users posted the majority of the contents [6]. Bozkurt et al. confirm that people believing in conspiracy theories are more likely to support anti-vaccine views [7]. Walter et al. showed that pro-Trump Twitter personas created by the Russian Internet Research Agency were more likely to express anti-vaccine positions [8]. Stoler et al., [9] based on the vaccination gap between Republican and Democratic states shown by Kates and Tolbert [10], suggest that right-wing media and opinion leaders shape vaccine views. In addition, states that received more votes for Trump when compared with Biden during the last presidential elections had higher levels of vaccine hesitancy [11], and [11] further provides plenty of evidence-based arguments and references to support the idea that Trump "might cause greater vaccine hesitancy among followers". Stoler et al. also show that positive feelings for Trump were associated with being unvaccinated, and higher approvals for Trump were associated to COVID-19 vaccine hesitancy [9]. In line with our results, a systematic review suggests that anti-vaccination communities on Twitter were previously described as better connected when compared with pro-vaccination communities, and that most discussion about vaccines on Twitter during 2019 were from anti-vaccine supporters [12]. A study analyzing French tweets identified a similar structure of the anti-vaccination community to ours, with the rightwing community constituting the echo chamber for anti-vaccine tweets, with, in comparison, a smaller left-wing community which is less susceptible to anti-vaccine contents [13]. Indirectly proving the association between Trump's supporters and anti-vaccination attitudes on Twitter, a study showed that Twitter's suspensions and moderations after the attack to the US capitol on January 6, 2021 – shortly after our analysis was concluded, lead to a global reduction of misinformation about vaccines on Twitter [14]. In their analysis, in line with Saini et al. [5], also Lenti et al. further confirm our findings concerning the number of retweets, which are higher for anti-vaccine supporters when compared with other communities [14].

It is important to note that during this time, between the publication of the original manuscript and the publication of this revised version of the paper, we learned how important public willingness to get vaccinated is for global health. For this reason, and despite the retraction, we think that our paper is still relevant, as it sheds light onto the dynamics for which political beliefs can dangerously interact and intersect with public health and global health agendas; further, it describes the role of social media and political actors in this process, providing important lessons for the time ahead. In this context, we believe that changing our conclusions and considerations, with 2 years of delay, would not do a good service to science: past interpretations, regardless of whether time proves them right or wrong, should be considered as relevant themselves – constituting further material for research, allowing for retrospective analyses and a better comprehension of past and present events. Thus, this version of the manuscript is a revised version of a paper, which has been written in late 2020, and published in early 2021. And therefore, it should be read as a paper published in early 2021, not in early 2023.

A final note is about Trump, and his role in the anti-vaccination community – as this may have been the primary motive for the retraction of our paper in PLOS ONE. In the version published in PLOS ONE we stated in the abstract (but not in the conclusions, where we precisely described Trump's role) that "Trump, before his profile was suspended, was the main *driver* of vaccine misinformation on Twitter." Our data showed, instead, that Trump was the main *influencer* in the anti-vaccine community. We regret that this formulation was not discussed with the editors at PLOS ONE, or with the peer reviewers, highlighting that this imprecision in the language could have easily been corrected, without the need to retract the article. In this version of the manuscript we rectified the terminology. To ensure clarity, we refer to "influencer" as defined by Oxford Languages – i.e., "a person […] that influences another" or, in marketing terms, "a person ***with the ability to influence*** potential buyers of a product or service" [15]. For Cambridge Dictionary, "a person or group that ***has the ability to influence*** the behavior or opinions of others", meaning he or she has the *potential* to influence others [16].

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Introduction

Vaccinations are a great medical achievement of the last century, given their fundamental contribution to lowering the presence of otherwise widespread diseases in the population and thus in greatly reducing mortality. Despite the available evidence and the scientific consensus on the necessity and the safety of vaccines, an anti-vaccination movement has been growing over the past decades [1], with a consequent decline in vaccination rates and the possible resurgence of diseases such as measles [2]. This movement, which has gained momentum after the infamous publication of Andrew Wakefield's study linking vaccines to autism in 1998 [3], has been lately growing its strength, taking advantage of social media as communication channels [4, 5]. In a postmodern world in which medical expertise is being questioned [6, 7], the growing grip of the anti-vaccination movement on the general public is of great concern, especially amidst a global pandemic that could be solved by the development of safe and effective vaccines. Therefore, while we navigate through the COVID-19 pandemic and the concomitant infodemic, the importance of presenting proper information concerning vaccines to the public is of utmost importance.

In order to tackle the vaccination issue, the causes of the success of the anti-vaccination movements need to be carefully analyzed. It has been shown that vaccination choice is influenced by the belief in alternative medicine, the belief in conspiracy theories, by morality, religion and personal ideology, the emotional appeal or the lack of trust in authorities [8], as well as by the readability and engagement of pro- versus anti-vaccination articles [9]. Most studies primarily focus on two aspects, the psychological attitude connected to vaccination choice [10-12] and the role of the Internet and in particular social media [8, 13-18]. In fact, anti-vaccination supporters find fertile ground on Facebook and Twitter [17, 19, 20], as these platforms offer a digital space for people to share any kind of content, including science-related or medically sensitive contents, which have the potential to reach a vast audience. Studies have particularly focused on the relevance of the Internet and social media in shaping personal or parental choice about vaccination [13, 14, 17]. For instance, parents who decide not to vaccinate their children tend to shape their opinions after having been in contact with online information on the topic [21], and most individuals do not consider the credibility of the source of information [22-25]. In addition, anti-vaccination profiles and groups online have been shown to generate content that is based on personal experiences and opinions, whereas pro-vaccination groups and institutions have the tendency to quote experts and cite scientific literature when sharing their views online [9, 23]. Therefore, the adopted language, the frequency of use of social media, the type of content that is generated, and their emotional appeal, could all constitute factors that determine the success of the anti-vaccination movement online. Furthermore, a recent study suggested Twitter data could be a valid tool to measure beliefs among the general public concerning public health [26] and vaccine hesitancy [27]. Therefore, in order to identify strategies to decrease the spread of vaccine misinformation online and to identify potential communication strategies to be used by healthcare organizations and professionals, we decided to quantitatively analyze the online behavior of Twitter users, after having determined whether they support or contrast the use of vaccines.

A recent study has identified that former US President Donald Trump was likely to be the largest driver of the COVID-19 misinformation infodemic [28]. This is relevant for public health because fake news, of any kind, have been shown to have affected various democratic votes, including the 2016 US elections and Brexit [29-31], and for some politicians, social media and fake news, including those concerning vaccines, could therefore be instrumental to hold on power and determining the future course of our global society. Vaccination policies are not excluded from the aspects that can determine and shape electoral results, especially during a pandemic that could be solved with vaccines. In fact, both vaccine hesitancy and political populism are driven by the distrust in expertise and ideas of a bottom-up society [32], and political views play an important part in shaping vaccination choice [33].

Materials and Methods

Definition of pro-, anti-vaccination and control users

Profiles belonging to the pro-, anti-vaccination or control group were initially automatically identified for their use of hashtags associated with the respective groups, and then manually screened to ensure users truly expressed opinions in line with expectations for any given group. Control individuals were identified for their use of #control hashtags, which were selected via an online Random Word Generator tool (available at https://randomwordgenerator.com). Each control profile was selected with a different randomly generated word. Pro-vaccination individuals were identified for their use of the #vaccineswork hashtag, whereas anti-vaccination profiles were identified for their use of either the #vaccineskill or the

#vaccinesharm hashtag. These were chosen as they are the most widely used hashtags within the pro- and anti-vaccine communities.

Scoring the number of tweets, replies and retweets

We manually calculated the number of tweets, replies and retweets published in the previous 24 hours for all the 50 profiles we analysed in each group. This included the number of science-, vaccines-, conspiracy theory- and children-related tweets, as well as 'emotional' tweets. In order to determine the overall number of tweets, replies and retweets, we used the freely available tool online TweetStats (www.tweetstats.com). After feeding a Twitter username, the website returns the number of contents generated on average in a month since the profile was initially set up, as well as the percentage of replies and retweets. In order to calculate the normalized percentage of tweets concerning a given topic against the overall number of tweets, we divided the number of tweets concerning a topic of interest – which were generated in the 24 hours before the analysis – for the number of average tweets per day. This number generally fluctuates between 0% (no contents of the analysed topic) and 100% (all contents are associated to a given topic). However, this percentage can occasionally exceed 100% due to fluctuations between the number of tweets published on average in a day and the actual number of tweets published in the 24 hours prior to analysis.

Statistical analysis

Ordinary one-way ANOVA with Tukey's multiple comparison test was used to compare the number of contents, tweets, replies and retweets between the different groups, as well as the differences between the number of retweets per tweet, the number of conspiracy theories-associated contents, the number of emotional tweets or children-related tweets, the total engagement per day, the average engagement per tweet and the number of followers. The statistical analysis was preceded by the elimination of behavioural outliers (excluded with ROUT, Q=0.1%). Behavioural outliers predominantly included profiles sharing a vast number of contents per day. They were excluded for two reasons: a) because their online behaviour is greatly different when compared with the rest of the users within the same group (e.g., much greater number of tweets per day), they could be bots; b) or they could be real users with behaviours which are not representative of a wider population. The Chi-square test was used to determine differences in users' behavioural patterns and in particular to determine whether users belonging to different groups would be more or less prone to disclose personal information (name, surname and personal picture), their education or profession status. In general, 50 profiles were analysed for each individual group and experimental analysis, unless differently specified. Each individual tweet was retrieved using the aforementioned hashtags through the Twitter search function, was assessed, and categorized. A manual analysis has been preferred to automated analyses since it was important to ensure each tweet we analysed was in fact containing, for example, anti-vaccine discourse, or pro-vaccine communication, content concerning vaccines, or conspiracy theories; at the time of the analysis and to our knowledge, no automated algorithm can perform these tasks efficiently and better than humans.

Language analysis

Using TweetStats, we retrieved the 5 most used words on Twitter for each individual profile belonging to each group (n=42) and compiled a list of the most used words for each group. We assigned a value to each word, depending on how often it was observed to be among the top 5 words used by a profile. For instance, a score of 42 indicates that 100% of analysed profiles included the word of interest among the 5 most used words on Twitter, whereas 0 indicates that none of the profiles used that particular word often enough. We performed two normalization analyses: The first compared the most used words in the pro- and anti-vaccination groups with words predominantly used by control profiles, and the second compared the most used words in the pro- versus anti-vaccination group. For example, a value of 18 indicates that a particular word has been used 18-times more in one group when compared with another one (such as the word "vaccines in the anti-vaccination group, when compared with the control). If a word was not used in a given group, we arbitrarily doubled the number of times the word was used in the comparison group. In the analysis, we used lemmas – i.e., words were clustered for plurals or variations of the same word with identical meaning. For example, the word "vaccine" and "vaccines" were considered as one lemma ("vaccine"), as well as the words "Dr", "Doctor" and "Doctors". Words were further clustered per topic. For instance, the category "politics" included words such as "Trump", "Democrats", "Conservative" or "elections"; similarly, the cluster "phrasal" included "Don't", "I'm", "We", etc. As before, we determined whether this clusters are over- or under-represented among different groups by performing a comparison between the most used clusters in one group versus another group.

Engagement

Engagement was calculated as the sum of likes, comments and retweets. The average engagement was determined by dividing the total engagement for the total amount of tweets published in a given time.

Network generation and analysis

In order to generate pro- and anti-vaccination networks, we considered n=42 profiles for our analysis. For each of these profiles, assigned to one of the two groups, we used TweetStats to retrieve the profiles of the 10 most retweeted users. This allowed us to identify a larger number of individuals, directly or indirectly involved in the anti-vaccination community. Our analysis considered profiles regardless of their personal position in the vaccination debate. We generated the networks with Cytoscape and retrieved the average number of neighbours, the clustering coefficient, the density of the network and the characteristic path length from the Cytoscape Analyzer Tool. In order to optimize the graphical representation of the webs, we removed clusters of individual profiles that were not connected with other clusters. We further highlighted in yellow those profiles with a number of edges (connections with other profiles) between 2 and 4, in orange those with a number of edges between 5 and 9, and in red those with 10 or more edges. The size of the node (profile) in the web was also linearly scaled depending on the number of connections. Finally, we analysed the 10 most retweeted profiles for each profile with more than 5 edges and included them in our analysis.

Education and personal information

In order to define whether a profile was trackable, and ascribable to a real person, we scored the number of individuals publicly declaring their name, surname and utilizing a profile picture of a seemingly real person (n=42 for each group). We defined a profile as trackable when all these criteria were met, and not trackable when at least one of the above-mentioned criteria was not met. "Not defined" (nd) was assigned when the judgment could not be made, for instance when profiles represented institutions without a verification badge. Further, we scored whether profiles indicated either their education or profession status in their Twitter headline. "Yes" indicates that the profile declares either their education or profession publicly, whereas "No" indicates that neither of the two is indicated, and "nd" is assigned when the judgement could not be made. For instance, when profiles represented institutions without a verification badge.

Results

Anti-vaccination supporters tweet less, but engage more in discussion

In order to understand whether the success of the anti-vaccination discourse is due to a particularly pronounced activity of anti-vaccination supporters online, between September and November 2020, we measured the number of Twitter actions on average in a month for each profile belonging to the control, anti-vaccination and pro-vaccination group (Fig 1A). Control profiles were selected for the use of randomly chosen hashtags (#control). Anti-vaccination users were identified by their use of the #vaccineskill and #vaccinesharm hashtags, which are widely used by the community. Finally, pro-vaccination communicators were identified by their use of the #vaccineswork hashtag (S1 Fig). We defined Twitter actions as the sum of tweets, replies, and retweets in a given month (Fig 1B). As expected, anti-vaccination profiles were the most active on Twitter, with 536 actions per month, compared with an average of 277 actions for the control group and only 144 actions for the pro-vaccination group (Fig 1C), suggesting the latter is not engaged enough, and highlighting a first pitfall in the pro-vaccine communication strategy online. However, once we calculated the number of tweets per month, we were surprised to learn that anti-vaccination supporters were those tweeting the least (42 tweets per month), when compared with control and pro-vaccination profiles (123 and 93 tweets per month, respectively) (Fig 1D). This was largely compensated by the engagement of the anti-vaccination group in discussions, be it through replies or retweets. Anti-vaccination profiles replied 13 times more than control and pro-vaccination profiles (Fig 1E), retweeted 7.4 times more than their pro-vaccination counterparts, and 31.3 times more than control profiles (Fig 1F). As already pointed out by these data, the anti-vaccination group scored the highest number of retweets per Tweet (S2 Fig), highlighting that most anti-vaccination supporters in our study act as an echo chamber for the pool of content generated by a small fraction of users. Behavioral outliers, which were excluded with 0.1% confidence interval (ROUT, Q=0.1%), suggest that a small fraction of users belonging to this group are producing most of the content, which is then shared by the community at large. Data also suggest that pro-vaccination individuals and groups are more prone to generate new content and are not very engaged with a broader community with similar interests.

Anti-vaccination support on Twitter is associated with a general belief in conspiracy theories and emotional behaviors

As we have seen, our data suggest that the anti-vaccination community constitutes an echo chamber for misinformed views about vaccines generated by a smaller number of profiles. In order to understand whether these dynamics are established by factors previously associated with vaccine hesitancy [8, 9, 23], we quantified the number of conspiracy theory (CT)-associated contents (tweets and retweets), as well as the number of emotional contents (either depicting emotional situations or adopting emotional language) shared by control, anti-vaccination and pro-vaccination profiles. Furthermore, we calculated how dedicated the different groups were to share scientific and vaccines-related contents. We found that both pro- and anti-vaccination profiles shared a larger number of science- and vaccines-related contents when compared with control profiles (for scientific content: 2.5, 3.4 and 0 per month, respectively; for vaccines-related content: 1.2; 1.5 and 0 per month, respectively) (Fig 2A, B). Normalization of the aforementioned data for the total number of contents on any given topic indicates that the pro-vaccination group was the most interested in science and vaccines, when compared with anti-vaccination and control groups (Fig 2A', B'). Additionally, the anti-vaccination group was the only one circulating conspiracy theories (with an average of 2 contents per month). (Fig 2C, C'). Most conspiracy theory-related tweets were associated with fake news concerning ruling elites, masonries, and techniques of population control – often associated to public figures such as Bill Gates or to the ongoing COVID-19 pandemic –, flat Earth ideology or pedophilia scandals such as 'pizzagate', but also more bizarre ones. The anti-vaccination group shared a larger number of emotional contents per month (and/or content with emotional language) when compared with the pro-vaccination group and control group (1.5, 0.4 and 0 per month, respectively) (Fig 2D). The normalization of these data for the total number of contents on any given topic shows that anti-vaccination supporters adopted emotional language and/or published content containing emotional information in 25% of the cases, whereas the pro-vaccination group in only 0.3% of the cases (Fig 2D'). In line with what was previously reported [24, 38], this suggests that the emotional sphere, which is also connected to the belief in conspiracy theories, is a predominant character of individuals supportive of the anti-vaccination movement. In order to understand whether anti-vaccination contents are associated with conspiracy theories, we calculated the normalized number of vaccines-related contents and correlated it with the number of CT-related contents. As a positive control, we calculated whether the normalized number of science-related contents is correlated with the number of vaccines-related contents published by profiles associated with either the anti- or pro-vaccination groups. As expected, being vaccines-related contents considerable as scientific contents themselves, in both cases there was a clear correlation between the aforementioned factors (R^2=0.4654; p<0.0001**** and R^2=0.5924; p<0.0001****, respectively) (S3 Fig). For the anti-vaccine group, there was a strong and significant correlation between the number of published contents against the use of vaccination and the number of published contents concerning conspiracy theories (R^2=0.7479; p<0.00001****) (S4 Fig. A), suggesting that anti-vaccination support can be seen as a part of a bigger problem connected to beliefs in unsubstantiated claims. As pro-vaccine supporters did not share conspiracy theories on Twitter, there was no correlation between these contents and vaccines-related contents (S4 Fig. A'). While performing the analysis, we further realized that a large portion of anti-vaccination profiles were sharing contents associated to children, not necessarily in relations to vaccination. For this reason, we decided to quantify the number of children-related content produced in the three groups. In comparison to the control, both anti- and pro-vaccination groups shared a higher number of contents associated with children (control: 0; anti-vaccine: 1.2; pro-vaccine: 0.6 contents per month. 0%, 5.7% and 7.3% of the contents concern children, respectively) (S5 Fig). However, we noticed a substantial difference in the communication strategy and topics associated with children in the pro- and anti-vaccination groups. Pro-vaccination supporters generally shared contents depicting happy children after having received a shot, whereas anti-vaccination supporters often shared disturbing images of suffering children, or citations of discredited or non-existing physicians about the dangers of vaccines for children. Further, children-related content in this group is also associated with other conspiracy theories about pedophilia scandals, or more generally about sexual and psychological abuses of children.

Emotional language could aid the success of vaccination campaigns

As we previously described, anti-vaccination supporters share emotional contents with the use of emotional language. In order to understand whether this language is necessary for the success of the movement, we decided to perform an analysis of the most used words by the three different groups. We considered the 5 most used words for each individual profile and calculated the most used words for each individual group. Following normalization against the words predominantly used by control profiles, we identified a list of 10 words strongly associated with anti- and pro-vaccination groups (Fig 3A, A'). As expected, the lemma "vaccine" was the most represented in both groups, confirming that our initial criteria for inclusion were reasonable. To further highlight the differences between the two groups, we normalized the most used words in the two groups against each other (Fig 3B). Here we found that the most relevant words in the anti-Vaccination group were "President", "God", "People", and "Masks". In contrast, pro-vaccination profiles preferentially included words such as "Help", "Health", "Thanks" or "Research". In order to better determine the interests of the different groups, we clustered words according to topics, and found that anti-vaccination profiles were the most engaged in political discussion, with nearly a 6-fold increase compared with the pro-vaccination group (Fig 3C). Finally, we analyzed whether the use of emotional contents and language was associated with increased engagement, measured as the sum of likes, replies and retweets on each individual tweet, but found no significant correlation between the two factors for the anti-vaccination group (Fig 3D). On the contrary, the pro-vaccine group showed a significant correlation between the two aforementioned factors (Fig 3D'), suggesting that the use of emotional language could aid the success of the pro-vaccination communication strategy online.

Pro-vaccination supporters are more interested in their own education and profession

Previous studies showed that education might increase confidence in vaccine importance and effectiveness [34]. However, different studies reached different conclusions on whether education plays a role in shaping vaccination choice [35, 36]. We therefore decided to quantify the number of profiles associated with the three groups that declared their education or profession status. This analysis does not determine whether education plays a factor in shaping vaccination choice. However, it determines whether holding a position in the vaccination debate is associated with a self-perceived relevance of education. To determine whether the source of information is of relevance in this context, we scored the number of profiles publicly declaring their name and surname, together with a seemingly real profile picture. Here we show that the great majority of pro-vaccine profiles declared their identity when compared with the control (64% vs 30%, respectively), and that anti-vaccination supporters were particularly reluctant to do so (only 16%) (S6 Fig. A). Similarly, education and/or profession in the Twitter headline was declared 32% of the times in the pro-vaccination group, compared with 10% and 6% in the control and anti-vaccination group, respectively (S6 Fig. B).

The pro-vaccination group produces the most engaging contents

As we have discussed so far, our data suggest that the success of the anti-vaccination message is not determined by a larger production of original contents, and that the use of emotional language is a structural component of this group that does not influence engagement. Here we show that the pro-vaccination group produced the most engaging contents, whereas the anti-vaccination group produced the least engaging contents (Pro-vaccine: 15.2 engagement per tweet; control: 3.7; anti-vaccine: 0.8) (Fig 4A). The average engagement per tweet was 19.9 times higher in the pro-vaccination group when compared with the anti-vaccination group (and 5.5 times higher when compared with the control group) (Fig 4B). On average, pro-vaccination profiles were also those with a larger number of followers, when compared with control and anti-vaccination groups (mean: 1841; 605 and 338 followers, respectively) (Fig 4C). Here we show that contents published by the pro-vaccination group were more engaging than contents produced by most anti-vaccination profiles. In light of these results, we hypothesized that the success of the anti-vaccination movement is likely driven by a stronger sense of community, built around common interests (besides vaccines), and based on personal beliefs and emotional language. We therefore hypothesized the existence, in this community, of a pull of influencers producing the most engaging contents, with the vast majority of anti-vaccination profiles functioning as the recipient and echo chamber for these messages; whereas novel contents produced by most profiles in the anti-vaccination group receive little attention when compared with contents generated by an average pro-vaccination profile (illustrative scheme in Fig 4D).

Anti-vaccination supporters are engaged in a virtual community led by Donald Trump and other influencers

In order to determine whether the success of the anti-vaccination movement is due to the existence of a community of engaged individuals driven by a pull of influencers with large follows, we retrieved, for each individual profile of both the anti- and pro-vaccination group (n=42 each), the 10 most retweeted profiles, and included them in our analysis. We scored the number of connections (edges; E) they established with each other by building a Twitter web with Cytoscape [37]. We further retrieved the 10 most retweeted profiles for influencers with at least 5 connections to other profiles in our web and included these connections in our webs, as well. The pro-vaccination (Fig 5A) and anti-vaccination Twitter webs (Fig 5B), scaled 1:1, show the extent of the ramifications of the latter in comparison with the former (Fig 5A, B). The size of each node (profile) is scaled linearly depending on the number of edges. Color is also indicative of the number of edges, and thus of the relevance of the node in the web (no color: $E<2$; yellow: $2\leq E\leq 4$; orange: $5\leq E \leq 9$; red: $E \geq 10$). Close ups (not equally scaled, for better readability) show the most relevant sections of the pro- and anti-vaccination webs (Fig 5A', B'). The average number of neighbors in the web was 1.45-folds higher in the anti-vaccination web when compared with the pro-vaccination web (2.8 and 2 neighbors, respectively). The clustering coefficient was also higher in the anti-vaccination web (0.021 and 0.007, respectively), as well as the density of the network (0.005 vs 0.003, respectively) and the characteristic path length (1.6 vs 1.4, respectively) (Fig 5C). In addition, the pro-vaccination web had a similar number of nodes and edges, whereas the anti-vaccination web had a larger number of edges than nodes. Therefore, the number of edges per nodes, which indicates the number of existing connections for each individual profile in the web, was much larger in the anti-vaccination group when compared with the pro-vaccination group (1.51 vs 1.02 connections per profile, respectively) (S7 Fig), confirming that anti-vaccination supporters are well-connected in a community. With an $E\geq 5$ cut-off, we identified only one large influencer in the pro-vaccination web (the World Health Organization, E=5) (Fig 5D), whereas, according to the same criterium, we identified 14 large influencers, with the largest one being former US President Donald Trump (E=26), 5.2 times more relevant than the World Health Organization in the pro-vaccine web. Other influencers included Trump's family members, politicians and public figures known to support his presidency, as well as individuals and unverified popular profiles that are fully committed to the anti-vaccination cause (Fig 5E). Therefore, here we identified, starting from our sample of analyzed users, the pull of relevant influencers that are likely to determine the opinion about vaccine of many people. These influencers include Trump – who was himself an anti-vaccination supporter, and others, such as activist Charlie Kirk or vaccine-denier Eileen Iorio. The retrieved Twitter webs and associated communities of pro- and anti-vaccine users and influencers present snapshots taken at a given moment of time (the time of our analysis), which can be expected to change with changing opinion, circulating contents, and relevance of users within and outside of the community.

Figures

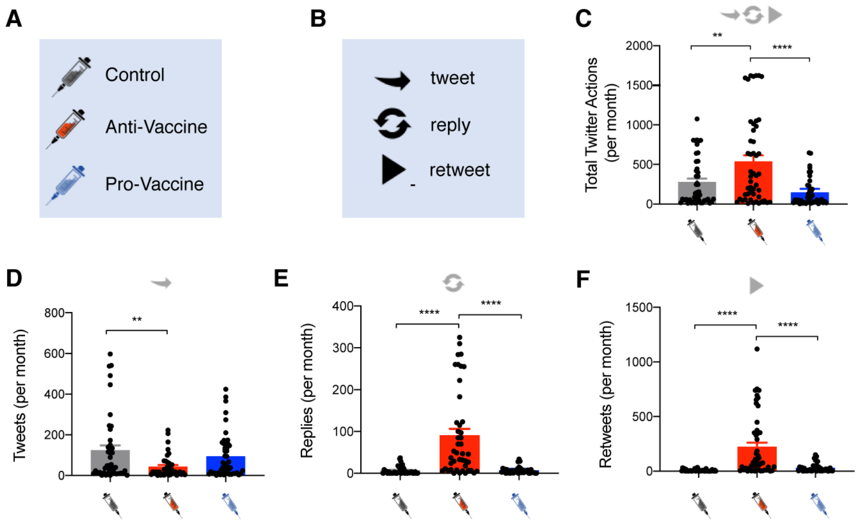

Figure 1. Anti-vaccination supporters are more engaged on Twitter. We analyzed the behavior of three different groups: control (grey), anti-vaccination (red) and pro-vaccination (blue) (**A**). We calculated the number of tweets, replies and retweets per month (**B**). The anti-vaccination group scored the highest number of total Twitter actions (the sum of tweets, replies and retweets) per month (**C**). Anti-vaccination supporters tweeted less than control and pro-vaccination individuals (**D**), but they engaged in more discussion via an increased number of replies (**E**) and Retweets (**F**). Ordinary one-way ANOVA; $^{**}p<0.01$; $^{****}p<0.0001$; Outliers were excluded with ROUT, Q=0.1%; n=50.

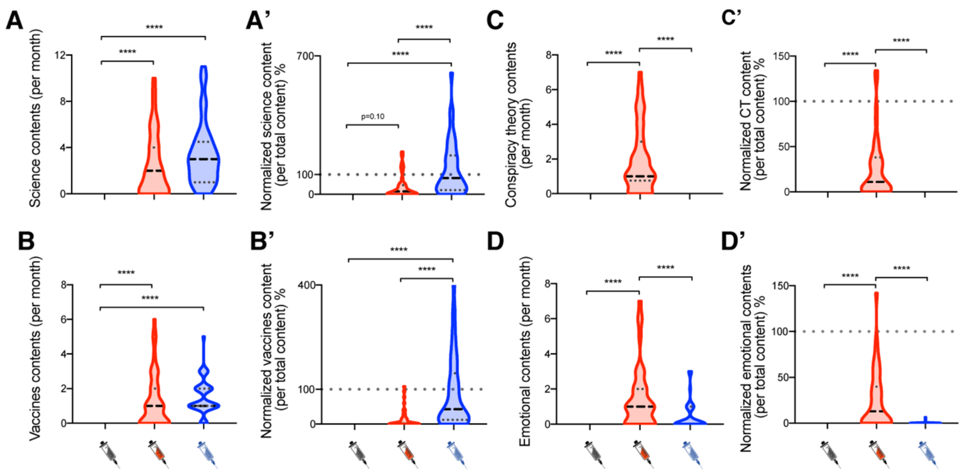

Figure 2. Anti-vaccination supporters are active science and vaccine communicators, share conspiracy theories and emotional content. Both anti- (red) and pro-vaccination profiles (blue) share a larger number of science- and vaccine-related content per month, when compared with control profiles (grey) (**A, B**). We calculated the number of science- and vaccines-related content (tweets and retweets) published in the 24 hours before data analysis

and normalized it for the total number of tweets published on average during a single day. 100 percent indicates that all generated contents are estimated to be science- or vaccines-related **(A', B')**. Natural fluctuations above 100 percent are due to a variable Twitter activity during the 24 hours prior to data analysis compared to an average day. Anti-vaccination supporters publish conspiracy theories, whereas control and pro-vaccination individuals do not publish this type of material **(C, C')**. Anti-vaccination supporters share a larger number of tweets and retweets with emotional contents (and with emotional language) compared with the pro-vaccination and control groups (**D, D'**). Ordinary one-way ANOVA; ****p<0.0001; Outliers were excluded with ROUT, Q=0.1%; n=50.

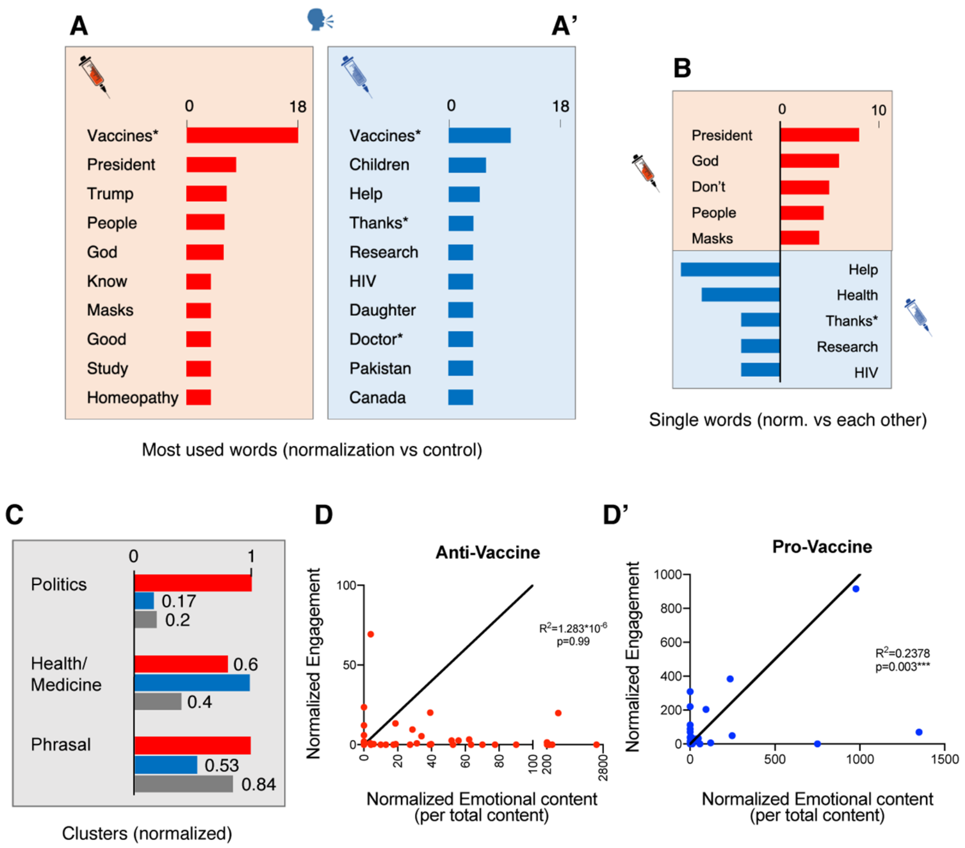

Figure 3. The anti-vaccination group utilizes emotional language, but this does not determine the success of their tweets (engagement). Most used words on Twitter by the anti- (red) and pro-vaccination groups (blue) normalized against the words predominantly used by the control-group (grey). Asterisks* indicate that words have been clustered in lemmas (e.g., "vaccine" and "vaccines"). n(profiles analyzed)=42. Max=18 indicates that a particular word is used 18-times more in that specific group, when compared with the control. (**A, A'**). Most used words by anti- and pro-vaccination profiles normalized against each other. Asterisks*

indicate lemmas. n(profiles analyzed)=42 (**B**). Words are clustered for topic and normalized, with the value of 1 being assigned to the group utilizing the cluster of words the most. The most relevant clusters are shown. Words related to politics are greatly enriched in the anti-vaccination group; words related to health and medicine are predominantly used by pro- and anti-vaccination profiles, when compared with the control; phrasal words are underrepresented in the pro-vaccination group. Asterisks* indicate lemmas. (**C**). For the anti-vaccination group, the normalized number of emotional contents (relative to the total number of contents generated by a given profile) does not correlate with the number of engagements received on average for a single tweet ($R^2=1.293*10^{-6}$; $p=0.99$); n=50 (**D**). Conversely, pro-vaccination profiles tweeting emotional content produce more engaging contents ($R^2=0.2378$; $p=0.003$); n=50 (**E**).

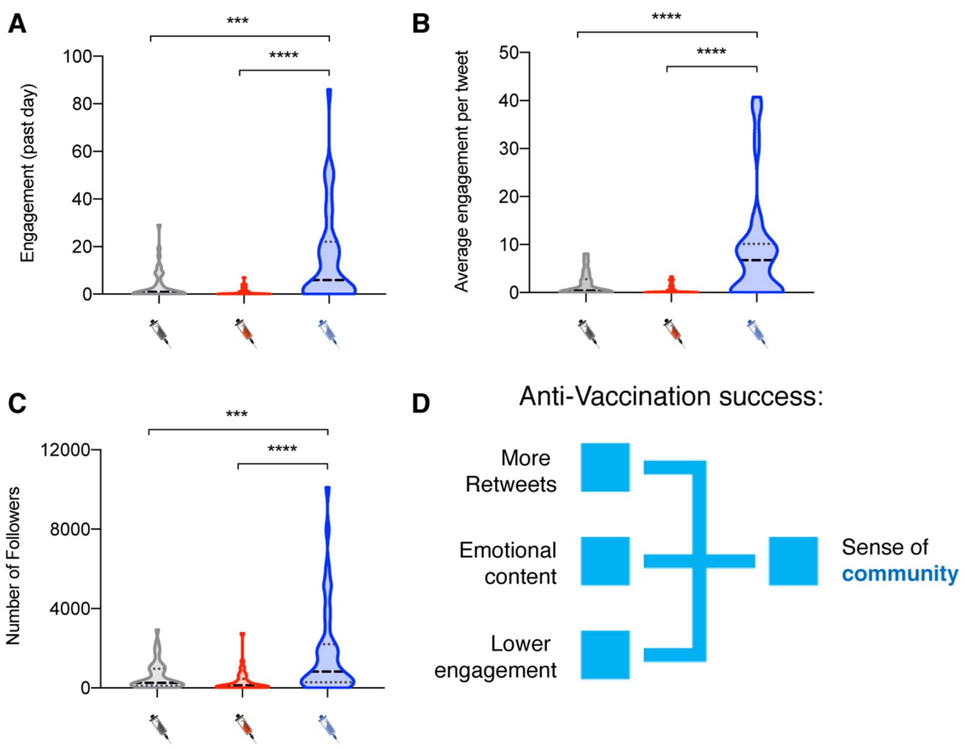

Figure 4. Pro-vaccination profiles have more followers and produce more engaging content. Pro-vaccination profiles (blue) generate more engagement in one day when compared with the control (grey) and anti-vaccination groups (red) (**A**), and normalization shows they produce more engaging content irrespectively of the number of contents generated in a given day (**B**). Pro-vaccination profiles have a larger number of followers when compared with the control and anti-vaccination groups (**C**). Hypothetical model to illustrate the results described so far. Anti-vaccination supporters are more engaged on Twitter, as they retweet contents more often than control and pro-vaccination profiles. They also share emotional content, although

they generally produce less engaging content than their pro-vaccination counterparts. Despite the use of emotions as a tool to convey their message, given the lower engagement of anti-vaccination tweets, we hypothesized that a sense of community driven by common interest is key for the success of the anti-vaccination movement online (**D**). Ordinary one-way ANOVA; ***p<0.001; ****p<0.0001; Outliers were excluded with ROUT, Q=0.1%; n=50.

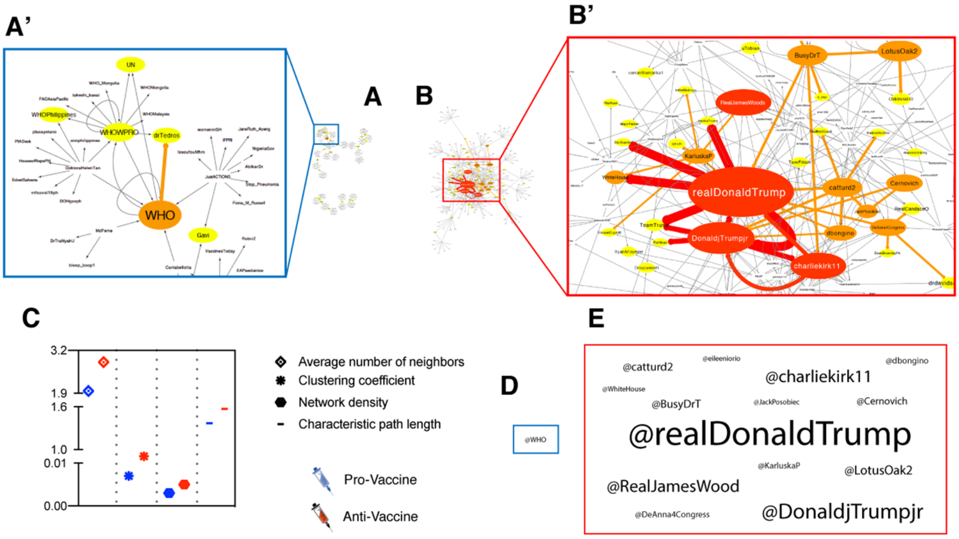

Figure 5. Anti-vaccination profiles establish a well-connected community sharing contents produced by a pull of influencers, whose most prominent exponent is Donald Trump. The pro-vaccination Twitter web (**A**). Close up of the most relevant portion of the pro-vaccination web, which highlights the World Health Organization as the main influencer for the pro-vaccination group (**A'**). The anti-vaccination Twitter web (**B**). Close up of the most relevant portion of the anti-vaccination web, which highlights Donald Trump, its political entourage and public figures supporting his presidency as the main influencers for the anti-vaccination group (**B'**). The pro-vaccination and anti-vaccination Twitter webs are scaled 1:1 (**A, B**). For better readability, close up representations of the pro- and anti-vaccination webs are not equally scaled. Yellow color represents Twitter profiles (nodes) with 2 to 4 anti-vaccination profiles preferentially retweeting their contents within the top 10 most retweeted users (edges; 2≤ E ≤4; n=42). Orange nodes represent profiles with 5 to 9 edges (5≤ E ≤9; n=42), whereas red nodes indicate profiles with more than 10 connecting edges (E ≥10; n=42). Size of the nodes is linearly scaled depending on the number of edges connecting the node (**A-B'**). The average number of neighbors in the web, the clustering coefficient, the density of the network and the characteristic path length of the anti-vaccination (red) web is greater than the

pro-vaccination counterpart (blue) (**C**). Graphical representation and web parameters were generated with Cytoscape. Graphical representation of the main influencers in the pro- and anti-vaccination Twitter webs (threshold: E ≥5; n=42). The size of the name tag assigned to the Twitter profile are linearly scaled for the number of edges. The pro-vaccination influencer cloud only contains one profile (World Health Organization) (**D**), whereas the anti-vaccination cloud contains 14 profiles, with former US President Donald Trump being the largest influencer (**E**).

Discussion

The anti-vaccination community and political implications

In this paper we show that anti-vaccination supporters produce fewer original contents on Twitter but share more contents than users belonging to the pro-vaccination or control group. However, we also show that the average engagement, calculated as the sum of comments, likes and retweets received by an anti-vaccination tweet, is extremely low when compared with tweets published by pro-vaccination profiles. This indicates that most anti-vaccination supporters are unlikely to influence vaccination choice for many individuals. Instead, our data suggest that the success of the anti-vaccination movement online is likely based on common beliefs and interests, through which users establish a well-connected community and constitute an echo chamber for contents generated by a smaller fraction of profiles. We define these latter users as anti-vaccination influencers. We identify former US President Donald Trump as the main influencer in the anti-vaccination web, at the time of our analysis, between September and November 2020. Despite him not having published direct anti-vaccination tweets in recent times (i.e., during his presidency), Donald Trump consistently shared anti-vaccine contents in the past, often associating vaccines to autism. Nonetheless, prior to the suspension of his Twitter profile, he had the ability to influence – politically and potentially on other topics, such as vaccines, the great majority of individuals associated with the anti-vaccination movement. Besides Trump, we identify his son Donald Trump Jr, Charlie Kirk, a popular evangelical Christian and Republican activist who supported Trump's presidency, James Wood, a popular actor and producer who is also a strong supporter of Trump – to be among the largest influencers in the anti-vaccination network on Twitter. Among others, there are also profiles fully dedicated to spread the anti-vaccination message online, including authors of books on the dangers of vaccines, and non-verified profiles including Catturd2, a 'cat' who defines itself as “The MAGA turd who talks shit”. Interestingly, in a recent study Trump was identified as the largest driver of the COVID-19 infodemic [28], underlining the necessity of a scientific movement that prompts politicians to base their campaigns on evidence-driven policies.

The polarization of the anti-vaccine debate

Our data suggest that anti-vaccination supporters share conspiracy theories. This process is likely driven by the polarization of social media feed, where users are exposed to information, news and views identified by algorithms as close to their interests. In fact, a recent study observed an increasing polarization of anti-vaccination contents on social media [38]. Conspiracy theories of various kinds, as well as anti-vaccination beliefs and political extremism tend to be associated with each other [39, 40]. Due to the polarization of the debate on social media, sharing or reading politically rightwing tweets could increase the chance that a hesitant person gets in touch with anti-vaccination beliefs. In line with this, it was previously shown that anti-vaccine users form a polarized network with little to no interaction with outsiders, in which users strengthen their positions by sharing each other’s contents [41-43]. We therefore encourage social media to change the polarized way they present information to users to halt the anti-vaccination infodemic and increase debate between communities. We welcome initiatives to suspend profiles that clearly share disinformation about scientific topics and are likely to have significant negative effects on society. Anti-vaccination influencers could however be targeted in other ways, too. These actions include ‘shadow bans’ for contents related to vaccines for anti-vaccination profiles – which could force a tweet’s organic reach to drop (i.e., a small number of people would read the content); info banners for tweets containing unverified information about medically-sensitive topics could also be effective tools to limit the spread of misinformation about vaccines. Finally, we encourage social media and the scientific community to discuss the possible introduction of science knowledge tests, which could be required for users that intend to share contents containing medically-sensitive information. These tests could inform users about vaccines and other scientific topics, thus likely reducing the amount of circulating fake news, without imposing an a priori restriction of individual freedom of speech. Furthermore, as the strength of the anti-vaccination movement relies on the structure of its community and the existence of social media as a tool, health organizations should consider restructuring decisional pathways to identify solutions in line with the times. These could include involving citizens in decision-making processes, thus building a more engaged community when it comes to public health policy. Direct involvement of citizens in these processes could be complicated but they should at least be given the chance to voice their concerns and influence decision-making. Furthermore, health organizations could lobby ‘indirect’ anti-vaccination influencers to become active pro-vaccination communicators. The value of positive influencers has been proven in a pilot study using a social network for Multiple Sclerosis patients [44], and their presence could counteract problems related to the lack of editorial review and fact-checking on social media [45]. Positive influencers should include celebrities, as they can influence online searches of health-related information [46], and their voices could aid public health efforts, including vaccination campaigns [47]. A combination of these approaches could transform social media from sources of misinformation to valuable tools to gather trustworthy, relevant news and knowledge.

Towards a better communication strategy for vaccinations

Finally, our data suggest that the use of people-centered, first-person narratives with emotional language could aid the communication strategy of pro-vaccine health organizations and individuals. The power of first-person narratives over population-based statistical evidence could be due to an effect known in psychology as “psychic numbing”, according to which the higher the number of people involved in a disaster and the least people feel empathic about it. Personal stories, involving first person narratives, are more attractive and stimulate empathic responses more efficiently [48-50]. Given that this type of communication seems to be a structural component within the anti-vaccination community, it may be required for users to build strong connections. We therefore encourage health organizations to adopt a less sterile, technical language when communicating with the general public. This language should be scientifically sound, but also simple, emotional, and understandable. At the same time, adopting a pro-active long-term strategy for improving the general public’s science literacy and ability to read and understand at least basic scientific information will be an important complementary strategy.

Limitations of the study

1) The results of our study have been gathered by manually analyzing and categorizing thousands of tweets from many different users. This approach, which allows for a precise definition and categorization of each tweet, is time consuming and thus limits

the overall sample size – i.e., the overall number of profiles taken into consideration in our analysis.

2) Our study was conducted between September and November 2020, and thus all our results represent a snapshot of the situation on Twitter during this period. The ban of many profiles in January 2021 has dramatically altered the Twitter landscape, and with it, it profoundly altered the composition of anti-vaccinations and pro-vaccination webs.
3) Similarly, changes in Twitter policies profoundly altered the number of tweets on vaccines and conspiracy theories, as well as they may have had a profound effect on the language adopted by anti-vaccine influencers (later confirmed by Lenti et al. [51]). This analysis, thus, needs to be considered valid for a very limited and specific period, although the lessons learned may be valuable for a long time.

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Supporting information

Supplementary Figures Fig. S1 to S7

Response to issues listed in the retraction notice

Additional files:

Pro- and Anti-vaccine Twitter webs