Characterizing the Diffusion of Misinformation Regarding the CoronaVac Vaccine in Brazil

Gabriel P. Oliveira, Beatriz F. Paiva, Ana Paula Couto da Silva, Mirella M. Moro

Universidade Federal de Minas Gerais (UFMG) – Belo Horizonte, Brazil

{gabrielpoliveira,beatriz.paiva,ana.coutosilva,mirella}@dcc.ufmg.br

Abstract. *The start of the vaccination against COVID-19 was an essential step towards the end of the pandemic. In Brazil, CoronaVac was the first vaccine to be applied in the immunization campaign, and it is one of the most used today. Still, CoronaVac has specific components that have driven the spread of misinformation online. In this work, we compare the dissemination of misinformation on Twitter about the approval of such a vaccine for adults and children. The results show that misinformation is significant on Twitter and there has been a substantial change in the style of such content shared between 2021 and 2022, moving from a false narrative about the development of the vaccine to raising suspicions on the approval process by the health regulatory agency.*

1. Introduction

Historically, vaccines have played a key role in controlling diseases and epidemics worldwide. For COVID-19, the successful development of vaccines in late 2020 and early 2021 represented a fundamental step for moving out from the pandemic state. Brazil started its vaccination campaign on January 17, 2021, when the Brazilian Health Regulatory Agency (Anvisa) approved the emergency use of two vaccines against COVID-19: Covishield (Oxford/AstraZeneca) and CoronaVac (Sinovac), partially manufactured in Brazil by Fiocruz and Instituto Butantan, which are Brazilian biomedical institutes.

Specifically, CoronaVac was the first to be applied within the country and was also the most used in the first months of the campaign. Despite the feeling of hope by the beginning of vaccination, Brazil was experiencing a context of polarization and intense circulation of misinformation. Even before its approval, vaccines were already the target of such content. In particular, CoronaVac was the most poliitically used and also the most attacked one, as some politicians called it the "Brazil's vaccine". For example, misinformation content regarding CoronaVac reported that volunteers had died in the clinical trials[1] and that the vaccine was made with "cells from aborted babies".[2]

Despite the wide circulation of misinformation and the action of anti-vaccine groups, in the beginning of 2022, most of the Brazilian population had already completed their vaccination against COVID-19. The success of vaccination is partly due to the National Immunization Plan (PNI), which has long and extensive experience in organizing mass vaccination campaigns to achieve a high vaccination coverage. With the release of new safety and efficacy data for children, new misinformation types have emerged to discourage vaccination in this public. On January 20, 2022, Anvisa approved the use of CoronaVac for people aged 6 to 17 years, except for immunosuppressed people.

[1] Lupa Agency: https://piaui.folha.uol.com.br/lupa/2020/10/21/verificamos-vacina-chinesa-matou/

[2] Lupa Agency: https://piaui.folha.uol.com.br/lupa/2020/07/23/verificamos-coronavac-bebes-abortados/

In this context, this work aims to analyze the debate about CoronaVac on Twitter at the time of its approval by Anvisa, both for adults and children. We manually label the tweets into misinformation and non-misinformation to analyze their characteristics and diffusion on Twitter. The main contribution of this work is to reveal a subtle change in the misinformation content from 2021 to 2022, moving from a false narrative about CoronaVac to raising doubts about the vaccine and Anvisa's analysis procedures. In addition, our network analysis allows finding the main actors involved in the misinformation diffusion. All such results improve the knowledge on the debate regarding COVID-19 vaccines in Brazil and may help combat the misinformation spread in social networks.

2. Related Work

The COVID-19 pandemic has been a recurring subject in the media and social networks, mainly because it has transformed society and interpersonal relationships. Not surprisingly, COVID-19 has also been one of the most researched topics in the most diverse areas of knowledge, including virology, sociology, and computer science itself. In this section, we present a brief discussion about works that address the dissemination of misinformation and vaccination in the pandemic, especially in Brazil, the goal of this work.

The spread of misinformation on social networks took on new contours during the pandemic. Services such as WhatsApp are among the most used in the country and are the primary means of disseminating such content. In this sense, Martins et al. [2021] present the COVID-19.BR dataset from the collection and manual labeling of messages from public WhatsApp groups. Other research focuses on users who share misinformation, including Vijaykumar et al. [2021], who look at existing patterns in people when exposed to misinformation online. In addition, Roque et al. [2021] feature a *chatbot* based on information from reliable sources to answer questions about COVID-19 in order to facilitate the general population's access to verified and quality information.

The COVID-19 vaccination campaign began on January 17, 2021, when Anvisa approved the CoronaVac and Oxford/AstraZeneca vaccines for emergency use in adults. In such a context, work in Computer Science can be divided into two categories: modeling and content analysis. In the first group, Oliveira et al. [2021] use epidemiological models to analyze the control of the pandemic by vaccination in a context where Brazil had high numbers of cases and deaths from COVID-19. In contrast, Malagoli et al. [2021] analyze the debate about vaccination on Twitter at the time of the beginning of vaccination in the country. We use such a dataset in the methodology of this work (next section).

Overall, the amount of misinformation on Twitter has increased considerably, and its effect on the public debate is no longer insignificant. Especially regarding COVID-19, the fact that the knowledge about it is still being constructed facilitates the spread of such content. Although there are datasets assessing misinformation [Marinho et al. 2021] none of them uses Twitter data nor captures the period we want to analyze. To the best of our knowledge, there are no previous work analyzing the diffusion of misinformation regarding vaccination in Brazil. Therefore, we assess such a subject by assessing the approval of the CoronaVac vaccine for both adults and children.

Table 1. Overview of our datasets

	2021		2022	
Tweets	4,266	6.66%	2,603	13.98%
Retweets	2,908	4.54%	1,264	6.79%
Quotes	56,504	88.15%	14,559	78.16%
Replies	422	0.66%	200	1.07%
TOTAL	64,100	100%	18,626	100%

3. Methodology

In a nutshell, our methodology is composed of four main steps. We first gathered data from the Twitter debate of the CoronaVac vaccine use in Brazil (Section 3.1). Afterwards, in order to classify a tweet content as misinformation or non-misinformation, we performed a manual labeling process (Section 3.2). We then characterized the misinformation and non-misinformation tweets content with respect to the their popularity, the presence of external links and their content (Section 3.3). Next, we generated misinformation and non-misinformation diffusion networks, connecting users who published one or more tweets with those who shared them (Section 3.4). Finally, we present the limitations on the methodology proposed for this work (Section 3.5).

3.1. Data Collection

Our data collection focuses on Portuguese-language tweets that may be informative of the online debate on CoronaVac vaccine in Brazil. Specifically, we selected two events that raised a huge debate on Twitter: the approval of CoronaVac for emergency use in adults over 18 years old (January 17, 2021) and its approval for use in children aged between 6 and 17 years (January 20, 2022).

Concerning the first event, we selected a subset of tweets from a Twitter COVID-19 vaccination dataset gathered and made public available by the authors of [Malagoli et al. 2021]. From this dataset, here we only considered tweets with the keyword *coronavac* that were published on January 17, 2021. We labeled this first dataset as *2021*. Regarding the second event, we collect a new dataset, labeled as *2022*, by applying the Twitter API Search.[3] Again, we narrow down our data collection to the tweets referring the keyword *coronavac*, selecting only those published on January 20, 2022.

Table 1 provides an overview of our datasets. Tweets were classified according different types of interaction: *tweets*, *retweets*, *quotes* (retweet with comment) and *replies*. Overall, the amount of tweets is more than three times higher for adult vaccination (2021) when compared to children vaccination (2022). Furthermore, for both events, retweets correspond to the vast majority of the considered tweets (88.15% in 2021 and 78.16% in 2022). These numbers show that sharing content is an important part of the debate about vaccines on Twitter. Then, it is crucial to understand how such content spreads over online social medias and how people are affected by it.

3.2. Manual Labeling

The second step categorizes tweets regarding their content: misinformation or non-misinformation. To this end, we manually labeled the tweets with at least one retweet,

[3]Twitter API Search: https://bit.ly/3oW8RFs

because we are interested in analyzing the diffusion of misinformation. We do not consider quotes as retweets, since quotes may be used to fact-checking a misinformation. After applying this filter, we labeled 1,010 tweets from 2021 and 816 tweets from 2022.

The manual labeling of the remaining tweets was performed by two annotators with a high knowledge about the dataset and its context. To measure the quality of the labels, we use Cohen's Kappa coefficient, which measures the level of agreement between annotators [Cohen 1960]. This coefficient was 0.762 for 2021 and 0.617 for 2022, indicating a substantial level of agreement. In cases of non agreement, a third annotator was considered to define the class of the tweet. The final dataset with tweets and labels is publicly available in Zenodo.[4]

3.3. Misinformation and Non-Misinformation Characterization

The next step characterizes the tweets of each class (misinformation or non-misinformation) with respect to three different dimensions: popularity; presence of external URLs and; content analysis.

Popularity. To assess the popularity of misinformation and non-misinformation content, we look into the volume of tweets in each class and the number of unique users that share those tweets. Moreover, we analyze the reachability of those tweets, by means of the number of retweets per tweet and their number of *likes*.

Presence of external URLs. We analyze both classes of tweets regarding the presence of external URLs (e.g., links to news portals and YouTube videos) to verify if misinformation tweets present a higher number of sources and identity the most referenced. The presence of such URLs may reveal a tendency for misinformation spreaders to legitimate their content. We also identify the most shared media (e.g., traditional media outlets, blogs and news portals) in such tweets.

Content analysis. Next, we look into the contents of misinformation and non-misinformation tweets. Specifically, we first analyze the most frequent hashtags and words. Hashtags provide a first glance at what people are talking about. To deep analyze the topics conveyed by the tweets, we run the Latent Dirichlet Allocation (LDA) algorithm, a statistical model that works on the premise that each topic is a set of terms and each document is a mixture of a set of topics [Blei et al. 2001].

3.4. Misinformation and Non-Misinformation Diffusion Networks

The last step aims to analyze the processes of spreading misinformation on Twitter. We build a diffusion network, where the nodes are users, and a direct edge between a pair of users exists if they shared the same content, i.e., a link connects a user who posted the content (source) to the user who shared it via retweet (target). Moreover, edges are weighted by the number of tweets shared by the pair of users. This misinformation analysis follows the methodology introduced by Pierri et al. [2020].

Building such networks allows several analyses regarding their structure. We first find the main spreaders in the misinformation networks by using four centrality metrics: *(i) in-degree*, indicates the number of tweets shared by a user; *(ii) out-degree*, how many

[4]The dataset is available at: https://doi.org/10.5281/zenodo.6388125

times the user's tweets were shared; *(iii) betweenness*, indicates the importance of the user as a bridge in the network; and *(iv) page rank*, estimates the importance of a user, assuming that relevant users have more edges (i.e., have a higher in-degree) than others.

Then, we detect communities within such networks to analyze the aggregate behavior. To do so, we first select the 3-core in the misinformation networks, i.e., we filter all nodes whose degree is greater than or equal to three [Dorogovtsev et al. 2006]. We consider nodes with a lower degree as ephemeral, that is, they do not actively contribute to the process of misinformation diffusion. Next, we use the Louvain method to detect communities on them [Blondel et al. 2008]. This is a greedy optimization method that aims to optimize the modularity of the network's partitions.

3.5. Limitations

Our methodology has some limitations. First, the choice to only analyze tweets from the day of vaccine approval can exclude much of the discussion and the misinformation diffusion process in the following days. However, in this work we focus on a real-time analysis of the debate. Also, we choose LDA for topic detection due to its simplicity, but we are aware that the a maximum of 280 characters in a tweet can impact its performance. Recent work uses other methods, including dictionary-based approaches [Pierri et al. 2020]. Finally, Twitter still does not provide the way of broadcasting tweets, i.e., the intermediate steps in sharing. Such information would allow more in-depth analyses, such as analyzing the depth of diffusion of each topic and studying cascading processes.

4. Analyses and Results

In this section, we characterize the tweets concerning the CoronaVac vaccine approval debate. We first focus on their popularity (Section 4.1), then we look into the external links they share (Section 4.2). Afterwards, we delve deeper into the contents of the tweets that carry or not misinformation (Section 4.3). Finally, we present the misinformation and non-misinformation diffusion networks built from our labeled datasets (Section 4.4).

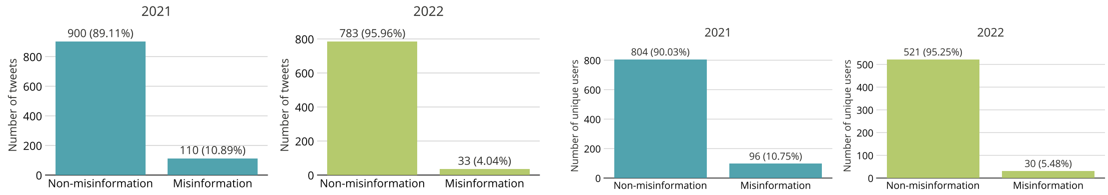
4.1. Popularity

We first measure tweets' popularity by their total number, the number of unique users who engaged in the Twitter debate, the total number of tweets' likes and the total number of retweets they trigger as well.

Total number of tweets and unique users. Figures 1(b) and 1(a) show the number of tweets and unique users for each event. There is a small fraction of tweets labeled as misinformation in both events. The users who shared misinformation also represent a small fraction of those who engaged in this debate. Interestingly, both measures dropped by nearly half when comparing data from 2021 and 2022. We believe that the decrease in the amount of the diffusion of misinformation regarding the CoronaVac vaccine may be related to the high acceptance rate of COVID-19 vaccine in Brazil.[5]

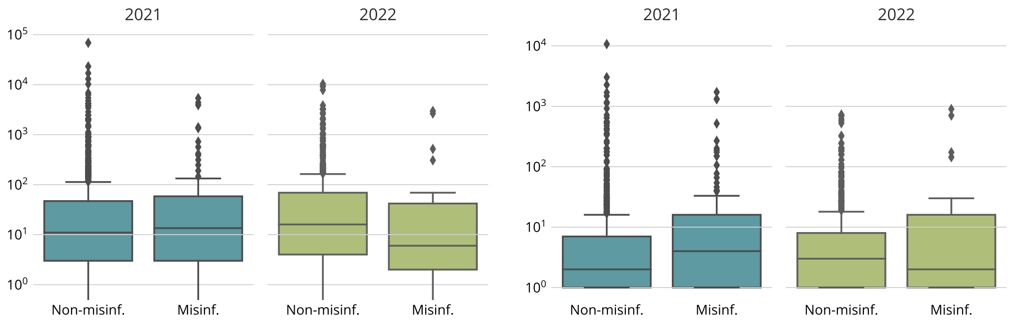
Reachability. To assess the tweets' reachability, we analyze the distribution of the number of likes and retweets they received. In Twitter ecosystem, the content that attracts

[5] According to data from the Ministry of Health, on February 16, 2022, approximately 70% of the total population of Brazil is vaccinated with two doses or a single dose.



(a) Tweets (b) Unique users

Figure 1. Number of tweets (a) and unique users (b) for misinformation and no-misinformation content. The sum of percentages of unique users can be higher than 100%, as users can tweet both misinformation and non-misinformation.



(a) Likes (b) Retweets

Figure 2. Distribution of the number of likes and retweets for misinformation and non-misinformation tweets. Note that the y-axis is on a log scale.

many likes and/or is frequently retweeted by the users is more likely to be displayed on users' timeline. In other words, retweets and likes may be seen as a measure of the strength of information diffusion, since the content may reach a large number of users, boosting the debate around a specific theme.

Figures 2(a) and 2(b) exhibit the number of likes and retweets, respectively. Overall, on the day of CoronaVac's approval for adult use (2021), misinformation content had a broader reach on the social network. Specifically, misinformation tweets have a higher median number of retweets than non-misinformation content (median retweets are 4 and 2, respectively). The results for likes are similar, as the median number of likes are 13 and 11 for misinformation and non-misinformation, respectively.

However, when analyzing the tweets on the day of approval of the same vaccine for pediatric use (2022), the median amount of retweets and likes of tweets with misinformation is slightly lower than 2021. In addition, non-misinformation (median retweets of 3, median likes of 16) content was more diffused than misinformation (median retweets of 2, median likes of 6), revealing an important change in the public debate. This result corroborates the hypothesis that the misinformation discourse lost strength in the meantime between the events, despite still being widely shared on Twitter.

We delve into the misinformation tweets with the highest number of retweets. Table 2 lists the top-3 tweets for each dataset. We observe a slight change of speech style of the most shared tweets with misinformation content. In 2021, such content mostly

Table 2. Top-3 shared misinformation tweets (translated into English).

Tweet	RTs	Likes
2021		
THE TRUTH. https://t.co/LMb0eQoqyu	1,719	5,382
After Doria says that Pazuello "lies", the Health Ministry shows that the CoronaVac studies were funded by SUS. https://t.co/MEfkvVBA68	1,323	4,373
After Doria says that Pazuello "lies", Health shows CoronaVac studies were funded with SUS resources. Ministry presented documents attesting to the federal investment in the acquisition of Butantan's vaccine https://t.co/pW4JvzRvHM	1,310	3,905
2022		
When Anvisa approved Coronavac for emergency use on Jan/21, it was announced that the approval was conditional on delivering immunogenicity studies until Feb/21. Even without such studies to date and without the approval for full use, the agency approved the vaccine for children. https://t.co/jn46hfkOtR	900	2,653
Anvisa authorized the use of Coronavac for children and canceled the registration of the Israeli spray against Covid-19. The claim to ban the second is a lack of studies that prove its effectiveness. Did they use the same effectiveness criteria to approve Coronavac?	704	2,973
Anvisa recommends Coronavac in the range of 6 to 17 years… How many doses will be needed? [pensive emoji] It's been 2 years and Coronavac still doesn't have a Definitive Registration or [emoji vaccine] for adults, imagine that, now it's recommended for children! https://t.co/jbOIR0SVCo	173	518

focused on spreading fake news regarding the CoronaVac clinical trials, declaring that they were funded by the Brazilian Federal Government. However, they were funded by Sinovac (the Chinese biopharmaceutical company that developed the vaccine) and Instituto Butantan, a Brazilian biologic research center linked to the Government of the State of São Paulo.[6] In 2022, instead, the most shared misinformation content aimed to raise doubts about the effectiveness of the vaccine for the target age group, as well as question the integrity of Anvisa's role in its approval. The most shared tweet questions the vaccine approval process, claiming that CoronaVac's immunogenicity data has not been delivered to the agency by the date of the beginning of the approval process. As a matter of fact, Butantan delivered such studies in May 2021.[7]

4.2. Presence of External URLs

It is not uncommon the presence of external URLs (or links) in misinformation content shared through online social medias. The goal is to provide evidence to "legitimize" the information, helping people to accept it, without further questioning [Pornpitakpan 2004, Pennycook and Rand 2021, Ecker et al. 2022]. In this section, we quantify the presence of external links in the tweets collected.

Figure 3 depicts the fraction of tweets with external URLs, for each type of content and event of interest. We observe a significant change on the pattern of sharing external links. In 2021, more than 35% of tweets with misinformation pointed to some external site, while this percentage for tweets with non-misinformation is just over 20%. In 2022, the trend is opposite: the proportion of tweets with links is much higher for non-misinformation (49.81%) than for misinformation (27.27%). These numbers may reflect the modification in the style of shared misinformation pattern in the two events. In

[6]BBC News Brasil: https://www.bbc.com/portuguese/brasil-55722632

[7]Agência Brasil: https://bit.ly/3uYwgtC

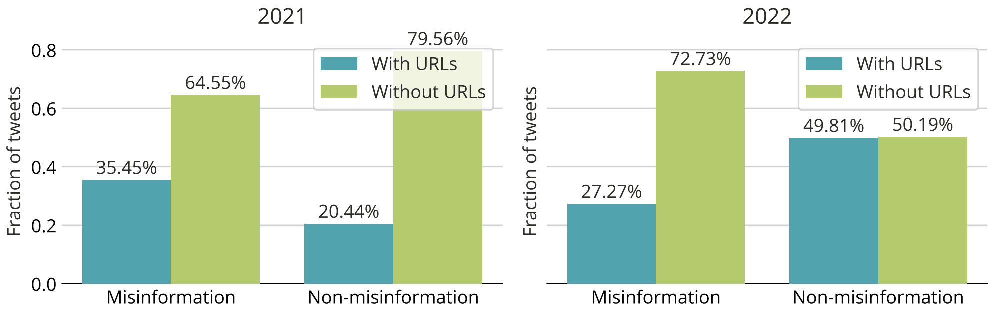


Figure 3. Fraction of misinformation and non-misinformation tweets with and without external URLs.

Table 3. Most shared URLs domains.

2021				2022			
Misinformation		Non-misinformation		Misinformation		Non-misinformation	
Domain	Tweets	Domain	Tweets	Domain	Tweets	Domain	Tweets
gazetabrasil.com.br	18	g1.globo.com	14	terrabrasilnoticias.com	3	glo.bo	27
r7.com	11	folha.uol.com.br	9	revistaoeste.com	1	noticias.uol.com.br	19
youtu.be	2	glo.bo	8	gazetabrasil.com.br	1	youtu.be	18

2021 the goal of misinformation spread was to create a false narrative regarding the use of Coronavac in adults; whereas in 2022, the goal was to rise questions and doubts regarding the role of Anvisa in the approval of its use in children. As previously mentioned, misinformation content is usually legitimated by the use of links to news portal or to videos [Pennycook and Rand 2021, Ecker et al. 2022].

Table 3 shows the most cited domains in misinformation and non-misinformation tweets. In summary, non-misinformation tweets pointed out to traditional media portals, including *G1*, *UOL* and *Folha de São Paulo*. YouTube also appears on the list of the most shared domains. Conversely, misinformation tweets mainly refer to far-right sites, such as *Gazeta Brasil*, *Terra Brasil Notícias* and *Revista Oeste*.

4.3. Content Analysis

To provide a deeper view of the Coronavac debate on Twitter, in this section we characterize the misinformation and non-misinformation content. We first look into the most used hashtags, followed by the analysis of the most frequent terms in the tweets. Finally, we identify the most relevant topics discussed in our data by applying the LDA algorithm.

Table 4. Most used hashtags (translated into English).

2021				2022			
Misinformation		Non-misinformation		Misinformation		Non-misinformation	
Hashtag	Tweets	Hashtag	Tweets	Hashtag	Tweets	Hashtag	Tweets
CoronaVac	5	CoronaVac	163	AuthorizeAnvisa	3	CoronaVac	45
EarlyTreatmentSavesLives	4	ComeVaccine	75	CoronaVac	2	VaccinesSaveLives	23
DoriaLiar	3	GoodbyeBolsonaro	47	children	2	Anvisa	18
R7	3	vaccine	34	teenagers	1	coronavirus	12
BolsonaroThePrideOfBrazil	2	BolsonaroOut	21	Estudioi	1	UOLNews	11

(a) 2021 (b) 2022

Figure 4. Word clouds with the top-40 most popular words in minsinformation tweets in our datasets. Words were translated into English.

Most Used Hashtags. Table 4 presents the five most shared hashtags for misinformation and non-misinformation tweets. Overall, in 2021, hashtags in tweets with misinformation and non-misinformation (*DoriaLiar, BolsonaroThePrideOfBrazil, GoodbyeBolsonaro*) reveal the political bias of the debate around vaccination in Brazil. Looking at the non-misinformation content, the most shared keywords were frequentely cited in tweets that expressed the happiness with the vaccine approval (e.g., *"Monica, Vanusa and Wilson. The portrayal of the first doses may be a marketing ploy, but for me it worked great. I'm thrilled to see such Brazilian faces. All health workers. I got hope again. #ComeVaccine"*, translated into English).

Regarding 2022, debate was mainly focused on Anvisa. Tweets with misinformation mostly cited the hashtag *#AuthorizeAnvisa*. These tweets pressured the agency either to release a nasal spray against COVID-19[8] or to authorize self-tests to detect virus infection as well. Tweets sharing non-misinformation reinforced the support for the vaccine approval, emphasizing its importance by using the hashtag *#VaccinesSaveLives*.

Most Frequent Words. Next, we look into the contents of the tweets, comparing again misinformation with non-misinformation content. Figure 4 shows the word clouds with the top-40 most frequent words in misinformation tweets.[9] Due to spacing reasons, we do not present the wordclouds for non-misinformation tweets. Tweets from 2021 cited political personalities (*Doria, Pazuello*), institutions (*SUS, Anvisa*) and words related to the development and test of the vaccine itself (*studies, paid, resource, China*). In 2022, tweets focused on the Anvisa institution (*Anvisa, anvisa_oficial*) and, as expected, on the vaccine public target (*children*).

Topic Detection. To identify the most relevant topics discussed in this dataset, we used latent LDA, a generative statistical model to automatically infer the topics in a collection of documents. We first applied LDA to all tweets jointly, and then we compared the distributions of the identified topics in each group of tweets, aiming at identifying differences between them. Before applying the LDA model, we cleaned the tweets by removing characters and words with none or limited analytical value (stopwords), as well as hashtags. This cleaning allows for a better identification of what is being mentioned in the posts.

[8] On January 19, 2022, Anvisa canceled the notification of an antiviral spray due to lack of studies to prove its effectiveness against Sars-Cov-2. https://bit.ly/3IbstN2

[9] The wordclouds do not consider language stopwords and keywords used to collect tweets.

Table 5. Most representative words (translated into English) in the topics inferred by the LDA algorithm.

	2021			2022		
	Topic 1	**Topic 2**	**Topic 3**	**Topic 1**	**Topic 2**	**Topic 3**
Misinformation	brazil anvisa oxford nurse shots take vaccinated tests can world	effectiveness low money china weknow analysis virus analyses times government	doria health studies paid shows resource pazuello lies after say	years anvisa children barra today now register approve released spray	children released spray against barra authorized anvisa approve years today	anvisa children studies register now approve authorized today spray against
Non-Misinformation	government health doria anvisa now pazuello oxford bolsonaro brazil against	anvisa take emergency oxford doria bolsonaro approval coronavirus brazil after	shots butantan comevaccine first millions brazil goodbyebolsonaro monica receive hooray	children anvisa child about against agency years first covid torres	children anvisa years teenagers health release range application butantan decides	children anvisa years approves teenagers vaccinate release doria shots release

We ran the LDA algorithm using the Gensim Python library to perform topic analysis, and we established the number of topics $k = 3$. The resulting topics are presented in Table 5, which shows the most representative words (according to the LDA output) for each topic.

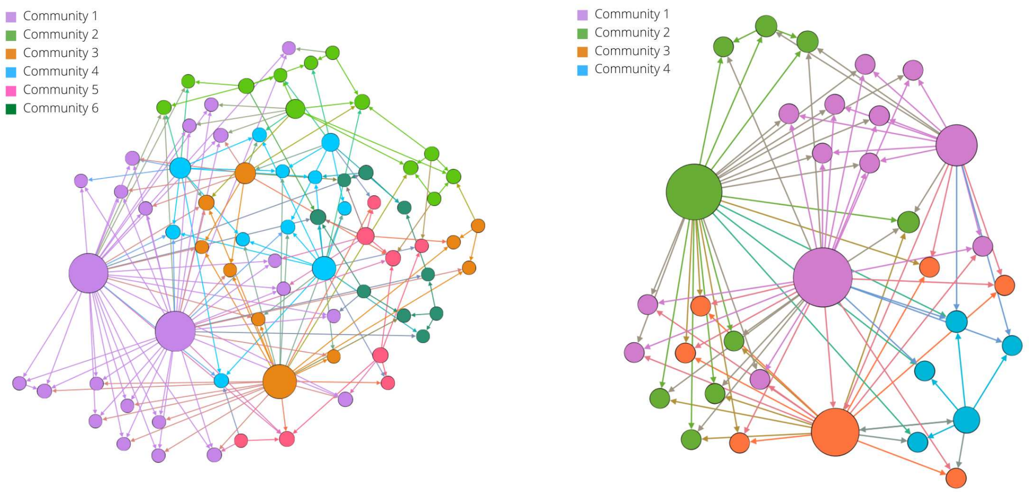
Overall, the results suggest the debate about vaccination on Twitter was mostly about by political subjects. For misinformation tweets in 2021, Topic 1 refers to Mônica Calazans, the first vaccinated person in Brazil, who was claimed to have already been vaccinated in the CoronaVac trials.[10] Topics 2 and 3 contain tweets questioning the vaccines effectiveness and relating the supposed federal funding for CoronaVac's clinical trials, respectively. Besides, Topics 1, 2 and 3 for misinformation in 2022 refer to the same subject, i.e., questioning Anvisa and the pressure to authorize the antiviral spray. Finally, all topics in non-misinformation tweets for both datasets refer to the vaccine approval.

4.4. Diffusion Network Analysis

Finally, we analyze how misinformation reaches the Twitter users in our dataset. We focus on the misinformation content because understanding its diffusion aids on fighting it. We build two misinformation diffusion networks and performed three analyses: topological characterization, misinformation spreaders identification, and community detection. Our analyses were performed using the Python *networkx* library [Hagberg et al. 2008] and the Gephi visualization software [Bastian et al. 2009].

Network Characterization. We first characterize the networks regarding three key topological properties: *average degree*, *density* and *average clustering coefficient*. Both 2021 and 2022 networks have low mean degree (1.22 and 1.13, respectively), indicating that most users share misinformation from a few sources. The low density values (0.00098 and 0.00072) reinforce such a result, as there are few connections between users. Finally, the low average clustering coefficients (approximately 0.0008 for both networks) reveal a weak tendency for users to organize into large misinformation-spreading groups.

[10] Mônica was a participant of the clinical trials, but she received a placebo. https://glo.bo/3rVMuBS



(a) 2021 (b) 2022

Figure 5. Communities detected in the 3-core of misinformation networks.

Main Misinformation Spreaders. To keep users' privacy, we do not disclose the ranking of the most influential users with respect to the *in-degree*, *out-degree*, *betweeness* and *page rank* network centrality metrics. Overall, our results show the presence of users aligned with far-right movements. We also observe the presence of verified accounts, which include politician figures such as minister of state and congressperson. These accounts may lead to huge misinformation spread, due to their high number of followers.

Community Detection. Figure 5 shows the communities extracted applying the algorithm described in Section 3.4. In both networks, Communities 1 are formed by the users with the highest out-degree, who are potentially the main misinformation spreaders. The verified accounts of politician figures belong to these communities. Communities 3 in Figure 5(a) and 2 in Figure 5(b) are formed by news portal accounts and far-right account users with high degree. Our analysis is a first look at the dissemination process by using network science metrics. For instance, we consider the out-degree to characterize the communities since it reveals the amount of content of a user shared by other accounts. We are aware of the possible limitations, such as the presence of bots. However, such results are promising for understanding the dynamics of content diffusion with misinformation since it was possible to identify and characterize the main actors involved in this process.

5. Conclusion and Future Work

This work presented an analysis of the discussion on Twitter about the approval of the emergency use of the CoronaVac vaccine in Brazil. Specifically, we analyzed tweets from two separate events on this topic: approval of adult use on January 17, 2021, and approval for pediatric use on January 20, 2022. We classified such tweets into misinformation and non-misinformation through a manual labeling process. Thus, from the annotated data, we analyzed such contents from different perspectives: external sources, the text itself, and the diffusion of the content in Twitter.

Our results reveal a significant presence of misinformation in the public debate, with the participation of verified accounts from public persons. In addition, there was a change in the style of shared misinformation, moving away from the construction of false narratives about the vaccine to raising doubts about it and public institutions, such as Anvisa. Thus, besides analyzing specific events, we contribute to understanding the dynamics of misinformation networks and reinforce the highly disseminating profile of such content. As future work, we plan to enhance our analyses by considering longer periods to better understand misinformation spread in the days following an event.

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