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The dramatic increase in anti-vaccine discourses during the COVID-19 pandemic: a social network analysis of Twitter

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ABSTRACT

Background/Aim: The first case of COVID-19 in Turkey was officially recorded on March 11, 2020. Social media use increased worldwide, as well as in Turkey, during the pandemic, and conspiracy theories/fake news about medical complications of vaccines spread throughout the world. The aim of this study was to identify community interactions related to vaccines and to identify key influences/influencers before and after the pandemic using social network data from Twitter.

Materials and methods: Two datasets, including tweets about vaccinations before and after COVID-19 in Turkey, were collected. Social networks were created based on interactions (mentions) between Twitter users. Users and their influence were scored based on social network analysis and parameters that included in-degree and betweenness centrality.

Results: In the pre-COVID-19 network, media figures and authors who had anti-vaccine views were the most influential users. In the post-COVID-19 network, the Turkish minister of health, the was the most influential figure. The vaccine network was observed to be growing rapidly after COVID-19, and the physicians and authors who had opinions about mandatory vaccinations received a great deal of reaction. One-way communication between influencers and other users in the network was determined.

Conclusions: This study shows the effectiveness and usefulness of large social media data for understanding public opinion on public health and vaccination in Turkey. The current study was completed before the implementation of the COVID-19 vaccine in Turkey. We anticipated that social network analysis would help reduce the “infodemic” before administering the vaccine and would also help public health workers act more proactively in this regard.

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1. Introduction

The outbreak of COVID-19, caused by the SARS-CoV-2 virus, in China at the end of 2019 spread rapidly throughout the world and was declared a pandemic by the World Health Organization (WHO) on March 11, 2020.¹ On the same date, the first COVID-19 case in Turkey was officially recorded.²

Due to the closures that were initiated due to the pandemic, as well as the social distance measures taken, the use of social media platforms to disseminate information increased.³ According to 2021 data, the use of social media increased by 11% around the world compared to the previous year, reaching 4.2 billion users (54%). Interestingly, social media usage in Turkey increased by 13% and reached 60 million users (70.8%).⁴

The use of social media platforms has been shown to increase significantly in situations such as natural disasters and crises, where fast information flow is needed. The use of social media is considered an opportunity in health crises due to the ease of accessing up-to-date information.^{5,6}


For example, during SARS, Ebola, and H1N1 outbreaks, there was an increase in the use of social media and compliance with protective measures such as hand-washing, face mask-wearing, and social distancing.^{7–9} Similarly, in the COVID-19 pandemic, the use of personal protective equipment, social

distancing, and even medical treatment protocols spread rapidly thanks to social media. International organizations, such as the WHO and the Center for Disease Control, shared information about COVID-19 on their websites, and it was disseminated to the most remote corners of the world for use. However, social media has also led to the rapid spread of uncontrolled misinformation about the pandemic, unfounded claims about the diagnosis, treatment, prevention, origin, and transmission of the virus, conspiracy theories, and pseudoscience-based treatments.^{10–13}

The term “infodemic,” which is defined by WHO as “too much information including false or misleading information in digital and physical environments during a disease outbreak,” came to the forefront with COVID-19, as the WHO announced in mid-February 2020 that both the new coronavirus pandemic and the infodemic were moving swiftly.^{6,14}

Treatment options and the advent of vaccines have caused conspiracy theories and misinformation about vaccines on social network sites.¹⁵ There was an increase in expert opinions throughout the national media centered on statements from anti-vaccine groups, conspiracy theories, and false perceptions about the speed of vaccine development, long-term side effects, and difficulties related to the COVID-19 vaccine.

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The internet and social media are extremely effective for disseminating information about the safety and efficacy of vaccines. However, it is difficult to change negative attitudes toward vaccines when individuals have been exposed to misinformation.^{16–18} It is highly probable that the parents who use the internet to obtain information about vaccines believe that there is no need to vaccinate healthy children and that the vaccine is more harmful than beneficial.¹⁹

To be able to learn and manage the perceptions of societal risks during the COVID-19 pandemic, monitoring social discourse on social media is of great value.²⁰ By allowing users to create and share content, social media exposes individuals to an ever-increasing amount of information and plays a role in spreading misinformation by bringing together people with similar thoughts, thus making them feel empowered.^{6,21,22}

Social network analysis (SNA) is an analytical method that is used to study the structure of social networks and the relationships between actors. Actors are represented by nodes, and relationships are represented as an edge between two actor nodes.²³ For example, actors can be workers from a business, and relationships can involve sending e-mails. If a worker sends an e-mail to another coworker, this can be represented by two nodes connected with an edge with an arrow pointing to the receiver.

Researchers have frequently used SNA for various research from different data sources, and research on Twitter has been growing in parallel. Twitter is one of the most influential social networks. All the content created can be accessed publicly, which enables researchers to gather information without the need for consent. Twitter is a micro-blogging site where users write about topics and interact with each other. They use hashtags, mentions, replies, and retweets, and follow other users to interact with them. Twitter can be a powerful tool for sharing information. One purpose of SNA is to identify influencers. The definition of influence on Twitter is “the potential of an action of a user to initiate a further action by another user.”²⁴ One of the metrics for measuring the influence is the markers of influence. These are physical representations of the potential for further action mentioned in the definition of influence. These markers are replies, retweets, mentions, and attributions.

Twitter is a network that exposes a user to messages written by selected individuals through the pathways formed by one user “following” another user. This network allows the examination of tweets with content related to vaccines in the context of a social relations network.²⁵

There has been a worldwide increase in studies related to interactions between social media and vaccines. These studies are based mostly on content analysis. No studies have been published on this subject in Turkey; therefore, information about online social networks related to vaccines in Turkey, the influential people or communities in this area, and the spread of evidence-based information and practices is limited. The aim of this study, based on SNA, was to determine the community interactions related to vaccines, to identify key influences and influencers before and after the COVID-19 pandemic, and to better understand communication about vaccines on Twitter.

2. Materials and methods

2.1. Ethical considerations

Messages, texts, or images shared on social media blogs, forums, etc. are considered part of the shared public domain. We collected data that were publicly posted on Twitter. Due to the nature of the information sent and the platform used, we assume that Twitter users expect the virtual space to be open to the public.²⁶ We changed the name of the Twitter user’s account to maintain his/her privacy.

2.2. Dataset

We collected two datasets with the keyword “aşı” (vaccine) on vaccination between June 1, 2019, and March 11, 2020, and March 11, 2020, and January 1, 2021. To distinguish how far back our data would go from the first COVID-19 case in Turkey, we first included the first three months of the pandemic, but the dataset was rather small, so we decided to use that as a reference and go back further. While experimenting with different timeframes through snowball sampling, we saw that after nine months, the dataset slowly grew larger. This indicates that before COVID-19, vaccine opposition on Turkish Twitter was rather low, so we decided that nine months before the first COVID-19 case should be the timeframe we use. For the second timeframe, the start date was the date of the first COVID-19 case in Turkey, and data were collected up till the date of this research to capture the recent state. The first dataset included all tweets before COVID-19, and the second dataset included all tweets following the start of COVID-19. These datasets were collected with Twint, an open-source Python package that enabled us to collect data without Twitter’s data restrictions. Twint is widely used in the literature as a web crawling method.^{27,28} A total of 131,172 tweets were gathered before COVID-19, and 955,305 tweets were gathered after the start of COVID-19. All our tweets were in Turkish, and none of the tweets were processed or filtered before the data preparation process. Tweet data included information such as its sender, date, time, tweet, mentions, hashtags, number of replies, list of users mentioned, etc.

2.3. Data preparation

To create a social network from tweets, we first cleaned irrelevant tweets from the datasets. We wrote Python code to obtain a list of all the hashtags used in the tweets. These hashtags represent information about what was tweeted. We filtered relevant hashtags, based on our research topic and only accepted tweets that contained relevant hashtags. When we searched “aşı” (vaccination) on Twitter, we also got results for “ası” and “asi” because of Turkish-only characters. We had many tweets that were irrelevant to our topic. For example, the “asi” hashtag is homonymous with “aşı” but they have different meanings. When the hashtags related to the vaccine were filtered, it was found that the hashtags #asi and #asi were still actively used by the fans of the TV series “Asi” (The title of TV series is Asi, a Turkish word meaning “rebel,” but its Turkish spelling is confused with the English spelling of the Turkish word

Table 1. Top 20 selected relevant hashtags based on their frequency.

Hastag	Translition	Hastag	Translition
Aşı	Vaccine	Coronavirusturkey	Coronavirusturkey
Coronavirus	Coronavirus	Coronawirus	Coronavirus
Koronavirüs	Coronavirus	Gripası	Fluevaccine
Koronavirus	Coronavirus	Korona	Corona
Koronawirus	Coronavirus	Saglik	Health
Corona	Corona	Hastane	Hospital
covid19	covid19	Kuduz	Rabies
Çin	China	Vaccine	Vaccine
Coronaviruesue	Coronavirus	sağlıkçınası	Vaccineforhealth
Coronavirüs	Coronavirus	Coronavirues	Coronavirus

“aşı” for vaccine as “ası”), which was popular in Turkey in the past. Therefore, we compiled a list of all hashtags used before and after COVID-19. A total of 8393 hashtags for the before period and 29956 hashtags for the after period were compiled. We filtered hashtags that appeared only once to reduce the number of hashtags. Then, we selected only tweets that contained relevant hashtags. This enabled us to eliminate irrelevant tweets about vaccinations. A total of 558 hashtags were selected. We decided that tags were relevant through peer review. For every hashtag selected, we checked its relevance to its context by reading tweets with that hashtag. While checking their relevance, we also coded the hashtags as pro or anti by looking at the context in which they were used. We did not include neutral hashtags because we wanted to focus on vaccine opposition; users who did not use pro or anti hashtags were marked as neutral. A list of the top 20 hashtags can be seen in Table 1.

Childhood vaccines were searched with hashtags that included #chickenpox, #MMR, #measles, #rubella, and #polio. However, it was seen that only the hashtags for #rabies and #flu vaccines were included in the top 20 list (Table 1).

After filtering relevant tweets, we wrote Python code that takes tweets and moves them to a new CSV file, which can be read as a social network by Gephi.²⁹ Social networks were created based on the interactions (mentions) between users on Twitter.

To map the anti-vaccine content in these datasets, we again checked all hashtags and marked users who tweeted with pro/anti-vaccination hashtags. Pro/anti-vaccination hashtags were also selected through peer review (Tables 2 and 3).

2.4. Using SNA to understand the vaccination network

In our case, influence is weighted in-degree. Weighted in-degree is the sum of all edges coming to the node with their weights and corresponds to the sum of all replies and mentions of that specific user in our case. Users with a high-weighted degree have many tweets that replied to or mentioned other users or that were replied to or mentioned by other users through high interaction with other users. Two types of scenarios can occur for influencers. They can have a high in-degree, which means that the user gets many replies or mentions, and a low out-degree, which means that the user does not reply or mention back. The second scenario is that they can have a high in-degree /high out-degree, which means they have high interaction, both coming to them and going from them.

These influencers are users with many followers and are in important positions regarding the spread of information. When they tweet, many other users see it, which gives the tweeter more potential for influence. Twitter’s follower count is the most basic metric for influence.²⁴

For example, Riddell et al. conducted research to identify the most influential emergency physicians on Twitter by measuring the user’s in-degree betweenness centrality and eigenvector centrality.³⁰ Furthermore, Sanawi et al. identified influencers on vaccination topics and used the user’s in-degree and eigenvector centrality in their analysis.³¹

Another metric for influence is betweenness centrality. SNA research points out that a central position implies the control of information flow. Xu et al. conducted research on Twitter and betweenness centrality and influence. They

Table 2. Examples for anti- and pro-hashtags before COVID-19.

Anti-Vaccine	English Traslation	Pro-Vaccine	English Traslation
Soneryalçın	Writer- journalist	Aşıcandır	Vaccineislife
Aşıkarsıtlığı	Vaccineopposition	Vaccineswork	Vaccineswork
Vaccine	Vaccine	Vaccination	Vaccination
Aşireddi	Retainvaccination	Aşihayatkurtarır	Vaccinesaveslives
Protestoediyorum	Iprotest	Aşıcandırhayatkurtarır	VaccineislifeandsavesLives
Moderntıp	Modernmedicine	aşıkarsıtlığıinsanlıksuçudur	Vaccineoppositioniscrimeofhumanity
Soneryalçın	Writer- journalist		

Table 3. Examples for anti- and pro-hashtags after COVID-19.

Anti-Vaccine	English Traslation	Pro-Vaccine	English Traslation
Kimesordunfahrettinkoca	Whodidyouaskfahrettinkoca	Haddinibilersoydede	Knowyourplaceersoydede
Haddinibilingursonmez	Knowyourplacebingursonmez	Ercümentovalı	Medical doctor3
Asiyahayır	Notovaccine	Asiolacağım	Iwillgetvaccinated
Billgates	Billgates	Bingursonmezhaddinibil	KnowyourplaceBingursonmez
Aşitruvaatı	Vaccinetrojanhorse	Bingürsönmez	Bingürsönmez
Pfizer	Pfizer	Vaccination	Vaccination
Aşıcifaşistler	Facistvaccinators	Aşıkarsıtlığı	Vaccineopposition
Zorunluaşiyahayır	Notomendatoryvaccination	Aşiolacağım	Iwillgetvaccinated
Çınaşısı	Chinesevaccine	Aşıhaftası	Vaccinationweek

found that higher betweenness centrality leads to a diverse range of information and enables influencers to interact with a bigger audience.³²

Our last metric is degree distribution. Degree distribution is the visual representation of nodes and their degrees in a sorted histogram representation. Degree distribution shows the number of highly connected nodes and fewer connected nodes.

2.5. Constructing networks and visualization

We created two social networks from the before and after COVID-19 datasets. Because Twitter is a platform where users create and share content and interact with others, we created a node for every user. Every node has a unique identity (ID) that corresponds to that user's Twitter ID, and no two users can have the same ID. Nodes also contain information, such as the number of tweets that a particular user tweeted on vaccinations during the indicated time frames. After creating nodes, we added edges that represented the interactions between users. When a user mentions or replies to a user, an edge is drawn from who wrote the tweet to the user who was mentioned or retweeted. There are also several interactions for every edge. The total number of interactions between two users

is stored as weights. We categorized users as anti-vaccination, pro-vaccination, mixed, and neutral. If users tweet with a related hashtag, then that node is categorized in the related category. If users tweeted both anti and pro hashtags, they were marked as mixed. Finally, if they did not use anti or pro hashtags, they were categorized as neutral. We used Gephi to visualize and analyze this social network. Visualizations of both networks can be seen in Figures 1 and 2. Constructing networks from mentions and retweets is common in SNA, and many different examples can be seen in the literature.²⁹

3. Results

3.1. Information on networks before/after COVID-19

Before COVID-19, the social network had 3,070 nodes and 1,252 edges. The diameter of the network was 2 and the average path length was 1.118, while the average degree was 0.408. The average clustering coefficient was 0.008. All of these metrics were calculated by Gephi.³³

After COVID-19, the social network had 38,241 nodes and 18,716 edges. The diameter of the network was 12 and the average path length was 3.258, while the average degree was

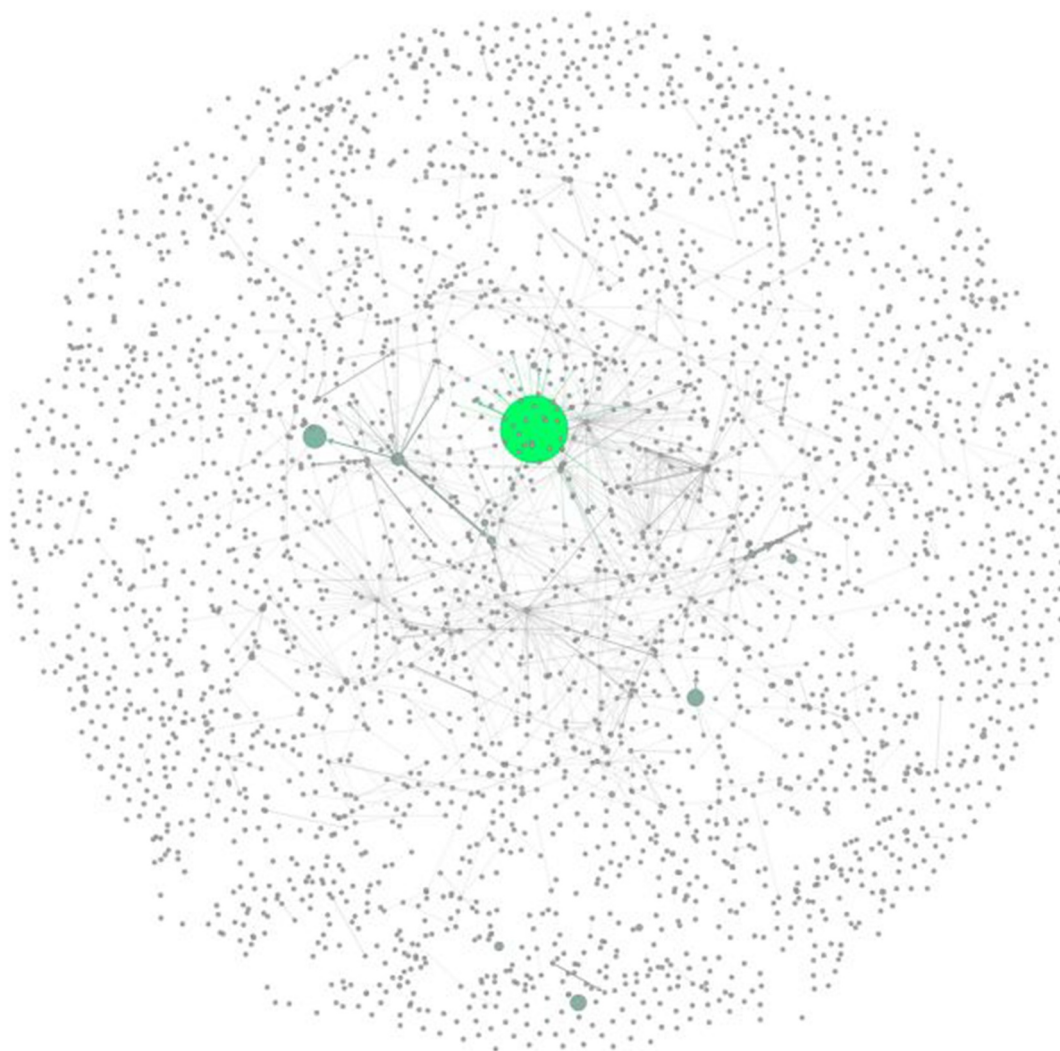


Figure 1. Social network visualization of twitter users on vaccination before COVID-19.

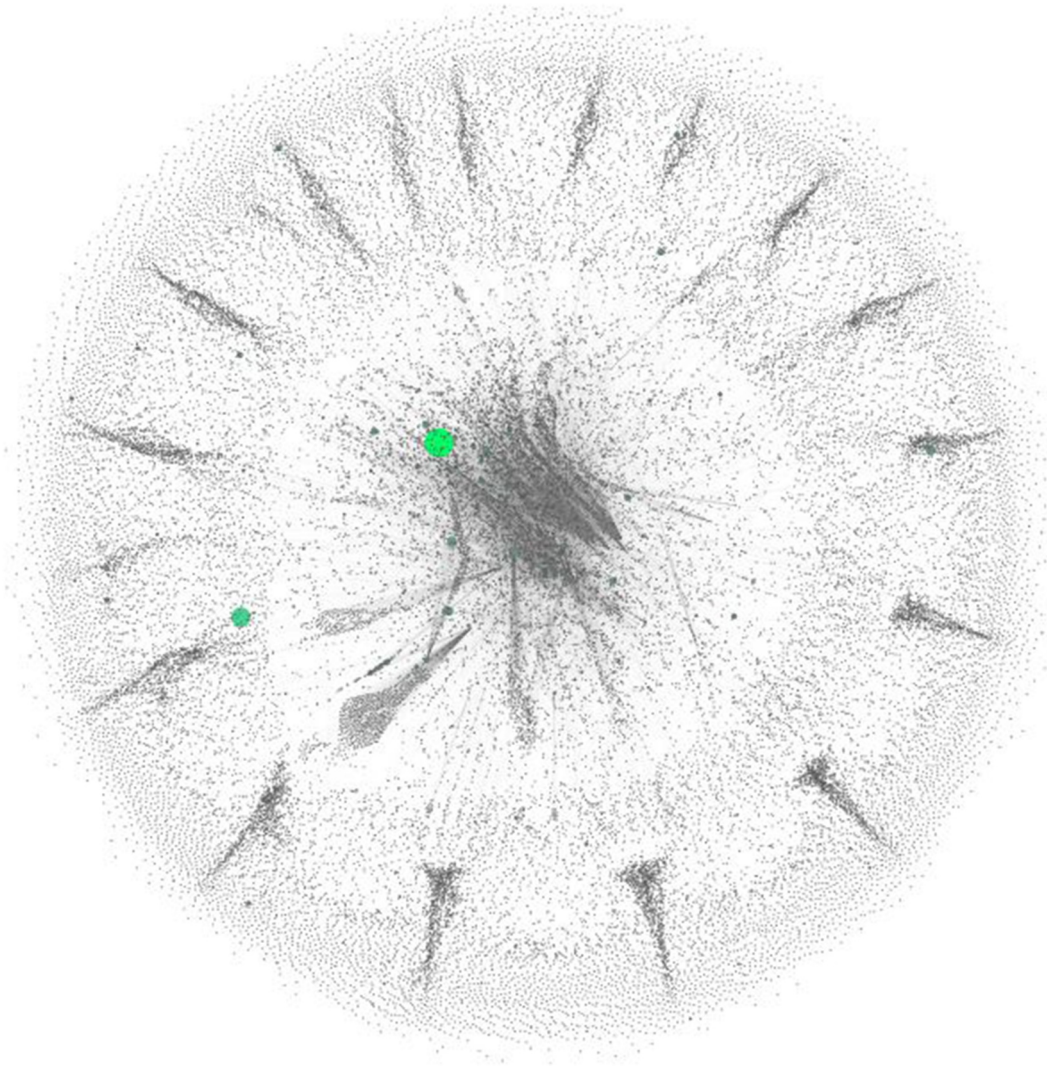


Figure 2. Social network visualization of twitter users on vaccination after COVID-19.

0.489. Our degree distribution graphs resemble a power law presence, which also supports the findings of influencers in the present network.

3.2. Finding the most influential users through networks

To find the most influential users in the network, certain metrics are used by researchers. One of these metrics is in-degree. In-degree represents the number of incoming edges to that node.³⁴ For our example, it is the number of mentions and replies the user has. A higher in-degree means that the user received many mentions and replies from other users. The top 10 most influential users are shown in Table 4, which is based on their in-degree and betweenness centrality scores in the pre-COVID-19 network. Visualization of the pre-COVID-19 Twitter network according to in-degree and betweenness centrality parameters is demonstrated in Figures 3 and 4.

A similar analysis was performed in the post-COVID-19 Twitter network. The top 10 most influential users are shown in Table 5 and are based on the in-degree and betweenness

Table 4. Top 10 most influential users in pre-COVID-19 Twitter network according to in-degree and betweenness centrality measures.

Username	In-Degree	Username	Betweenness centrality
Newspaper ¹	92.0	TV channel	37.6
Ministry of Health	55.0	News channel editor	28.0
Writer- journalist	39.0	Social media phenomenon ¹	23.0
Minister of Health	27.0	Social media phenomenon ²	15.0
Journalist	25.0	Publisher	8.0
Citizen ¹	16.0	Medical doctor ¹	7.0
Citizen ²	16.0	Social media phenomenon ³	6.0
Citizen ³	14.0	Social media phenomenon ⁴	5.0
TV channel	14.0	Medical support account	5.0
TV show producer	14.0	Social media phenomenon ⁵	2.0

Newspaper¹: Conventional media; **Writer- journalist**: Author of “dark side of modern medicine”; **Journalist**: Journalist, news presenter, and columnist; **Social media phenomenon¹⁻⁴**: Accounts sharing about politics; **Social media phenomenon⁵**: An account sharing about health and medicine; **Medical doctor¹**: A doctor who is a child and adolescent psychiatrist.

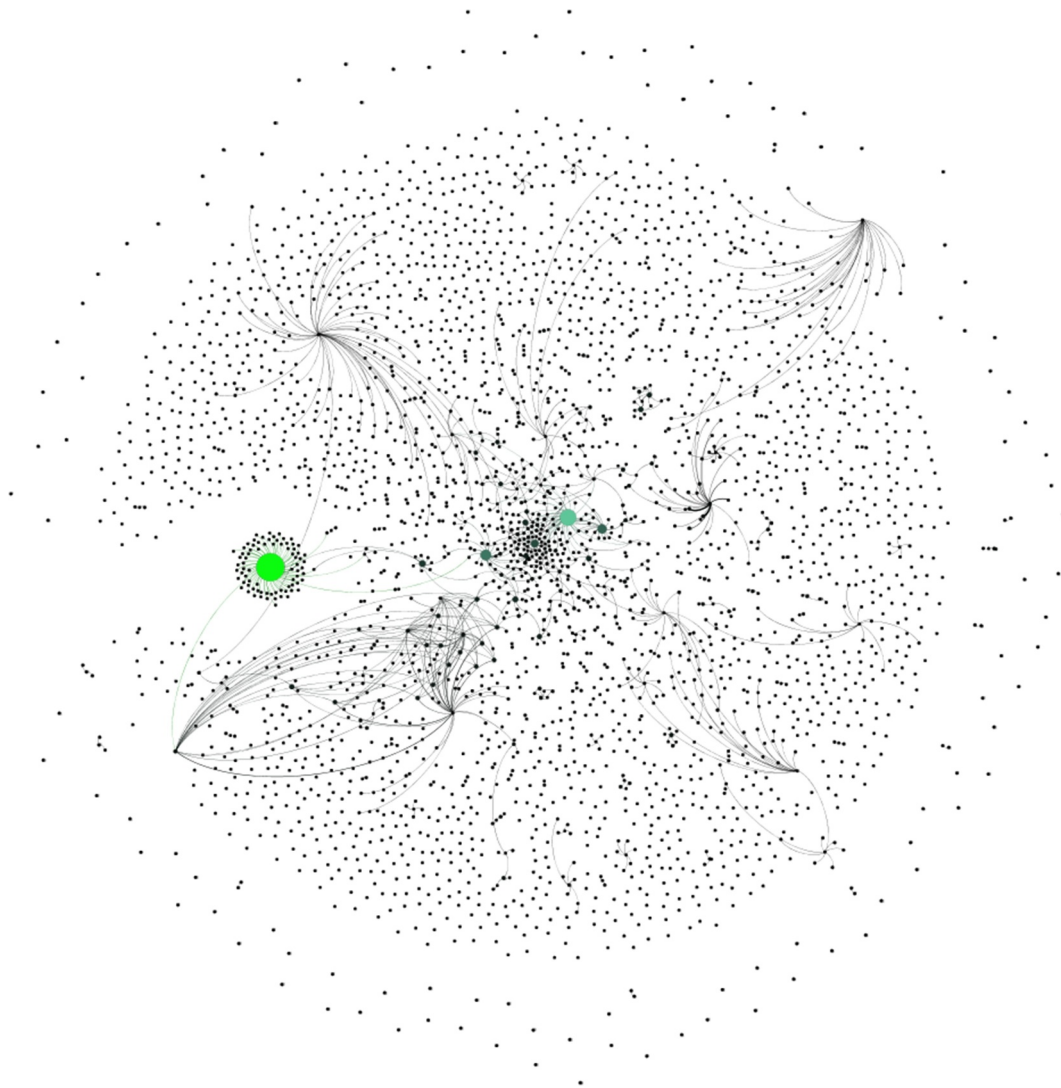


Figure 3. Visualization of pre-COVID-19 network according to In-degree. Size and color of the nodes are bigger and greener the more in-degree increases.

centrality scores.³⁵ Visualization of the post-COVID-19 Twitter network according to in-degree and betweenness centrality parameters is demonstrated in Figures 5 and 6.

3.3. Pro vs. Anti-vaccination supporters among networks

Members of our network utilized many hashtags related to what they were talking about. These hashtags also served as a summary of the tweet's content. By looking at which users utilized pro-vaccination, anti-vaccination, or both, we found that in the pre-COVID-19 network, the number of only pro-or anti-vaccination supporters was low. However, after COVID-19, there was a huge increase in these numbers. After COVID-19, anti-vaccine supporters were 22 times greater than pro-vaccine supporters. In addition, anti-vaccination supporters made up 26.51% of the networks in the post-COVID-19 network compared to 1.7% in the pre-COVID-19 network (Table 6). Anti-and pro-vaccination supporters can be visualized in Figures 7 and 8 in the pre-COVID-19 and post-COVID-19 networks, respectively.

4. Discussion

Immunization services are recognized as one of the most important and cost-effective public health achievements in the prevention of vaccine-preventable diseases and related deaths. However, in recent years, concerns about the safety and side effects of vaccines have started to spread rapidly on the internet. The WHO indicated that anti-vaccination is one of the 10 problems threatening global health in 2019.³⁶ Anti-vaccination movements have become a global trend and have been reported by approximately 90% of countries in the world.³⁷ Especially during the pandemic, news and rumors about vaccines became more visible on social media, opposition to the COVID-19 vaccine increased, and there were concerns that this situation would negatively affect vaccination studies.³⁸

In a study conducted in Denmark, France, Germany, Italy, Portugal, the Netherlands, and the UK in April 2020, 7.2% of the respondents stated that they did not want to be vaccinated for COVID-19.³⁹ Another study conducted in the USA revealed that 12% of those who participated in the study

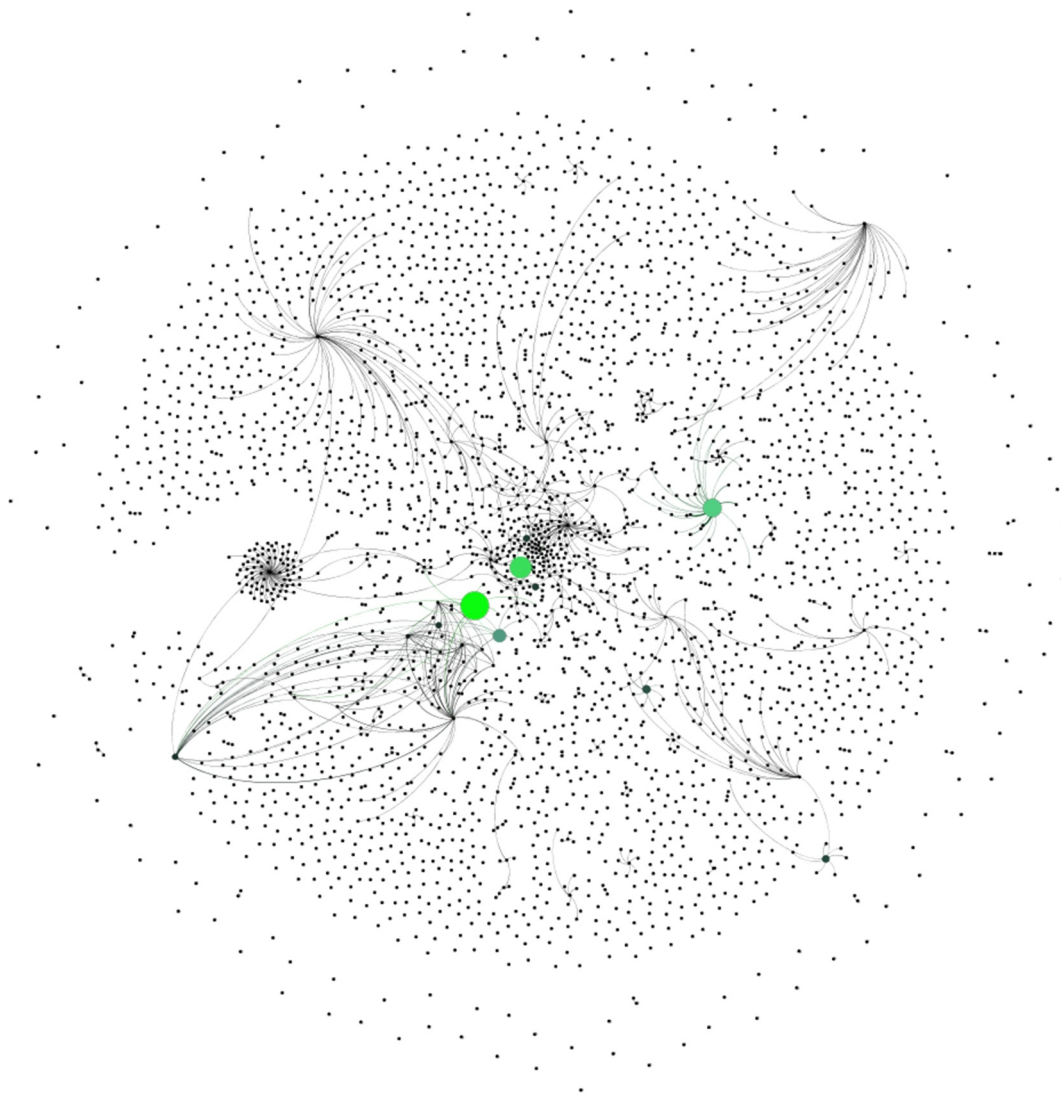


Figure 4. Visualization of pre-COVID-19 network according to betweenness centrality. Size and color of the nodes are bigger and greener the more betweenness centrality increases.

would not be vaccinated, and 82% were worried about the safety of the vaccine.⁴⁰ In the USA, individuals living in rural areas with a low income and low education levels are more hesitant to get the COVID-19 vaccine; in Australia, people living with a low income and disadvantaged areas and women are more hesitant to get the vaccine than men.^{41,42}

In Turkey, as in other countries, misinformation about the COVID-19 outbreak appeared on the internet and in social networks; some groups say that there is no virus, and there are rumors that the vaccine will have a microchip to control us. For example, a group of people tweeted, “They will put chips inside us, I don’t trust the vaccine.” Other users tweeted, “If you don’t get vaccinated, you will be a traitor. If you get vaccinated, you will be chipped.” In a study conducted with vaccines in England and Turkey in the first six months of the pandemic, 31% of the participants in Turkey and 14% of those in the UK emphasized that they were undecided about getting a COVID-19 vaccine.⁴³ According to a study conducted in Turkey between December 25–29, 2020, when the vaccination process had not started yet, 14% of the participants never thought of getting vaccinated.⁴⁴

The number of Twitter users in Turkey has reached 13.6 million, which is 7th in rank among the countries with the most Twitter users in the world.⁴⁵ The findings of the present study show that society is focusing largely on vaccine-related issues on the COVID-19 pandemic, and public interest is increasing in the areas related to the vaccine.

When the pre-and post-COVID-19 network characteristics were examined, it was observed that the density of the network, both peripheral and central, increased after COVID-19. In addition, network diameter and average path length increased, which points out that the network grew bigger with better-connected users.

Before COVID-19, anti-vaccine proponents gathered around anti-vaccine writers and took a stand against those who supported compulsory vaccination after COVID-19.

For example, a journalist-author whose book about the side effects of vaccines (published in November 2019) was at the forefront of the posts of anti-vaccine supporters in the pre-COVID-19 period. With the publication of the anti-vaccine book *Vaccine Whistleblower* (#cdcwhistleblower) and the movie *Vaxxed* (#vaxxed) published in the USA

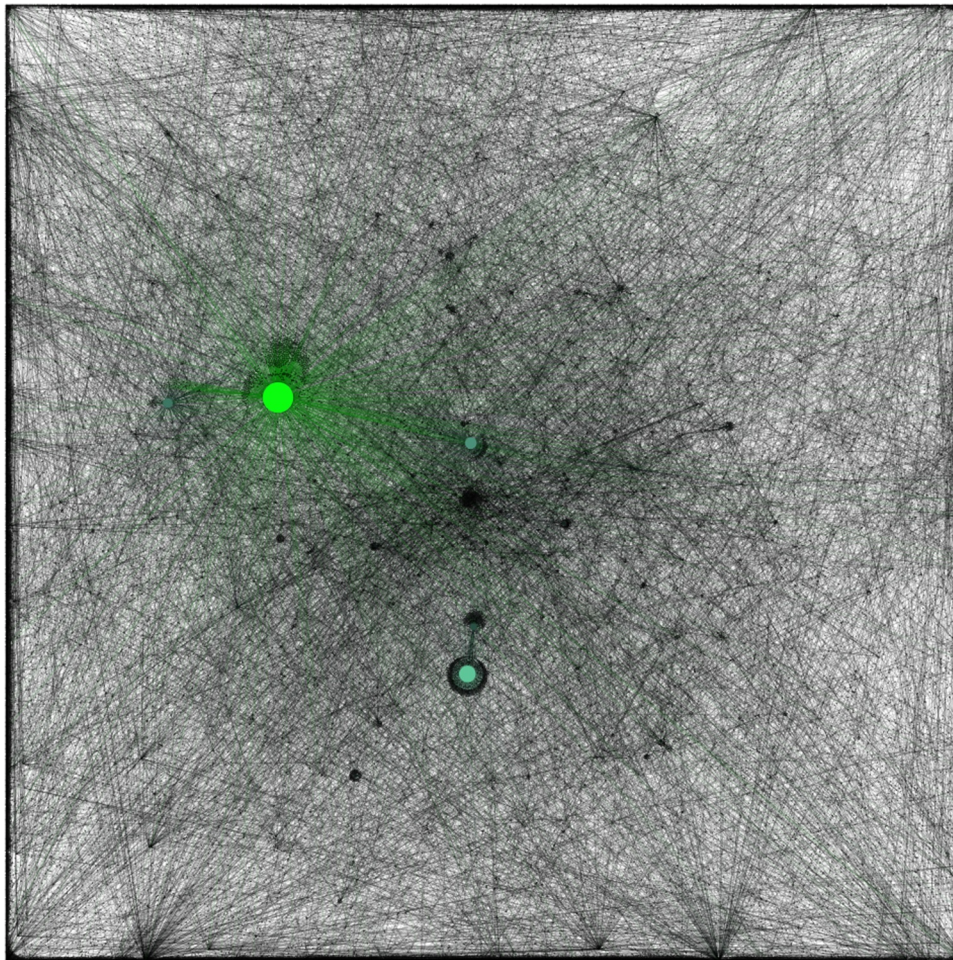


Figure 5. Visualization of post-COVID-19 network according to the In-degree. Size and color of the nodes are bigger and greener the more in-degree increases.

between 2014–2015, there was a steady increase in the anti-vaccine discourse on Twitter in the time period of the study.⁴⁶ Similar to the example given in our study, the author of an anti-vaccine book published in Turkey was highlighted by those who defended the view against the vaccine.

Before COVID-19 cases were detected in Turkey, multiple hashtags, including #coronavirus, #koronavirus, #covid19, and #çinaşısı were gaining tweet momentum. In our study, in the period before March 11, 2020, an epidemic of COVID-19 had started in Europe and Iran, thus affecting Twitter users.

It was on January 13, 2021 that the first coronavirus vaccine was made in Turkey, and by this date the study data had been completed. Even though the Synovac ((Chinese vaccine) and BioNtech (Pfizer) were not yet available in Turkey, the hashtags #pfizer and #Çinaşısı took place among the ones mostly preferred by Turkish Twitter users. The reason for this is thought to have been that the Turkish government intended to purchase these vaccines for use in the country and thus the public may have grown curious about the news of them. From our perspective, the discourse on vaccines in social media, which started before the vaccine arrived in the country, has changed over time and is linked to unfolding daily life events and updated views on vaccines.

It was noteworthy that pre-and post-COVID-19 childhood vaccines (#chickenpox, #MMR, #measles, #rubella, #polio, and #polio) especially the measles vaccine, were not included in the network. Whereas, in 2019, measles cases had increased all over the world, including Turkey, and some studies have shown the effect of this situation on Twitter.^{46,47} We are of the opinion that further research on the reflections of childhood immunization programs and vaccines on social media is required.

There is no legal regulation on vaccinations created and recommended for children by the Ministry of Health in Turkey. In other words, vaccination is not a mandatory practice. On the other hand, in the post-COVID-19 period, hashtags were mostly about concerns regarding the obligation to receive the vaccine, which were shared by users. It has been determined in our study that accounts advocating the view that the COVID-19 vaccine should be obligatory have received intense criticism. Similar to our study, mandatory vaccination in Italy after the 2015 measles epidemic led to polarized and politicized reactions.⁴⁸ It was also observed that most tweets about the vaccine were posted during the period when compulsory vaccination was legally approved in Italy.⁴⁹ In our study, while most of the tweets were neutral toward vaccination, polarized users tended to post more about anti-vaccine and pro-vaccine topics following COVID-19 than they did before.

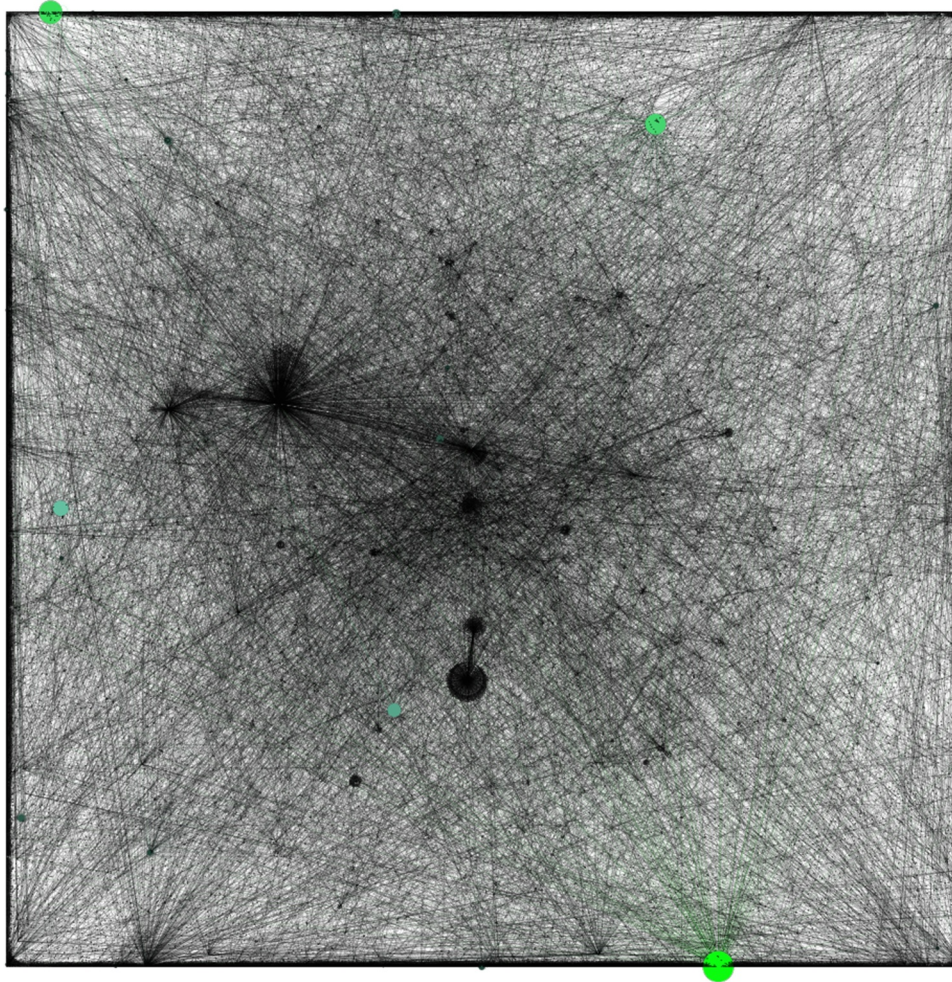


Figure 6. Visualization of post-COVID-19 network according to betweenness centrality. Size and color of the nodes are bigger and greener the more betweenness centrality increases.

The user accounts that receive the most interaction (in-degree) in the network before and after COVID-19 are those of various newspapers, media members such as writers and TV presenters, official organizations, and authors who write books about the side effects of vaccines. After COVID-19, the Minister of Health received the highest level of activity within the network in Turkey. Before and after the first case emerged in Turkey, the Minister of Health made frequent press statements. Especially after the first case, these statements were made almost every night and broadcast live on TV. The whole country followed these statements regularly. Decisions regarding the pandemic period, which were actively announced on social media and traditional media, set the agenda. The president's account also received a high volume of activity on Twitter following COVID-19. Discussion about the vaccine was politicized by some users on Twitter, making politicians appear more influential within the network. Vaccines, COVID-19 treatment, and pandemic measures have become part of the political debate in many parts of the world. It was determined in this study that various opposing press and media outlets were mentioned most of all in the post-COVID-19 period.

Media and press organizations which most strongly controlled the information flow around the network were found to be active before and after COVID-19 in betweenness centrality. Their activity shows the degree of the presence of an actor in the network among other actors. According to betweenness centrality, the highest interaction on Twitter was R.T., Minister of Health. Despite the active use of social media by the Minister of Health, few physicians in the network drew attention. Compared to other occupational groups, health professionals are unwilling to use social media for professional purposes.⁵⁰ Studies have shown various concerns, such as misinformation, unprofessionalism and time as potential reasons for the health professionals' unwillingness to use it.⁵¹ Since social media has become a big part of our daily lives, medicine, education, the active participation of physicians in this field has become a necessity.⁵²

The YouTube platform and physicians who conducted vaccination studies were added to the betweenness centrality table after COVID-19. Users shared content containing the word "vaccine" and the phrase "@YouTube." It was thought that the removal of videos that made negative comments about the

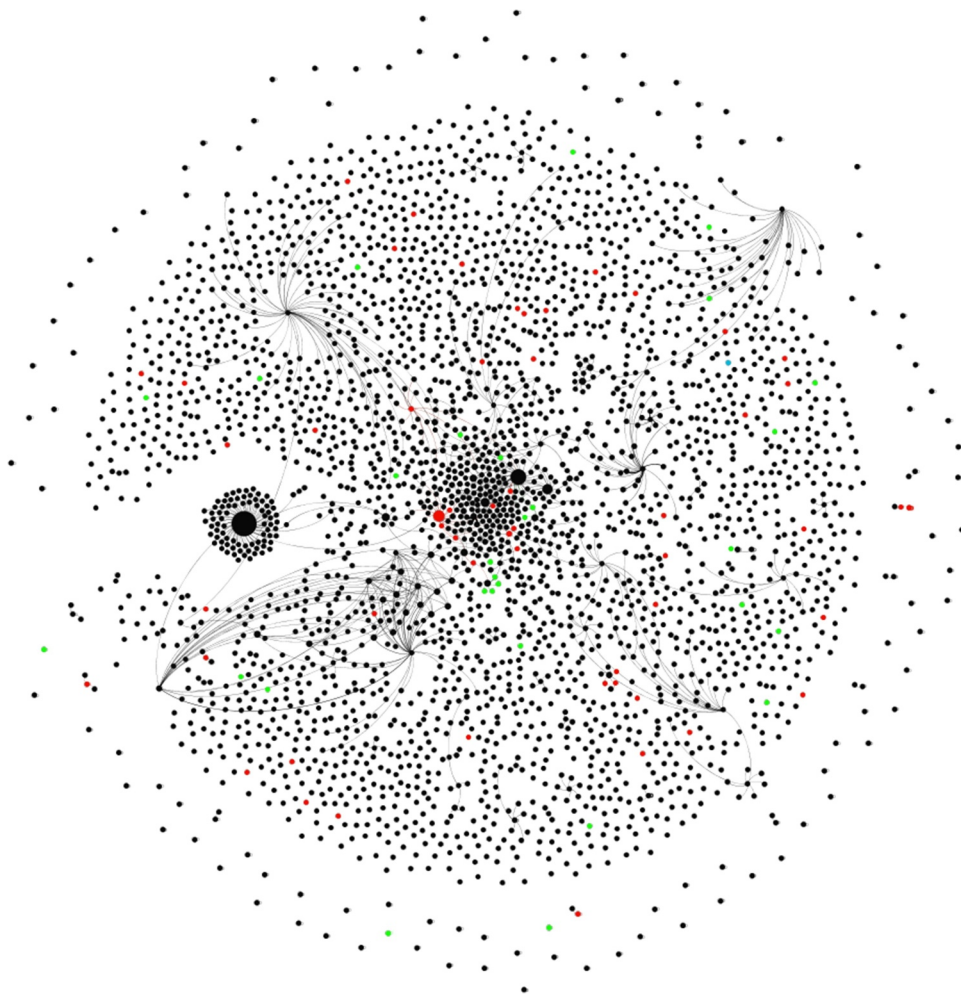


Figure 7. Visualization of anti/pro vaccination supporters before COVID-19 by in-degree. Red is anti, green is pro vaccination and black are neutral and blue is mixed.

COVID-19 vaccine might have pushed users toward this action. It should be noted that Twitter discussions are constantly evolving and potentially changing weekly.

When the interactions of users in the network after COVID-19 were examined, the rate of those who did not interact with other users was observed to be 80.59%. This value was very close to that of the pre-COVID-19 network. This shows that the COVID-19 pandemic did not affect the interaction rate among users. When the interaction types were examined, 17.4% of the interactions between users were in the form of direct responses to another user. Direct interactions, such as mentions, are used to construct networks in many research studies.⁵³ The interaction of influencers on the network, as far as we could see, consisted largely of users talking about influencers. We could not observe influencers replying to or mentioning other users. This shows that there was a one-way flow of information between the influencers and network members. The ratio of users against vaccine in the network to users for the vaccine was 22.65. In other words, for every 22 anti-vaccine users, there was one user who supported the vaccine. It has been determined in our study that while the number of anti-vaccine users increased 1400% in the post-COVID-19 period, the number of users supporting the vaccine increased by only 60%.

This shows that in the vaccine discussions that started with COVID-19, conspiracy theories, information pollution, and rumors spread on social media increased the opposition to vaccines and made them visible on social media.

4.1. Conclusion

We used SNA to analyze vaccine sensitivity in the population. This study investigated the ongoing vaccine discourse on the Twitter network, examined society's opinions about vaccines, and identified key players. We found increased interactions on vaccinations after the COVID-19 pandemic, that anti-vax content increased during this period, and that a key role in the network was played by the Minister and Ministry of Health and media and press organizations.

In our study, we observed that there was one-sided communication between influencers and other users. Experts, institutions, and organizations dealing with public health will be more effective against anti-vaccine discourses if they advise against false information on social media using their own accounts. In addition, well-known people, scientists, officials, and physicians should be encouraged to actively share using

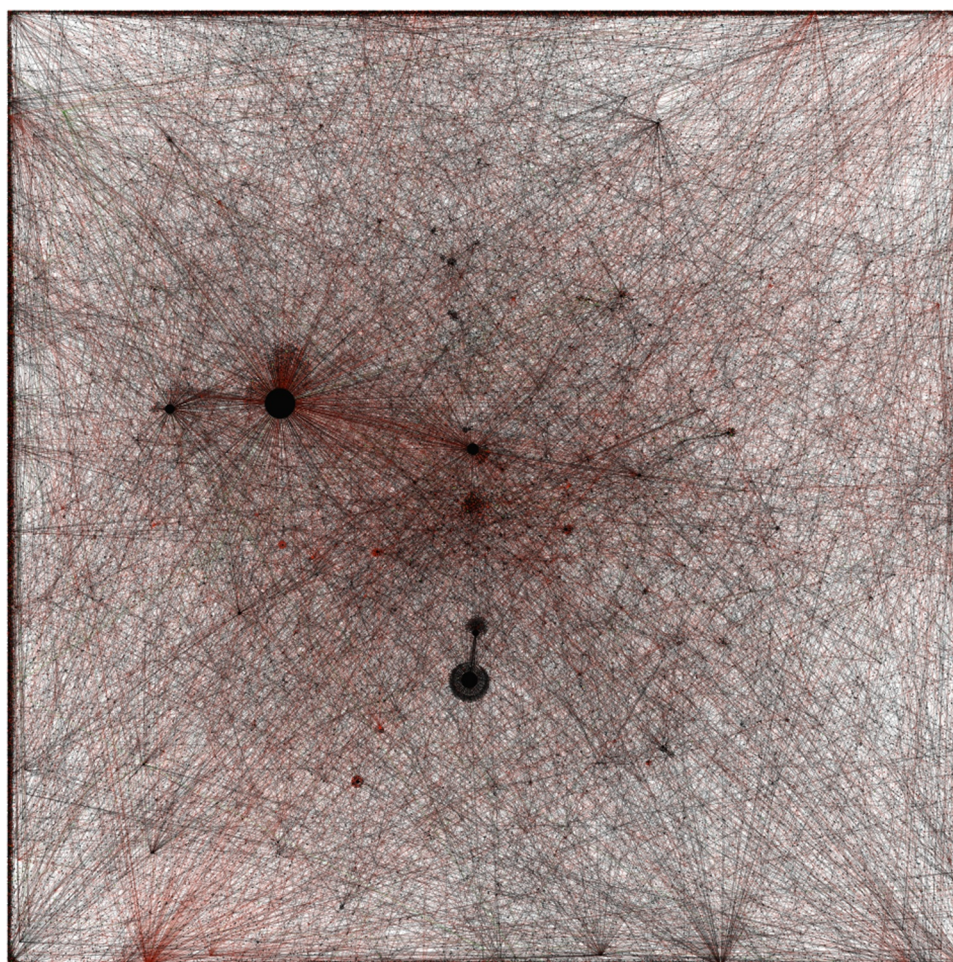


Figure 8. Visualization of anti/pro vaccination supporters after COVID-19 by in-degree. Red is anti, green is pro vaccination and black are neutral and blue is mixed.

Table 5. The top 10 most influential users in post-COVID-19 Twitter network according to in-degree and betweenness centrality measures.

Username	In-Degree	Username	Betweenness centrality
Minister of health	2282.0	Minister of Health	0,014194
Newspaper ¹	1582.0	Newspaper ¹	0,01209
The president of Turkey	889.0	Newspaper ²	0,004751
Ministry of Health	701.0	The president of Turkey	0,004003
Newspaper ²	585.0	Ministry of health	0,002672
Medical doctor ²	329.0	Youtube	0,001664
Writer	326.0	Medical doctor ²	0,001407
TV channel ²	208.0	Medical doctor ³	0,001187
Citizen ⁴	206.0	Writer	0,000999
Journalist	181.0	Journalist	0,000937

Newspaper^{1,2}: Conventional media; **Medical doctor²:** A famous psychiatrist; **Medical doctor³:** A doctor who works on vaccines; **Writer:** Anti-vaccine historian and philosopher writer.

traditional media and social media. In particular, physicians should be encouraged to actively use social media, and their training on how to use social media can be supported.

Our study was completed before January 13, 2021, the date of the first COVID-19 vaccination in Turkey. For this reason, we predict that SNA will help reduce misinformation regarding vaccines and all and help public health workers to act more proactively before vaccination.

Table 6. Users and network statistics before and after COVID-19 in Turkey.

	Pre-COVID- 19		Post-COVID- 19	
	Number of users	Percentage of users to total users	Number of users	Percentage of users to total users
Mention	1,042	83.23%	15,867	84.67%
Reply	210	16.77%	2,869	15.33%
Users with no interaction	2,483	80.88%	30,818	80.59%
Anti-Vaccination	54	1.7%	10,136	26.51%
Pro-Vaccination	29	0.94%	449	1.17%
Neutral	2986	97.26%	29549	72.04%
Mixed	1	0.03%	109	0.29%

4.2. Principal findings

Interest in vaccination increased after the pandemic, as shown by the increase in tweets on the topic.

The official social media account of the Ministry of Health was key to linking the network to the vaccination topic.

It was observed that the number of physicians who set the agenda regarding the vaccine during the study period was very few, and the physicians and authors who had attitudes toward mandatory vaccination received a great deal of reaction.

4.3 Limitations

The most important limitation of this study is that it was time dependent. Public sentiment on Twitter can change over time. Vaccination-related network information available on Twitter provides an overview of vaccine perception, but we assume that it may not reflect a broad vaccine perception in the general population as our study is limited to Twitter. Our study is based on network analysis only; no content analysis was performed. In the future, studies that include content analysis can be carried out. The use of Twitter is one of the limitations of our study. Our classification of pro-and anti-vaccination users is based only on the hashtags used without an analysis of the content of tweets. A no-vaccination or a pro-vaccination hashtag can be used in a tweet with an opposite meaning. Also, from a methodological point of view, classifying users as pro or anti could be done in alternative ways. Because we were experienced with content analysis and not experienced with sentiment analysis, we classified hashtags and tweets by peer review. Another limitation is that this study was based only on Twitter analysis. Since different platforms are preferred by various audiences, we think that future vaccine networks and data studies will encourage the analysis of public sentiment on other social media platforms. This study considers the two periods before and after the pandemic as a whole and does not consider temporal variations during the two periods.

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