A network-based approach to QAnon user dynamics during COVID-19 infodemic

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ABSTRACT

QAnon is an umbrella conspiracy theory that encompasses a wide spectrum of people. The COVID-19 pandemic has helped raise QAnon conspiracy theory to a wide-spreading movement, especially in the US. Here, we study users’ dynamics on Twitter related to the QAnon movement (i.e., pro-/anti-QAnon and swing users) in the context of the COVID-19 infodemic and the topics involved using a network-based approach. We find that it is not easy for swing users to convert their attitudes, although Twitter is suspending malicious pro-QAnon users as much as possible. We also find that QAnon clusters include many bot users. Furthermore, our results suggest that QAnon continues to evolve amid the infodemic and does not limit itself to its original idea but instead extends its reach to create a much larger umbrella conspiracy theory. A network-based approach in this study is important for both nowcasting and forecasting the evolution of the QAnon movement.

Keywords  COVID-19, infodemic, networks, QAnon conspiracy theory, user dynamics

1 Introduction

1.1 A brief history of QAnon

With the arise of populism worldwide in recent years, many conspiracy theories have become increasingly popular. Conspiracy theories and populism are relevant to each other. They usually contain two roles; i.e., the powerful elites who control social resources and privilege, and the ordinary people described as the vulnerable victims [1].

One of the popular conspiracy theories is QAnon.

QAnon is an umbrella conspiracy theory that encompasses a wide spectrum of people, including Trump supporters, COVID-19 deniers and anti-vaxxers. An anonymous government official known as ‘Q’ emerged on 4chan (anonymous English-language forum) in 2017, declaring that there is a cabal of upper hierarchy elites controlling the States, using their power to covertly abuse children (#pizzagate); The theory encourages people to follow Donald Trump (this conspiracy theory emerged during his presidency) and believes that Trump will arrest all the members in the ‘Deep State’ including Hillary Clinton and Barack Obama and finally bring the cabal to justice [2, 3, 4, 5]. Although QAnon is not an extreme organization, extremists existed amongst the QAnon movement. On January 6th 2021, an organized group of pro-Trump protesters rushed into the US Capitol. This well-known violence proved that far-right extremists existed amongst QAnon believers.

During the COVID-19 pandemic, QAnon used controversial and popular social topics to get more exposure. For instance, QAnon conspiracy theory blamed China for its long-term cover-up of the coronavirus; diffused an idea that mandated quarantine helped protect Joe Biden during the election; questioned the travel ban and advocated use of hydroxychloroquine; arbitrarily connected COVID-19 to the presidential election and China so that the coronavirus is just a media hyped tool to secure the Democrats’ victory in the election; and even introduced discord element such as ‘Black Lives Matter’ to the 2020 US presidential election [6].
Meanwhile, QAnon arbitrarily connected COVID-19 to the US presidential election and China to extend its beliefs. Surveys about the QAnon conspiracy theory discovered that the majority of the US citizens who have heard of QAnon think the conspiracy theory is harmful to the country. There are, however, many people holding middle positions (referred to as ‘swing users’) who consider QAnon as neither harmful nor helpful; they can not be neglected as they have the potential to become the pro-QAnon in the long run.

QAnon has been on main stream Social Network Services (SNSs) for a long time before Facebook, Twitter, and YouTube realized that the poor reputation of QAnon conspiracy might induce more social problems. In 2020, these platforms removed thousands of QAnon accounts. Facing this reality, QAnon supporters began to look for new spirit home on SNSs, such as Parler and Telegram. Parler is a US micro-blog SNS and famous for Trump supporters discussion; there are active QAnon channels for QAnon discussion across various countries on Telegram. QAnon is still cloaked in mystery but one thing for certain is that the COVID-19 infodemic has helped QAnon to become a wide-spreading movement.

1.2 Related work

The COVID-19 infodemic is a situation where the overabundance of COVID-19 related mis/disinformation is exploding on SNSs, making it difficult for people to retrieve trustful information about the pandemic. Some research has analysed the linguistic features of the QAnon phenomenon. used a BERT-based topic model to examine the QAnon discourse across multiple languages and discovered that the German language is prevalent in QAnon groups and channels on Telegram. used VADER to assess QAnon-related users’ positions towards Trump and Biden and employed a BERT model to describe user profiles. They found that the majority of QAnon users were Donald Trump supporters and their Twitter profiles contain ‘MAGA’, ‘God’, ‘Patriot’ and ‘WWG1WGA’. analysed QAnon comments on YouTube and found substantial international discussions about China, Russia and Israel. These findings suggest that QAnon has become an world-wide topic rather than a US domestic conspiracy theory.

Nowadays, the task for SNSs to detect QAnon communities and ban malicious users is becoming more complex. It was not until January 2021 that Twitter’s rules and policies gained the public’s considerable attention. It was reported that 355K Twitter users involved in the 2020 US Presidential Election were removed. In addition, Twitter removed more than 70,000 accounts that diffused harmful QAnon-associated content after the well-known US Capitol riots in January 2021. Meanwhile, whether or not the removal of misbehaving users contributes to a healthier social community is still controversial. has discovered that more than 60% of the purged users survived for more than two years before they were removed by Twitter, which asks us whether the purge is efficient enough.

1.3 Research questions

QAnon appears to take the advantage of the overabundance of COVID-19 mis/disinformation to gain political influences. It spreads mis/dis-information and induces negative emotions, which are harmful to the innocent public, including ‘swing users’—those who have the potential to become pro-QAnon in the long run. Although several aspects of QAnon have been investigated thus far, there is a lack of evidence of how QAnon evolved during the COVID-19 infodemic.

Our research questions are thus summarized as follows:

RQ1: What factors influenced swing users’ behaviours during the QAnon movement?

RQ2: What kind of topics does QAnon users spread?

2 Data and Methods

In this section, we explain our dataset and methods used for a network based approach to characterize QAnon dynamics during the COVID-19 infodemic.

2.1 Data

Over a 12 months period between February 20 2020 and March 1, 2021 we used the Twitter Search API to collect 880,278,195 (from 58,519,206 unique users) Twitter posts (including tweets and retweets) by querying COVID-19-related keywords: ‘corona virus’, ‘coronavirus’, ‘covid19’, ‘2019-nCoV’, ‘SARS-CoV-2’, ‘wuhanpneumonia.’ This dataset is named the base dataset. In addition, we filtered English language tweets containing at least one of the terms...
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‘QAnon’, ‘#QAnon’ or ‘deep state’, producing 308,631 tweets from 135,740 accounts. This subset is named the QAnon dataset. Both datasets were used in this study.

2.2 Identification of pro-/anti-QAnon and swing users

As QAnon is a conspiracy theory with for and against opinions, we expected to identify a characteristic retweet (RT) network where pro- and anti-users are segregated. We constructed a RT network using the QAnon dataset and applied the $k$-core decomposition ($k = 2$) to understand the swing users’ dynamics, where each node represents a user and directed edges between nodes represent retweets. As expected, this resulted in a RT network with two major clusters. We decided which cluster corresponds to the pro- or anti-QAnon group by manually examining large indegree users in each cluster (who were retweeted many times) in terms of their tweets and profile descriptions.

Additionally, we identified ‘swing users’ in the RT network; if a user retweeted posts both pro- and anti-QAnon users decided above, at least once, between February 20 2020 and March 1, 2021, the user was categorized as a ‘swing user’. Because the RT network consists of two clusters (i.e., pro- and anti-QAnon groups), we can trace whether a swing user finally migrated to the pro- or anti-QAnon group. The former type is called the ‘pro-QAnon-learning’ and the latter type is called the ‘anti-QAnon-learning’. Moreover, we recorded the month when a user met the swing user criterion above, referred to as ‘birth month’, in all swing users. The birth month data was used to characterize swing users in terms of network positions.

2.3 Human/bot classification

To classify users into bots and humans, we used the Botometer API v4. The Botometer is a well-recognized tool for automatically detecting bots based on supervised machine learning. The Botometer model is trained with 1200 features, covering six categories including account’s metadata, retweet & mention networks, temporal features, content information and sentiment [15]. The Botometer has been applied in series of research to quantify the online behaviours of bots [16, 17]. This tool computes ‘complete automation probability’ (CAP) for each user that ranges within the range of $[0, 1]$. The higher the value, the higher the probability that the user is a bot. In this study, we set CAP=0.7 as the threshold for human/bot classification, which means if the CAP for a user is larger than 0.7, this user is considered as a bot. We validated that this threshold provides a reliable human/bot classification in the previous study using the same dataset [18].

2.4 Hashtag co-occurrence networks

Furthermore, we constructed hashtag co-occurrence networks for both the base and QAnon dataset in order to understand the topical diversity of QAnon conspiracy theory. In this network, each node is a hashtag and undirected edges between nodes represent the co-occurrence of two hashtags. We generated a retweet network from the base dataset, applied the $k$-core decomposition ($k = 10$) to it, and then extracted all the neighbors of ‘#QAnon’ and itself. Recall that the base dataset include multiple languages (not only English). From the resulting network, we used a RT network (1000-core) for further analysis and obtained 336 unique hashtags (nodes). Similarly, we constructed a RT network ($k = 10$-core) from the QAnon dataset that contains only English tweets and obtained 323 unique hashtags.

The modularity-based community detection algorithm, the Louvain method [19], was applied to the hashtag co-occurrence network to identify clusters using the software Gephi [20]. Finally, we assigned the resulting modularity class IDs to each node of the hashtag co-occurrence network for further analyses.

3 Results

3.1 Network of pro-/anti-QAnon and swing users

Figure 1a shows the retweet network (2-core) constructed from the based dataset between February 2020 and March 2021, showing that pro- and anti-QAnon clusters are actually segregated. We see that the pro-QAnon cluster ($n = 40, 512$) is much larger in size than the anti-QAnon cluster ($n = 5, 480$) (Table 1a) and swing users are spotted in between (Fig. 1a). Among them, there are more swing users ($n = 332$) in the anti-QAnon cluster than those ($n = 199$) in the pro-QAnon cluster. We checked users’ activity in August 2021 to estimate how many pro- and anti-QAnon users were suspended by Twitter (Fig. 1b). From Fig. 1a to b, 25,318 users were suspended or closed in the pro-QAnon cluster, but only 653 users were so in the anti-QAnon cluster (Table 1b).

[https://gephi.org/](https://gephi.org/)
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Table 1: QAnon users’ statistics
(a) Summary of pro- and anti-QAnon users

|                        | #pro-QAnon | #anti-QAnon |
|------------------------|------------|-------------|
| All users (between February 2020 to March 2021) | 40,512     | 5,480       |
| Suspended users (or closed users, checked in Aug 2021) | 25,318 | 653         |
| Bots                   | 8,239      | 2,861       |
| Humans                 | 6,016      | 2,592       |

(b) Swing users

|                        | #pro-QAnon-leaning | #anti-QAnon-leaning |
|------------------------|--------------------|---------------------|
| Swing users            | 199                | 332                 |
| Suspended (or closed)  | 131                | 100                 |
| Bots                   | 44                 | 116                 |
| Humans                 | 19                 | 118                 |

We then looked into the dynamics of swing users. Recall that swing users are those who retweeted both pro- and anti-QAnon users (see 2.2). In Fig 1c, swing users are mapped on the RT network and differently coloured by ‘birth month’. We can see that most of the late swing users (July 2020, grey) are located in the pro-QAnon cluster, which means they are pro-QAnon-leaning. By contrast, early swing users (April for red) are located near the anti-QAnon cluster, which means they are anti-QAnon-leaning. Middle swing users (May 2020, orange) are located in-between. Above all, the tendency of swing users is migrating from anti-QAnon to pro-QAnon. Regarding to the swing users among them, accounts of over 131 of the pro-QAnon-leaning users were suspended or closed, whereas accounts of approximately 100 of the anti-QAnon-leaning users were suspended or closed by Twitter (Tables 1a and 1b). A dynamic visualization of swing user dynamics is available online.

Figure 1d shows the unique swing users for each month, reflecting the fact that many swing users emerged in the early stage of the COVID-19 pandemic. Similarly, Figure 2 show that the number of tweets and users peaked in April 2020 in swing users, except for the number of the number of pro-QAnon-learning swing users, which gradually increased month-by-month (Figure 2b blue). In other words, they changed their attitude to the pro-QAnon.

All there results indicate that although Twitter actively suspended malicious users to mitigate the spreading of mis/disinformation, the unneglectable amount of swing users migrated into the pro-QAnon cluster.

3.2 Prevalence of bots in QAnon clusters

There are 8,239 bots and 6,016 humans in the pro-QAnon cluster while there are 2,861 bots and 1,592 humans in the anti-QAnon cluster as showed in Table 1a. When focusing on the swing users (n = 531 in total), there are 160 bots and 137 humans. In both cases, the majority of users in QAnon clusters are bots. This result is different from other mis/disinformation phenomena during the COVID-19 infodemic (e.g., see [18]). Note that we can not obtain all the bot scores because of user suspensions by Twitter or inaccessible due to private settings, and thus the number of bots and humans reported here could be smaller than the real. All these findings suggest that unlike other misinformation phenomena, bots play a major role in distributing QAnon-related (mis/dis)information regardless of the pro- or anti-QAnon group.

3.3 Hashtag co-occurrence network as a conspiracy theory umbrella

The global hashtag co-occurrence network (1000-core) was constructed using the base dataset. The resulting network is illustrated in Fig. 3 (n = 336). This visualises the whole image of the topic landscape for QAnon conspiracy theory in the context of the COVID-19 infodemic, as the base dataset includes multiple languages and diverse COVID-19 topics. Here, we see that the three most popular topics are ‘US politics’, ‘News’ and ‘Daily life’. Furthermore, #QAnon has even co-occurred with human rights hashtags, such as ‘#LGBT’ (k = 1,418), ‘#METOO’ (k = 1,073) and

https://youtu.be/AeN0DtlwsRY
Figure 1: Network of pro-/anti-QAnon and swing users. (a) Active users from February 2020 to March 2021; (b) Active users in August 2021, in which Magenta denotes pro-QAnon, green denotes anti-QAnon. Large nodes are swing users. (c) Network positions of swing users from February to July 2020. February: cyan, March: blue, April: red, May: orange, June: black, July: grey. (d) the number of unique pro- and anti-QAnon swing users per month.
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Figure 2: Swing users’ activity aggregated based on birth month. (a) # of tweets by pro- and anti-QAnon-leaning users. (b) Unique # of pro- and anti-QAnon-leaning users.

‘BLACKLIVESMATTER’ \((k = 6,390)\), which is consistent with [6]. Note that \(k\) denotes degree (i.e., number of occurrences). The co-occurrence patterns of popular hashtags can reflect the topical diversity of QAnon conspiracy theory, which consequently facilitates greater exposures to users (especially to swing users) amid the pandemic.

Furthermore, we find an isolated cluster (class 1) of Japanese hashtags in left-bottom in Fig. 3 which is related to JAnon, QAnon’s Japanese counter-part. JAnon users also believe that (former) President Trump is a hero in the fight against the Deep State. We also find topical relations between QAnon and France (French language tweets, class 9), Spain (Spanish language tweets, class 7), and Italy (Italian language tweets, class 4) topics, which proves that QAnon is becoming a global conspiracy theory topic, especially in Western countries. In addition, the religion hashtags relevant to the ‘apocalypse’ Trump supporters believe in were connected to #QAnon. They believed that Trump was sent by God [21]. In actuality, there is a tweet mentioning ‘Armor of God!! #qanon #wearethefakenews #factsmatter #wwg1wga #wakeupamerica #covid-19 #unitednot’.

Because QAnon is a US conspiracy topic, we then focused on English tweets using the QAnon dataset. The 10-core English hashtag co-occurrence network \((n = 232)\) comprises the four conspiracy theory-related topics, including ‘#WHO’, ‘#TRUMP’, ‘#5G’ and ‘#BILLGATES’; these topics were discussed previously [18]. In addition, we observed the well-known QAnon hashtags such as ‘#WWG1WGA’ \((k = 624)\), ‘#MAGA’ \((k = 337)\), ‘#THEGREATAWAKENING’ \((k = 244)\); it seems that QAnon debunking information was also heard in the network. For instance, ‘#FAKENEWS’ \((k = 94)\), ‘#FAKENEWSMEDIA’ \((k = 15)\), ‘#CONSPIRACY’ \((k = 31)\) were identified as well. Since ‘#FAKENEWS’ is identified in both global and English hashtag co-occurrence networks, we suppose that there could be, at least, two voices towards QAnon, one is pro-QAnon and the other is anti-QAnon, which is consistent with our QAnon users visualizations (Fig 1). In addition, we are able to identify ‘#FAKENEWS’ and its 64 neighbours, indicating there was a voice of debunking QAnon-related news.

These two hashtag co-occurrence networks indicate that QAnon has been evolving a much larger conspiracy umbrella worldwide, which may potentially attract vulnerable users, including swing users who are neutral to pro- and anti-QAnon groups.

3.4 Hashtag preferences of swing users

To understand what topics in Fig. 3 concerned swing users, we examined the hashtags in relation to the pro- and anti-QAnon users. The results are summarized in Table 2. The three most popular topics are the same as the ones described above: US politics (class 5), COVID-19 (class 0) and News (class 2) (Fig. 4).

We computed the ratio (%Anti/%Pro) of anti-users’ %hashtags to pro-users’ %hashtags to show the hashtag preference of swing users.

Here, a higher ratio means a stronger tendency to the anti-QAnon side. If \(%\text{Anti}/%\text{Pro} > 1\), the users are holding anti-QAnon tendency in that hashtag topic; if \(%\text{Anti}/%\text{Pro} < 1\), the users are holding pro-QAnon tendency in the topic; and if \(%\text{Anti}/%\text{Pro} = 1\), the users are holding balanced or neutral in the topic (Table 2). It turns out that in the JAnon topic, swing users were holding a balanced tendency, but all the users showed anti-QAnon tendency. It is pointed out that swing users were holding anti-QAnon tendency but all the users were persisting in pro-QAnon in Italian and
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Figure 3: Global hashtag co-occurrence network. Numbers denote hashtag classes. ‘#QANON’ is in class 0 (green).

Table 2: Anti & pro swing users’ hashtags % in Fig. 3

| Topic class | Swing users | All the users |
|-------------|-------------|---------------|
|             | %Anti | %Pro | %Anti/%Pro | %Anti | %Pro | %Anti/%Pro |
| 0 | US politics | 24 | 76 | 0.3 | 20 | 80 | 0.3 |
| 1 | J-Anon | 51 | 49 | 1.0 | 68 | 32 | 2.1 |
| 2 | News | 45 | 55 | 0.8 | 30 | 70 | 0.4 |
| 3 | Lockdown | 39 | 61 | 0.6 | 28 | 72 | 0.4 |
| 4 | Italy | 54 | 46 | 1.2 | 33 | 67 | 0.5 |
| 5 | COVID-19 | 44 | 56 | 0.8 | 30 | 70 | 0.4 |
| 6 | Daily life | 32 | 68 | 0.5 | 27 | 73 | 0.3 |
| 7 | Spain | 32 | 68 | 0.5 | 28 | 72 | 0.4 |
| 8 | India | 52 | 48 | 1.1 | 30 | 70 | 0.4 |
| 9 | France | 31 | 69 | 0.4 | 22 | 78 | 0.3 |

Indian tweets. By contrast, swing users and all the users commonly shared pro-QAnon tendency in the topics of France, Spain and US Politics.

In summary, not many swing users were holding anti-QAnon tendency. We also found that Japanese users are more anti-QAnon, while users concerned with US politics are more pro-QAnon.

4 Discussion

Regarding RQ1, we found that swing users are largely affected by pro-QAnon information. Swing users were gradually migrating from the anti-QAnon cluster to the pro-QAnon one; in particular, the late swing users significantly exhibited such tendency (Fig. 1c). Recall that pro-QAnon swing users preferred ‘US politics’-related contents (Table 2), which consists of articles from right-wing media (e.g., ‘@DailyCaller’ and ‘@gatewaypundit’). However, these contents are more attractive to late swing users; e.g., the July swing user ‘@paulamjohns’ has an outdegree of 177, of which 174 edges pointed to the pro-QAnon users. This reminds us that simply removing malicious users may not be enough to
protect swing users from the attraction of diverse pro-QAnon contents. An alternative approach is to intervene in swing users with an adequate timing by showing trustful information sources, with the purge of malicious users. This mixed strategy may help swing users alter their attitudes toward anti-QAnon side. To this end, we need to better inform swing users about the potential harm of QAnon while avoiding their further approaching the pro-QAnon cluster.

Regarding RQ2, we found that QAnon has been evolving to a diverse and global conspiracy theory umbrella. Previous work [22] pointed out that QAnon lacks both a clear organizational structure and a centralization of interpretive duties, compared with other extreme organizations. However, QAnon became a popular conspiracy theory during the COVID-19 infodemic. Not only do we find ‘US politics’, but also QAnon has spread to other countries including France, Spain, Italy and Japan (JAnon). In addition, we can identify human rights topics, such as ‘#LGBT’ and ‘#BLACKLIVESMATTER’, as well as the COVID-19 related topics, such as ‘#STAYHOME’ and ‘#SOCIALDISTANCING’. These results suggested that QAnon has been growing in an semantic network, thereby forming a larger conspiracy theory umbrella.

In conclusion, swing users play a key role in the evolution of QAnon conspiracy theory. It is possible to influence their positions by feeding them with trustful information at adequate timing. Here, we advocate adopting an alternative approach to better inform swing users about the nature of QAnon to avoid the ‘backfire effect’ of their further approaching the pro-QAnon community. As shown, the number of pro-QAnon users has been decreasing at least on Twitter platform but it does not necessarily mean that QAnon users have vanished. They might have moved to other social media platforms and are looking for a chance to revive, while increasing topical diversity to attract neutral or swing users. Therefore, a network-based approach in this study is important for both nowcasting and forecasting the evolution of the QAnon movement in terms of social and topical dynamics.

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Figure 5: English QAnon hashtag co-occurrence network

The degree is represented along with each hashtag. The color saturation and label size of a node is proportional to its degree.

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