

# “Is it a Qoincidence?”: A First Step Towards Understanding and Characterizing the QAnon Movement on Voat.co

Antonis Papasavva<sup>1</sup>, Jeremy Blackburn<sup>2</sup> Gianluca Stringhini<sup>3</sup>, Savvas Zannettou<sup>4</sup>,  
and Emiliano De Cristofaro<sup>1</sup>

<sup>1</sup>University College London, <sup>2</sup>Binghamton University, <sup>3</sup>Boston University, <sup>4</sup>Max Planck Institute for Informatics  
antonis.papasavva@ucl.ac.uk, jblackbu@binghamton.edu, gian@bu.edu, szannett@mpi-inf.mpg.de, e.decrisofaro@ucl.ac.uk  
– iDRAMA Lab –

## Abstract

Online fringe communities offer fertile grounds for users to seek and share paranoid ideas fueling suspicion of mainstream news, and outright conspiracy theories. Among these, the QAnon conspiracy theory has emerged in 2017 on 4chan, broadly supporting the idea that powerful politicians, aristocrats, and celebrities are closely engaged in a global pedophile ring. At the same time, governments are thought to be controlled by “puppet masters,” as democratically elected officials serve as a fake showroom of democracy.

In this paper, we provide an empirical exploratory analysis of the QAnon community on Voat.co, a Reddit-esque news aggregator, which has recently captured the interest of the press for its toxicity and for providing a platform to QAnon followers. More precisely, we analyze a large dataset from /v/GreatAwakening, the most popular QAnon-related subverse (the Voat equivalent of a subreddit) to characterize activity and user engagement. To further understand the discourse around QAnon, we study the most popular named entities mentioned in the posts, along with the most prominent topics of discussion, which focus on US politics, Donald Trump, and world events. We also use word2vec models to identify *narratives* around QAnon-specific keywords, and our graph visualization shows that some of QAnon-related ones are closely related to those from the Pizzagate conspiracy theory and “drops” by “Q.” Finally, we analyze content toxicity, finding that discussions on /v/GreatAwakening are less toxic than in the broad Voat community.

## 1 Introduction

Broadly speaking, conspiracy theories typically credit secret organizations or cabals for controversial, world-changing events, while rejecting explanations given by officials [22]. In many cases, conspiracies posit that important political events or economic and social trends are the product of deceptive plots mostly unknown to the general public. A prominent example relates to the disappearance of Malaysia Airlines Flight MH370, which is alleged to have been taken over by hijackers and flown to Antarctica [44].

The ability to find like-minded people, at scale, on social

media platforms has helped the spread of conspiracy theories in general, and politically oriented ones in particular. For instance, the Pizzagate conspiracy theory emerged during the 2016 US presidential elections, claiming that candidate Hillary Clinton was involved in a pedophile ring [40]. Even when widely debunked, conspiracy theories can help motivate detractors and demotivate supporters, thus potentially threatening democracies.

Over the past few years, a new conspiracy, known as “QAnon,” has emerged that is somewhat related to Pizzagate. It originated on the anonymous Politically Incorrect (/pol/) board of 4chan by a user going by the nickname “Q,” who posted numerous threads claiming to be a US government official with a top-secret Q clearance, in October 2017 [10]. They explained that Pizzagate is real and that many celebrities, aristocrats, and elected politicians are involved in this vast, satanic pedophile ring. Q further claimed that President Donald Trump is actively working against a cabal within the US government trying to defeat his crusade. QAnon incorporates many theories together into a broadly defined *super-conspiracy theory*. QAnon adherents also believe that many world events, including the COVID-19 pandemic, are part of a sinister plan orchestrated by “puppet masters” like Bill Gates [31]. Zuckerman [72] argues that QAnon supporters create a vast amount of material that eventually becomes viral. For instance, the book “QAnon: An Invitation to a Great Awakening” [70], written by QAnon followers, ranked second on the Amazon best-selling books list [32].

After Reddit banned many popular QAnon-related subreddits in September 2018 [54, 46], QAnon followers reportedly migrated to Voat.co. Voat is a news aggregator, structured similarly to Reddit, where users can subscribe to different channels of interest, known as “subverses.” Newcomers are not allowed to create new submissions, but they can upvote or downvote submissions and comments, as well as being able to create comments on existing submissions. Once users manage to get a total of ten upvotes on their comments, they can create new submissions to any subverse.

As with many “fringe” platforms (e.g., Gab), Voat was designed and marketed vigorously around unconditional support of freedom of speech against the alleged anti-liberal censorship perpetrated by mainstream platforms. A year after its

creation, HostEurope.de stopped hosting Voat because of the content posted [4] and, shortly after, PayPal froze their account [16]. In August 2015, Voat was thrust into the spotlight when Reddit banned various hateful subreddits (e.g., /r/CoonTown and /r/fatpeoplehate [57, 55]) and a large number of users reportedly migrated over [43, 2, 15].

**Research Questions.** In this paper, we focus on the QAnon-focused community on Voat. More specifically, we set out to answer the following research questions:

**RQ1** What does activity by the QAnon movement on Voat look like?

**RQ2** Which words and topics are most prevalent for and best describe the QAnon movement on Voat? What narrative are shared and discussed by QAnon adherents?

**RQ3** How toxic is content posted on QAnon subverses? How does it compare to popular subverses focusing on general discussion?

**Methodology.** To address RQ1, we provide a temporal analysis of the most popular QAnon-focused subverse, /v/GreatAwakening, in comparison to a *baseline* dataset, which includes the four most popular subverses (in terms of posting activity) focusing on general discussion: /v/news, /v/politics, /v/funny, and /v/AskVoat.<sup>1</sup> We also analyze submission engagement and user activity. Then, we detect popular named entities, and use topic detection tools as well as word embeddings along with graph representations of QAnon-specific keywords in an attempt to define the narratives around the QAnon movement (RQ2). Finally, to study toxicity within these communities (RQ3), we use Google’s Perspective API [48] to measure how toxic the posts in our dataset are.

**Main Findings.** Overall, our work provides a first characterization of the QAnon community on Voat, and more precisely of /v/GreatAwakening. Among other things, we find that subverse to attract many more daily number of submissions than the four (popular) baseline subverses. Indeed, users tend to be quite engaged, with two of the most active QAnon submitters creating over 3.75% of the submissions of the baseline subverses as well. Also, we analyze user profile data and find that over 17.6% (2.3K) unique users registered a new account on Voat when Reddit banned QAnon subreddits in September 2018.

Then, using a word2vec model to illustrate words closely related to QAnon-specific keywords, we show that the movement still discusses, among others, its predecessor Pizzagate conspiracy theory, the posts of the user Q, and other social media. We also show that the most prominent topics of discussion are centered around the US, political matters, and world events, while the most popular named entity of the discussion is President Trump. Finally, we find that the QAnon community on /v/GreatAwakening is 16.6% less toxic than on baseline subverses.

<sup>1</sup>As discussed later in Section 3, we also identify 16 other subverses related to QAnon but find them to be inactive, thus, we only focus on /v/GreatAwakening.

## 2 Background

In this section, we discuss the history, origins, and beliefs of the QAnon movement. We also provide a high-level explanation of the main functionalities and features of Voat.

### 2.1 QAnon

**Origins.** QAnon originates from posts by an anonymous user with the nickname Q. On October 28, 2017, Q posted a new thread with the title “Calm before the Storm” on 4chan’s Politically Incorrect board (/pol/). In that thread, and over many subsequent cryptic posts, Q claimed to be a government insider with Q level security clearance.<sup>2</sup> The user claimed to have got their hands on documents related to, among other things, the struggle over power involving Donald Trump, Robert Mueller, the so-called “deep state,” and Hillary Clinton’s pedophile ring [69]. The deep state is believed to be a secret network of powerful and influential people (including politicians, military officials, and others, that have infiltrated governmental entities, intelligence agencies, etc.), and that allegedly controls policy and governments around the world behind the scenes, while officials elected via democratic processes are merely puppets. Q claims to be a combatant in an ongoing war, actively participating in Donald Trump’s crusade against the deep state [56].

**Ongoing activities.** Q has continued to drop “breadcrumbs” on 4chan and 8chan, giving birth to a community named after the nickname of the anonymous user: “QAnon.” The community is devoted towards decoding the cryptic messages of Q to figure out the real truth about the evil intentions of the deep state, pedophile rings run by aristocrats, and updates on the noble, multi-front war President Trump is waging. Although this movement was not initially very popular, mostly confined to a small group [69], it has since grown substantially via mainstream social networks like Facebook, Reddit, and Twitter. For example, QAnon adherents around the world have staged protests [14, 11], and there are at least 25 US Congressional candidates with direct links to QAnon who will appear on ballots during 2020 US Presidential Election [3].

**Relevance.** Previous work studied the dangers and threats conspiracy theories pose to democracies and the general public. Specifically, Douglas and Sutton [23] explain how the conspiracy theory surrounding the global warming phenomenon potentially threatens the whole world. The authors note that the uncertainty, fear, and denial of climate change cause people to seek other explanations. Alarming, climate change conspiracy theories can be harmful as people who believe them often deny to take environmentally friendly initiatives. Therefore, governments and many environmental organizations face significant challenges towards convincing people to take action against global warming.

Sternisko et al. [64] and Schabes [61] argue that conspiracy theories, including QAnon, are extremely dangerous for democracies. In fact, government officials and media often

<sup>2</sup>Q access authorization is the US Dept. of Energy equivalent to the US Dept. of Defense top-secret clearance.

get involved in starting or promoting such conspiracy theories to benefit their political agendas and interests. For instance, California city councilwoman Pam Patterson publicly asked God to bless her city, country, *and QAnon*, during her farewell address [62]. At a recent rally for Donald Trump, the person that introduced Donald Trump used the QAnon motto “where we go one, we go all” to conclude his speech [37]. With the 2020 U.S. Presidential Elections looming, the FBI has recently described the QAnon movement as a domestic terror threat [37], and its followers as “domestic extremists.”

**QAnon on social networks.** Mainstream social networks like Reddit, Twitter, and Facebook are trying to ban QAnon-related groups and conversations. Specifically, Reddit was the first social network to ban numerous subreddits devoted to QAnon discussion in 2018 [19, 46, 65]. Then, Twitter put restrictions on 150K user accounts and suspended over 7K others that promoted this conspiracy theory. Twitter also reported that they would stop recommending content linked to QAnon [9, 45]. Facebook recently announced they were banning QAnon conspiracy theory content across all their properties [7], with YouTube following shortly thereafter [33].

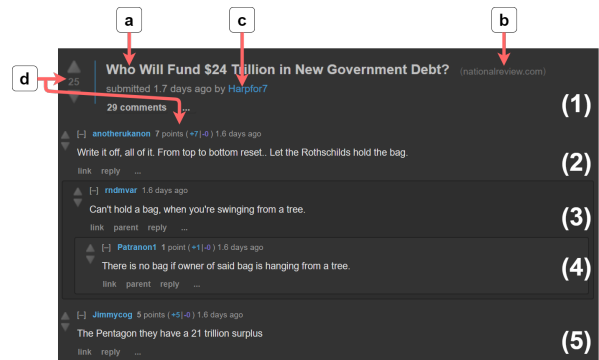
## 2.2 Voat

Voat is a news aggregator launched in April 2014, initially under the name “WhoaVerse” and renamed to Voat in December 2014.

**Main features.** Areas of interest, called “subverses,” group posts on Voat. Similar to Reddit, users were able to register new subverses on Voat on demand but this functionality has been disabled since June 2020. When a user registers a new subverse, they become the *owner* of the subverse. The owner of a subverse can delete it and nominate moderators and co-owners, who can then delete comments and submissions. Notably, Voat limits the number of subverses a user may own or moderate to prevent a single user from gaining outsized influence.

Users can register on Voat using a username, a password, and an email (optional). They can subscribe to subverses of interest, see, vote, and comment on submissions, but are ineligible to post new submissions at this point. Voat users refer to themselves as “goats,” due to the mascot of the platform that resembles an angry goat.

**Submissions.** Figure 1 depicts an example of a Voat submission: (1) shows the submission, (2) and (5) are comments made under the submission, and (3) and (4) are child and grandchild of comment (2), respectively. A user can create a new submission by posting a title and a description or sharing a link and a description. If sharing a link, the title of the submission (see “a” in Figure 1) becomes a hyperlink to the source website. The source website also appears next to the title of the submission (see “b”), along with the username of the user that posted the submission (“c”). Note that some subverses allow users to post anonymously. Other users can then comment on the submission (comment 2 and 5 in Figure 1), or comment on comments of other users (comments 3 and 4). Also, users can “upvote” or “downvote” the submission (“d”



**Figure 1:** Example of a typical Voat submission. Post with number (1) shows a Voat submission, while posts (2) to (5) are comments.

in the figure) or the comments of other users. Submissions and comments may have a negative vote rating based on the votes they receive from users.

A user becomes eligible for posting new submissions only if their *Comment Contribution Points* (CCP) is equal or greater than ten. Upvotes a user receives are added towards her CCP, while downvotes are subtracted. Note that users lose their eligibility to post new submissions once their CCP falls under ten.

**Ephemerality.** Each subverse has a limit of 500 active submissions at a time: up to 25 submissions in 20 pages (page 0 to page 19). When a user creates a new submission on Voat, that submission appears first on page 0, i.e., the subverse’s home page. At the same time, the submission at the end of page 19, usually the one with the least recent comment, disappears. That submission is still reachable, but only if one knows its direct link; it is archived and new comments cannot be posted. Notably, when a submission gets a new comment, it is bumped to the top of page 0, no matter when the submission was originally posted. However, it is not clear when submissions on Voat stop being bumped when they get new comments.

## 3 Data Collection

This section presents our data collection methodology as well as our dataset.

**Subverses.** Our first step is to identify Voat subverses that are related to the QAnon movement. To do so, we start from several articles from the popular press [26, 57, 54], which highlight how several subreddits banned from Reddit re-emerged on Voat. This happens for QAnon-related subreddits as well [19, 46, 65], thus, we search for subverses with same and similar names as the banned subreddits. We identify 17 subverses and, upon manual inspection, confirm that they are indeed devoted to QAnon-related discussions. However, we find that 16 out of 17 are essentially inactive, with less than 800 total posts over a period of almost 5 months. Therefore, we focus on the most active QAnon subverse, /v/GreatAwakening.

We also use the four most active subverses as a baseline dataset. More precisely, we select the top four, in terms of

posts, from the top-10 most subscribed subverses: /v/news, /v/politics, /v/funny, /v/AskVoat. In the rest of the paper, we refer to these four general-discussion subverses as the “baseline subverses.”

**Crawling.** We start crawling the five subverses on May 28, 2020, using Voat’s JSON API<sup>3</sup>, and stop on October 10, 2020. Voat does not provide an online listing of the archived submissions that fall out of the 20 pages limit, but these submissions are still reachable if one knows the direct link to it, i.e., the subverse it was posted in, and the submission ID. A manual inspection of the submission IDs in our database indicates that the submission IDs are monotonically increasing, and thus it is technically possible to collect submissions that fall out of the 20 pages limit by using submission IDs smaller than the ones we collect on the first day that our data collection infrastructure started operating. If the submission ID does not exist within the subverses we are interested in, the API will return a 404, and thus we could indeed enumerate through all possible submissions. That said, doing this would require us to make millions of requests to the Voat API, the majority of which would be 404s placing undue load on their servers, and, if we followed the Voat API usage limits, it would take several years to enumerate through all the possible submissions.

Hence, we use the following methodology to collect all the submissions’ comments, focusing only on data posted after May 28, 2020, inclusive. For each subverse, our crawler continuously requests the submissions pages from 0 to 19, using Voat’s API. For each submission, we obtain its submission ID, and query the Voat API again to collect the comments posted on that submission.

Voat’s API returns only up to 25 comments at a time (aka comment segments) for a given submission. Next, we note that Voat has a hierarchical, tree-like commenting system, similar to Reddit, with some submissions resulting in branching threads of varying depth. Thus, to ensure we collect all comments on a submission, our crawler implements a depth first search (DFS) algorithm where we start with the comments returned by the first request to the API, and then iteratively query for any child comments they might have. For each of the children discovered, we query for *their* children, until we fully explore the comment tree for the submission. The primary reason we went with a DFS implementation over breadth first search (BFS) implementation is due to the Voat API returning comment *segments*: a DFS simply required a bit less bookkeeping and is a more natural fit considering we are not guaranteed to get all comments at a given level with a single request. The crawler revisits the pages of every subverse, looking for new submissions, or updates on the ones already collected, numerous times per day, ensuring the collection of the full state of submissions before they fall off the page 19 limit.

**Dataset.** Table 1 lists the number of posts (submissions and comments) we collect for each subverse analyzed in this study. Our dataset spans posts from May 28 to October 10, 2020. Note that our dataset is missing some posts between

Subverse	Posts	Users
/v/GreatAwakening	152,315	4,915
/v/news	153,162	6,212
/v/politics	107,214	5,610
/v/funny	61,949	4,971
/v/AskVoat	35,643	4,282
<b>Total</b>	<b>510,283</b>	<b>13,084</b>

**Table 1:** Number of posts for each subverse in the dataset, along with the total number of user profiles collected.

June 9 and June 13 due to failure of our data collection infrastructure.

Besides submissions and comments, we also collect publicly accessible user profile data. More specifically, we collect profile data of the users posting a submission or a comment on /v/GreatAwakening and baseline subverses listed in Table 1. In total, we find 4.9K, 6.2K, 5.6K, 4.9K, and 4.2K unique usernames that have either created a submission or made a comment in /v/GreatAwakening, /v/news, /v/politics, /v/funny, and /v/AskVoat, respectively. The union of these results in 15K unique usernames, with 13K of these usernames having accessible profiles. The remaining ~2K (13.16%) of usernames we query result in a 404 error, which we believe is due to profiles being deleted or deactivated.

**Ethical considerations.** Note that we only collect openly available data and follow standard ethical guidelines [51]. Also, we do not attempt to identify users or link profiles across platforms. Moreover, the collection of data analyzed in this study does not violate Voat’s API Terms of Service.

## 4 General Characterization

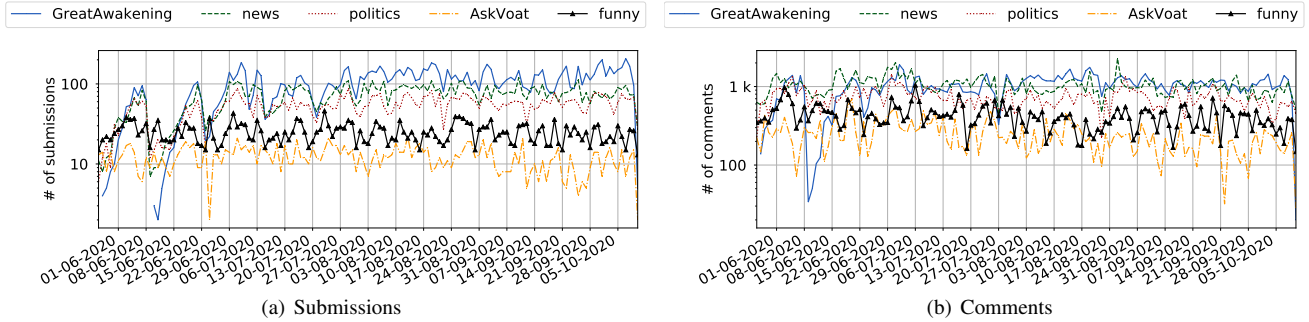
In this section, we analyze aggregate and user-specific activity, content engagement, and registrations for all subverses in our dataset.

### 4.1 Posting Activity

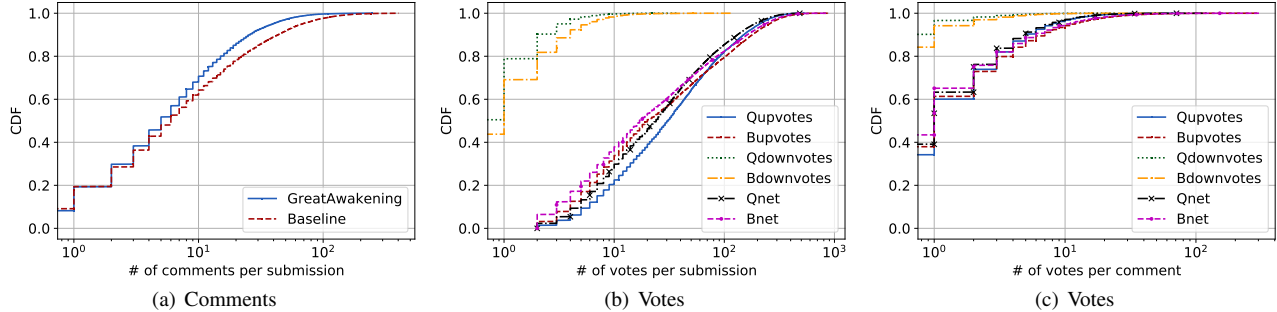
We start by looking at how often submissions and comments are posted on the collected Voat subverses. Figure 2(a) plots the number of daily submissions for the baseline and /v/GreatAwakening subverses (note log-scale on y-axis). From the figure, we see that, over a span of 4.5 months, /v/GreatAwakening has more submissions than the individual baseline subverses, with about 100 new submissions per day, on average. The next most active subverse is /v/news with about 70 new submissions per day. This is remarkable considering that, as of October 2020, /v/GreatAwakening has only 20K subscribers, while /v/news has 100K. When looking at comment activity (Figure 2(b)), /v/news and /v/GreatAwakening are close, with 1.06K and 1.01K comments per day, respectively.

We observe a peak in submission and comment posting activity on /v/GreatAwakening between June 29 and July 3

<sup>3</sup><https://api.voat.co/swagger/index.html>



**Figure 2:** Number of submissions and comments posted per day in baseline subverses and in /v/GreatAwakening.



**Figure 3:** CDF of the number of (a) comments and (b) votes per submission on /v/GreatAwakening (Q) and baseline subverses (B), and number of (c) votes per comment on /v/GreatAwakening (Q) and baseline subverses (B).

with the most submissions on July 2 (185 submissions and almost 1.9K comments). Manual inspection indicates the peak in submission activity may be related to Jeffrey Epstein’s ex-girlfriend, Ghislaine Maxwell, being arrested by the FBI [8]. Another peak in submission and comment posting activity appears between August 10 and August 21 with a peak of 183 submission on August 19. (Manual inspection does not reveal any clear link to a specific event). Finally, October 7 has the most submissions on /v/GreatAwakening for a single day (207), which we believe is due to Facebook announcing the ban of QAnon accounts, pages, and related content across all their platforms [7].

## 4.2 Engagement

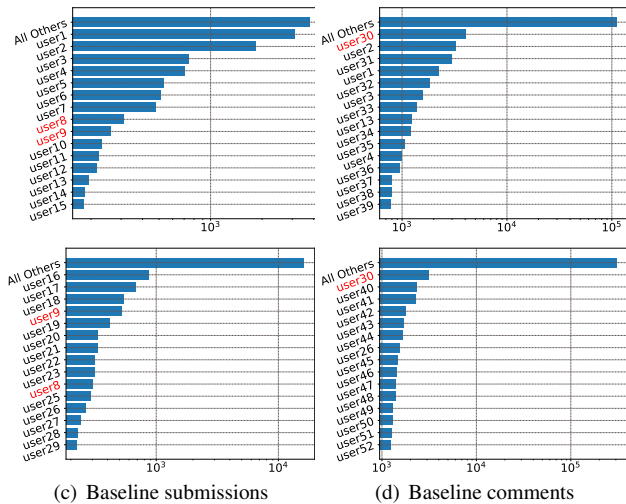
Next, we look at user engagement. Figure 3(a) plots the Cumulative Distribution Function (CDF) of the number of comments per submission. On average, submissions on /v/GreatAwakening receive 10.4 comments, while the baseline subverses’ submissions get 16.2 comments. Specifically, Figure 3(a) shows that only 14.9% and 22.3% of the submissions on /v/GreatAwakening and baseline subverses, respectively, have more than 20 comments. The median number of comments on /v/GreatAwakening submissions is 5 and on baseline subverse’s submissions is 6, while the most popular /v/GreatAwakening submission has 245 comments and the most popular baseline subverses’ submission has 403 comments. Our findings show that, although /v/GreatAwakening has the most submissions, the users of the baseline subverses are more engaged.

Next, we look at how often users upvote and downvote sub-

missions. We plot the CDF of upvotes, downvotes, and net votes (e.g., upvotes - downvotes) the submissions get in Figure 3(b). On average, /v/GreatAwakening gets 57.4 upvotes and 0.9 downvotes, while on baseline subverses we find 61 upvotes and 1.5 downvotes. The most upvoted submission has 537 and 870 upvotes on /v/GreatAwakening and baseline subverses, respectively, while the most disliked submission has 37 downvotes on /v/GreatAwakening, and 114 downvotes in the baseline subverses. Specifically, the title of the most upvoted /v/GreatAwakening submission is “The United States of America will be designating ANTIFA as a Terrorist Organization,” and the submission links to a tweet by President Trump. On average, the submissions of both /v/GreatAwakening and the baseline subverses tend to have a net positive vote count in the end; about 48.8 for /v/GreatAwakening and 54.1 for the baseline subverses.

We observe that 62.4% and 50.5% of the /v/GreatAwakening and baseline submissions, respectively, have more than 20 upvotes. On the contrary, only 0.46% and 1.79% of the submissions on /v/GreatAwakening and baseline subverses get more than 10 downvotes. We also run a two-sample Kolmogorov-Smirnov (KS) test on the distributions of upvotes, downvotes, and net votes, and reject the null hypothesis ( $p < 0.01$  for all comparisons).

Similarly, we plot the CDF of the number of upvotes and downvotes of comments in Figure 3(c). On average, comments get 2.2 upvotes and 0.18 downvotes on /v/GreatAwakening. Comments of the baseline subverses get 2.8 upvotes and 0.35 downvotes, on average. Again, we find statistically significant differences between the distributions via the two-sample KS test ( $p < 0.01$ ).



**Figure 4:** Number of submissions and comments posted per user on /v/GreatAwakening and baseline subverses.

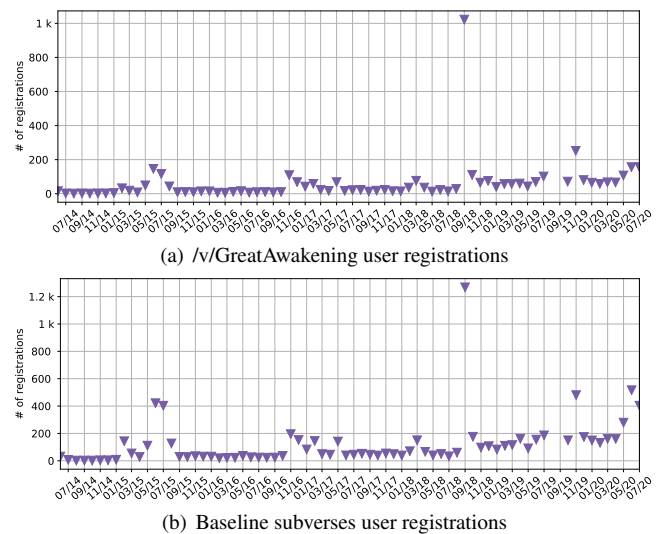
Overall, this shows that users of both communities tend to positively vote the content they encounter. Baseline subverses’ posts tend to be downvoted and upvoted more often when compared to the /v/GreatAwakening posts. This is probably due to the great difference of audience between the two communities. Notably, both communities seem to be engaging towards commenting and voting the posts they encounter in the platform.

### 4.3 User Activity

Next, we focus on user profile data to understand how often users post new submissions on both /v/GreatAwakening and baseline subverses. More specifically, we investigate whether the audience of /v/GreatAwakening and baseline subverses consume information from specific users due to Voat’s rule not allowing newcomers to post new submissions unless they have a CCP above 10.

To do so, we count the number of submissions users posted on /v/GreatAwakening and the baseline subverses. We find that the 13.5K submissions of /v/GreatAwakening were made by 346 users. The 21.9K submissions of the baseline subverses were made by 1.8K users. Figure 4 reports the top 15 submitters and commenters of both communities. To protect users’ privacy, we replace the original usernames with “user1,” “user2,” etc.

We observe that the top submitter, “user1” in Figure 4(a), posted 22.9% (3.1K) of the total submissions on /v/GreatAwakening. Excluding the top 15 submitters, the remaining 331 submitters (marked as “All Others” in the figure) are responsible for 28.2% (3.8K) of the submissions made on /v/GreatAwakening. This is not the case for submissions of general discussion as the top 15 submitters together are only responsible for 26.8% (5.8K) of the total submissions, as depicted in Figure 4(c). Excluding the top 15 commenters, /v/GreatAwakening (Figure 4(b)) and baseline subverses (Figure 4(d)) comment activity seems to fall on the broader audience of the communities since “All Others” post 80.9%



**Figure 5:** Number of monthly user registrations of (a) users engaging on /v/GreatAwakening and (b) users engaging in all baseline subverses.

(112K) and 92% (308.5K) of all the comments, respectively.

Manual inspection of our dataset shows that 22.8% (3K) usernames *overlap* between /v/GreatAwakening and the baseline subverses. Namely, “user8” and “user9” are amongst the top submitters of both communities, and “user30” ranks 1st commenter in both. Our results suggest that the audience of /v/GreatAwakening (20K subscribers) consumes content and submissions from a handful of users (349 submitters), and to a great extent, from “user1.”

### 4.4 User Registrations

We also analyze the registration dates of the users that post content in the two communities in an attempt to understand when these users registered a new account on Voat. Since 2015, online press outlets have reported that communities banned from Reddit often migrate to Voat [6, 46, 60]; thus, we investigate whether Voat user registrations increase when Reddit bans communities.

We find that, during the period our data collection infrastructure was active, over 15K users posted a submission or a comment on the subverses. Also, we find that 13.16% (2K) of these users deactivated their account, or their account was deleted by Voat, due to 404 errors our data collection infrastructure received from Voat’s API.

Figure 5(a) and Figure 5(b) plot the number of registered users engaged on /v/GreatAwakening and baseline subverses, respectively, per month. On /v/GreatAwakening, the average monthly registration is 4.1, 38.1, 22.75, 28, 125.9, 69.1, and 75 for 2014, 2015, 2016, 2017, 2018, 2019, and 2020, respectively. Similarly, every month 8.6, 118.1, 50.9, 65.5, 179.6, 142.1, and 200 new user registrations were made, on average, in the baseline subverses. Manual inspection of our dataset confirms that over 17.6% (2.3K) unique users registered on Voat in September 2018 only, i.e., the month Reddit banned many QAnon-related subreddits [54, 46, 65]. We also ob-

Topic	Words per topic for /v/GreatAwakening
1	know (0.010), nice (0.010), news (0.009), wallac (0.009), maxwell (0.008), fake (0.007), yeah (0.007), interest (0.007), sure (0.006), come (0.006)
2	covid (0.011), mask (0.009), test (0.006), vaccin (0.006), wear (0.005), coronaviru (0.005), viru (0.005), peopl (0.005), death (0.004), trump (0.004)
3	investig (0.005), arrest (0.005), trump (0.005), state (0.004), charg (0.004), china (0.004), comey (0.003), georg (0.003), presid (0.003), senat (0.003)
4	trump (0.015), elect (0.011), biden (0.009), vote (0.008), presid (0.008), happen (0.006), ballot (0.006), court (0.006), love (0.006), potus (0.006)
5	agre (0.011), debat (0.009), trump (0.006), chri (0.005), biden (0.005), hunter (0.005), kyle (0.005), look (0.004), jew (0.004), wray (0.004)
6	vote (0.015), exactli (0.009), fuck (0.009), win (0.008), poll (0.007), democrat (0.007), shit (0.007), delet (0.006), trump (0.006), biden (0.006)
7	black (0.006), white (0.006), right (0.006), peopl (0.005), live (0.005), america (0.004), trump (0.004), school (0.004), matter (0.004), nigger (0.004)
8	polic (0.006), amen (0.005), state (0.004), panic (0.004), trump (0.004), pray (0.004), netflix (0.004), correct (0.003), wait (0.003), health (0.003)
9	post (0.017), thank (0.014), link (0.013), video (0.010), great (0.007), twitter (0.007), say (0.007), read (0.006), articl (0.006), watch (0.006)
10	good (0.018), think (0.012), campaign (0.007), time (0.007), work (0.007), money (0.006), donat (0.005), point (0.005), lmao (0.005), billion (0.005)
Topic	Words per topic for baseline subverses
1	fuck (0.025), nigger (0.016), delet (0.016), faggot (0.015), kike (0.013), think (0.010), reddit (0.009), right (0.009), retard (0.009), shit (0.007)
2	trump (0.013), know (0.008), say (0.006), white (0.006), israel (0.006), jew (0.005), vaccin (0.006), presid (0.005), china (0.005), nice (0.005)
3	biden (0.022), vote (0.015), trump (0.013), democrat (0.013), portland (0.010), time (0.008), elect (0.008), jew (0.008), go (0.007), kyle (0.006)
4	anti (0.007), mean (0.006), christian (0.006), white (0.006), racism (0.006), cathol (0.006), hitler (0.005), jew (0.005), privileg (0.005), tranni (0.004)
5	peopl (0.007), white (0.006), think (0.004), work (0.004), want (0.004), govern (0.003), countri (0.003), state (0.003), jew (0.003), world (0.003)
6	mask (0.010), wear (0.007), polic (0.004), mail (0.003), peopl (0.003), court (0.003), ballot (0.003), go (0.003), time (0.003), need (0.003)
7	white (0.013), black (0.011), polic (0.008), nigger (0.008), peopl (0.008), kill (0.008), protest (0.007), racist (0.006), antifa (0.006), shoot (0.006)
8	covid (0.011), good (0.010), fake (0.007), news (0.007), year (0.006), test (0.006), coronaviru (0.005), true (0.005), viru (0.004), point (0.004)
9	link (0.017), debat (0.014), voat (0.012), post (0.011), comment (0.011), kamala (0.009), answer (0.007), dick (0.007), harri (0.007), read (0.007)
10	thank (0.028), yeah (0.008), live (0.007), matter (0.007), joke (0.007), florida (0.006), goat (0.006), shit (0.005), gonna (0.005), that (0.004)

**Table 2:** LDA analysis of /v/GreatAwakening and baseline subverses.

serve another spike in user registration in both communities between June and July 2015, probably due to Reddit banning a couple of hate-focused subreddits [57, 55, 52].

Although our dataset might not be representative of Voat’s user base as a whole, it provides an indication of the dates users decided to join the platform. Looking only at users engaged in baseline subverses (Figure 5(b)), we confirm that Voat received a high volume of new user registrations close to the periods of Reddit banning hateful subreddits and QAnon related subreddits. Future work, in conjunction with Reddit data, might help shed more light on the effect of Reddit deplatforming and consequent user migration.

## 4.5 Take Aways

Overall, this section answers our RQ1, i.e., what does activity by the QAnon movement on Voat look like? The most popular QAnon-focused subverse, /v/GreatAwakening, attracts many more submissions than the baseline subverses, despite they are among the top 10 most popular subverses on the platform regarding subscriber count. Also, /v/GreatAwakening has always more than 50 new submissions per day, with that number steadily increasing over time and staying above 100 new submissions per day since September 25, 2020. Whereas, the number of daily submissions stays in the same margins for the baseline subverses, except for /v/AskVoat, where we observe a decline in posting activity.

Moreover, we find that the audience of both communities tend to commend and upvote the submissions and comments they see in the subverse. Also, it is clear that the audience of /v/GreatAwakening consumes information from just a handful of users, while top submitters seem to overlap between the QAnon-focused subverse and the baseline subverses. Finally, we show that new user registrations peaked after Reddit banned hateful and QAnon subverses in June 2015 and in September 2018, respectively.

## 5 Narrative Analysis

In this section, we set out to shed light on the narratives of the QAnon movement on Voat aiming to answer RQ2. More specifically, we explore the most prominent topics that /v/GreatAwakening discusses, and detect the most popular entities they mention using entity detection. Finally, we use word embeddings and graph representations to visualize keywords most similar to the keyword “qanon.” We warn readers that some of the content presented and discussed in this section may be disturbing.

### 5.1 Topics

We analyze the most prominent topics on /v/GreatAwakening by running Latent Dirichlet Allocation (LDA) [12] on the text included in both the title and the body of all submissions as well as their comments. For every post, we remove all the URLs, stop words (e.g., “like,” “to,” “and”), and formatting characters, e.g., \n, \r. Then, we tokenize each comment and create a term-frequency inverse-document frequency (TF-IDF) array, which is used to fit an LDA model. We use a TF-IDF array instead of the default LDA approach as TF-IDF statistically measures the importance of every word within the overall collection of words, and more importantly because previous work suggests it yields more accurate topics [39]. We also use guidelines from Li [66] to build the LDA model.

In Table 2, we report the top ten topics, along with the words and their weights, discussed on both /v/GreatAwakening and the baseline subverses. For /v/GreatAwakening, users tend to discuss the US Presidential Elections, as suggested by words like “trump,” “elect,” “biden,” and “vote” across many topics. There are also discussions about the COVID-19 pandemic: “covid,” “mask,” “test,” and “vaccin” (topic 2). We also find a topic about the “Black Lives Matter” movement, including hateful and race-related words, such as “nigger,” “black,” “white,” (topic

Named Entity	#Posts	(%)	Entity Label	#Posts	(%)
Trump (PERSON)	5,953	3.94	ORG	69,056	45.75
one (CARDINAL)	3,623	2.40	PERSON	61,556	40.78
first (ORDINAL)	2,670	1.76	GPE	31,286	20.74
US (GPE)	2,022	1.34	DATE	29,496	19.54
Biden (PERSON)	2,009	1.33	CARDINAL	26,155	17.32
America (GPE)	1,733	1.14	NORP	20,665	13.69
China (GPE)	1,660	1.09	WORK_OF_ART	5,481	3.63
two (CARDINAL)	1,526	1.01	ORDINAL	5,225	3.46
American (NORP)	1,505	0.99	TIME	4,126	2.73
FBI (ORG)	1,447	0.95	LOC	3,900	2.58

**Table 3:** Top 10 named entities and entity labels mentioned in /v/GreatAwakening.

7). As for baseline subverses, we again find topics including elections, coronavirus, and Black Lives Matter, but with even more frequent hateful words such as “fuck,” “nigger,” “fag-got,” “tranni,” “kike,” “retard,” etc.

Overall, our topic detection analysis shows that discussions on /v/GreatAwakening and baseline subverses feature political matters and news, but also hate and racism. As for /v/GreatAwakening discussions, we find that the topics are more focused around political issues and President Donald Trump. We will further investigate toxicity in Section 6.

## 5.2 Named Entities

While topic modeling gives us an idea of *what* is being discussed, to get an understanding of *who* is being discussed, we extract the named entities used in our communities of interest. We do so in order to understand who conspiracies focus on and better define the narrative they might be pushing.

To obtain the named entities mentioned in each post, we use the `en_core_web_lg` (v2.3) model from the SpaCy library [63]. We choose this specific model over alternatives, e.g., MonkeyLearn, since, to the best of our knowledge, it is trained on the largest training set. Moreover, previous work [30] ranks this model as the second most accurate method for recognizing named entities in text. We select this solution over the first one because [30] explain SpaCy detects dates more accurately, compared to the one they rank first, Stanford NER. More specifically, SpaCy uses millions of on-line news outlet articles, blogs, and comments from various social networks to detect and extract various entities from text. Crucially, for our purposes, the model also provides an entity category label in addition to the entity itself. For example, the entity category for “Donald Trump” is “person.” The different categories range from celebrities to nationalities, products, and even events.<sup>4</sup>

In Table 3, we list the ten most popular named entities and categories from /v/GreatAwakening. We note that a post may mention an entity more than once. Therefore, we only report the number of posts that mention an entity at least once. Unsurprisingly, considering his central role in the QAnon conspiracy, “Donald Trump” is the most popular named entity on /v/GreatAwakening with almost 6K posts (3.94%) mentioning him. Other popular entities in-

<sup>4</sup>See <https://spacy.io/api/annotation#named-entities> for the full list of labels.

Named Entity	#Posts	(%)	Entity Label	#Posts	(%)
one (CARDINAL)	7,621	2.13	ORG	61,474	17.21
jews (NORP)	6,385	1.78	PERSON	58,383	16.34
first (ORDINAL)	5,401	1.51	NORP	40,808	11.42
Jews (NORP)	4,804	1.34	GPE	37,947	10.62
Trump (PERSON)	4,331	1.21	CARDINAL	35,050	9.81
US (GPE)	3,571	0.99	DATE	34,657	9.70
two (CARDINAL)	3,293	0.92	ORDINAL	9,043	2.53
America (GPE)	3,142	0.88	LOC	8,060	2.25
jewish (NORP)	2,948	0.82	WORK_OF_ART	7,320	2.05
Jew (NORP)	2,305	0.64	PERCENT	5,816	1.62

**Table 4:** Top 10 named entities and entity labels mentioned in all the baseline subverses in our dataset.

clude “US” (1.34%), “Biden” (1.33%), “America” (1.14%), “China” (1.09%), and “FBI” (0.95%). The most popular category is organizations (45.75%), followed by people (40.78%). Other popular labels include nationalities, religious, or political groups (NORP, 13.69%), books, songs, and movies (WORK\_OF\_ART, 3.63%), and times (2.73%).

In comparison, in Table 4, we list the ten most popular named entities and categories used in the baseline subverses. The most popular named entities for these subverses are “jews” (2.58%), “Trump” (1.21%), “America” (0.88%), and “jewish” (0.82%). The most popular labels organizations (17.21%), people (16.34%), and nationalities, religious, or political groups (11.42%).

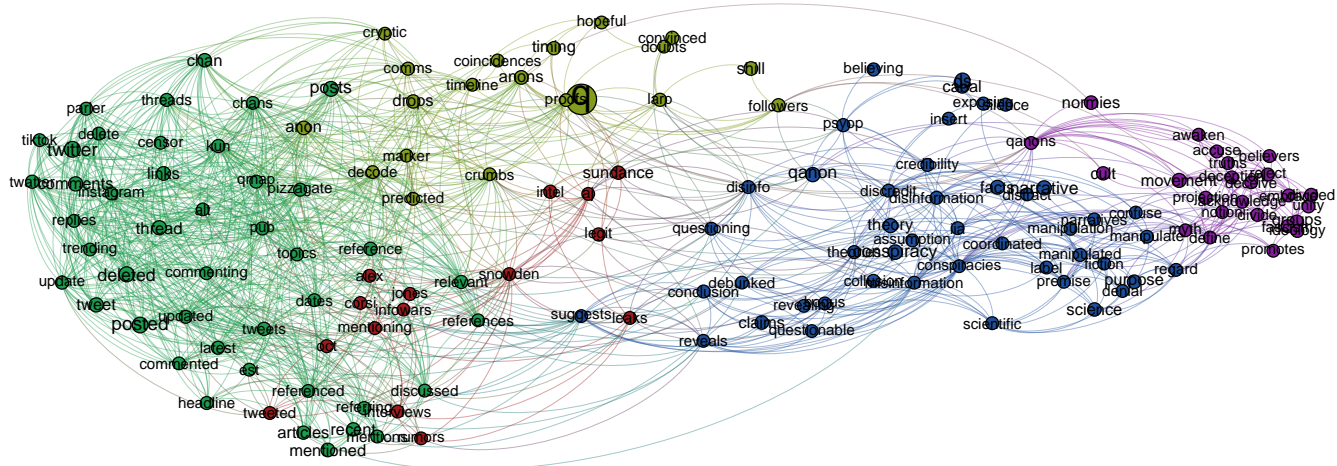
Overall, this suggests that discussions within these communities are related to US happenings and events, politics, and established organizations and institutions. Baseline subverses focus mostly on nationalities, and religious or political groups, while /v/GreatAwakening discussions focus on the US, President Trump, and the US Presidential elections.

## 5.3 Text Analysis

**Word Embeddings.** To assess how different words are interconnected with popular QAnon specific keywords (e.g., “qanon”), we use word2vec, a two-layer neural network that generates word representations as embedded vectors [41]. A word2vec model takes a large input corpus of text and maps each word in the corpus to a generated multidimensional vector space, yielding a *word embedding*. Words that are used in similar contexts tend to have similar vectors in the generated vector space.

To clean the QAnon posts before training the model, we follow a similar methodology as for the topic modeling presented Section 5.1. We train the word2vec model using a context window (which defines the maximum distance between the current word and predicted words when generating the embedding) of 7, as suggested by [35]. We limit the corpus to words that appear at least 50 times, due to the small size of our dataset. Finally, we train the word2vec model with 8 iterations (epochs) as, on small corpuses like ours, epochs between 5 and 15 epochs are suggested to provide the best results [41, 42]. (Choosing more epochs than 8 makes our model overfit and minimizes the word vocabulary, e.g., removing QAnon-specific keywords like “qanon.”) After train-





**Figure 6:** Graph representation of the words associated with the term “qanon” on Voat. We extract the graph by finding the most similar words, and then we take the 2-hop ego network around “qanon.” In this graph the size of a node is proportional to its degree; the color of a node is based on the community it is a member of; and the entire graph is visualized using a layout algorithm that takes edge weights into account (i.e., nodes with similar words will be closer in the visualization).

“qanon”		“q”	
Word	Cos Similarity	Word	Cos Similarity
conspiracy	0.636	anons	0.679
theories	0.582	larp	0.594
q	0.579	qanon	0.579
movement	0.570	drops	0.570
followers	0.561	proofs	0.557
conspiracies	0.549	cryptic	0.545
tweets	0.547	psyop	0.531
aj	0.545	posts	0.529
qanons	0.544	anon	0.526
discredit	0.538	crumbs	0.524

**Table 5:** Top ten similar words to the term “qanon” and “q” and their respective cosine similarity.

ing, our model includes a 5.6K word vocabulary.

**QAnon similar keywords.** Next, we find the top ten most similar words to “qanon” and “q” according to the model; see Table 5. We see that “qanon” is linked to words like “conspiracy,” “theories,” “movement,” and “pizzagate.” The term “q” seems to be closely related to the activity of Q himself, and the research the community does to decode his cryptic messages. This is evident due to “drops,” which refer to the specific, cryptic posts that Q leaves as breadcrumbs of information for adherents of the conspiracy to decode. These drops often hint at “psyops”, the alleged psychological operations the deep state and governments deploy to control society. Interestingly, the term “larp,” an acronym for “Live Action Role Playing,” is sometimes used in a derogatory fashion to imply that Q is just a troll playing a game. This indicates that even on a community devoted to the QAnon conspiracy, there is at least some degree of push back or dissent within the user base. We use graph representations to analyze this finding below.

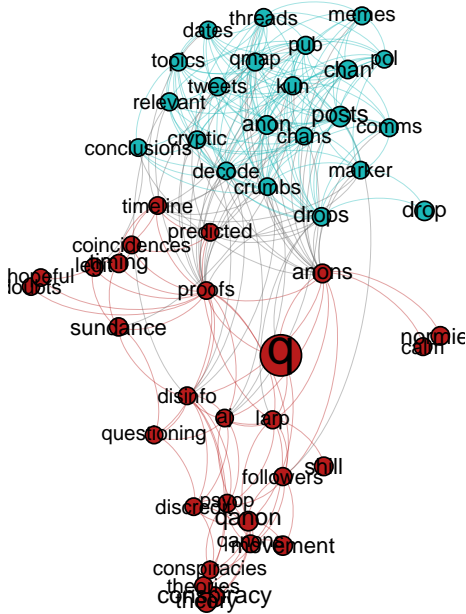
**Graph representations.** Finally, we follow the methodology by Zannettou et al. [71] to visualize topics within the word embeddings. Specifically, we transform the embeddings into a graph, where nodes are words and edges are weighted by the

cosine similarity between the learned vectors of the nodes the edge connects. We perform community detection [13] on the resulting graph, to gain new insights into the high-level topics that groups of words form.

**Visualization.** Figure 6 shows the two-hop ego network [5] centered around the word “qanon.” Whereas, Figure 7 depicts a graph centered around “q.” To improve readability (since our graph transformation results in a fully connected network), we remove all edges with a cosine similarity less than 0.6. We further color each node based on the community it belongs to. Finally, we apply the ForceAtlas2 algorithm [29], which considers the weight of the edges when laying out the nodes in the 2-dimensional space before producing the final visualization.

**Remarks.** Taking into account how communities form distinct themes, and that nodes’ proximity implies contextual similarity, we observe from Figure 6 that the “qanon” community (blue) is very close to the purple community, which seems to be discussing the movement itself (“qanons,” “believers”), while the blue community is discussing details of the conspiracy theory itself (“cabal,” “psyop,” “manipulation”). Next, the yellow community is focused on Q drops (“drops,” “timeline,” “decode”). In the green community, we come across the QAnon predecessor “pizzagate,” Q drop aggregators (e.g., “qmap,” which was recently shut down [68]), and other social media platforms (8“kun”, “twitter,” “instagram,” and 4“chan”).

Focusing on the contriver of the conspiracy theory, Figure 7 plots the discussion around Q. Interestingly, the community of “q” (red) has words like “larp,” “disinfo,” “doubts,” and “shill” (a term used for someone that might be hired by the government pretending to agree with a conspiracy) in close proximity of Q. On the other hand, we find terms like “followers” and “aj” (a term used to describe a man as supportive and perfect). This plot strengthens the hypothesis that although the community is devoted to the QAnon movement, at



**Figure 7:** Graph representation of the words associated with the term “q” on Voat.

the same time, there might be signs of chasm with regards to what the users on /v/GreatAwakening think of Q.

## 5.4 Take Aways

The analysis presented in this section allows us to identify and visualize the narrative around QAnon discussion (RQ2). We show that the QAnon community discusses online social media, political matters, and world events. Additionally, the main topic of conversation is President Donald Trump, and the US overall, and entities discussed are most typically organizations and individuals. These findings confirm that, regardless of the particular components of the conspiracy theory, Trump’s role in the conspiracy, e.g., as the alleged leader in the war against the deep state, is central.

Finally, our structural analysis of word embedding similarities provides some high level topics of discussion within the community. For example, we find that the term “larp,” an oft used criticism of Q implying he is merely playing a game, is often used in the same context as discussion of “qanon” himself. This is an indicator that adherents are well aware of criticisms of the source of their information, and perhaps some dissent within the community itself. Additionally, we see that the movement is well embedded across the Web, with external q-drop aggregators (e.g., qmap) and social media platforms are commonly discussed along with Q.

## 6 Toxicity Analysis

In this section, we analyze the toxicity of the /v/GreatAwakening community, compared to the general discussion subverses. Motivated by our findings in Section 5.1, which suggest toxicity, hate, and racism to

be existing in all subverses of our dataset, we analyze the content of each post according to how toxic, obscene, insulting, profane, and inflammatory they are. To do so, we use Google’s Perspective API [48]. We choose this tool, similar to prior work [47], as other methods mostly use short texts (tweets) for training [21], whereas, Google’s Perspective API is trained on crowdsourced annotations and comments with no restriction in character length, similar to Voat posts.

We rely on six models to annotate posts from all subverses:

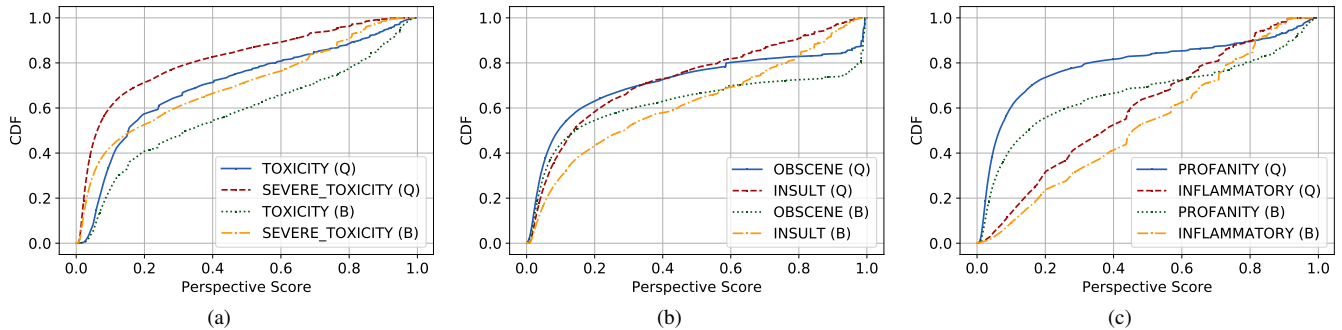
- *toxicity*: how rude or disrespectful a post is;
- *severe\_toxicity*: same as *toxicity* but less sensitive to posts that include positive uses of curse words.
- *obscene*: provides high scores for messages that likely contain indecent language.
- *insult*: quantifies how likely a message is to be negative and insulting towards an individual or a group.
- *profanity*: calculates the likelihood of a message containing slurs, swear, or curse words.
- *inflammatory*: how likely it is for a message to irritate others towards “inflaming” the discussion.

Note that all methods provide scores for textual posts. Therefore, we do not have scores for 4.8% (24.6K) of the posts in our dataset, since they only contain links or images, but no text.

In Figure 8, we plot the CDF of the scores for each model. The baseline subverses (B in Figure 8(a)) exhibit higher levels of *toxicity* and *severe\_toxicity*, compared to /v/GreatAwakening (Q in the figure). Specifically, 39.9% and 28.2% of the baseline posts have, respectively, *toxicity* and *severe\_toxicity* scores greater than 0.5, while only 23.3% and 13.7% of the QAnon posts have these scores greater than 0.5. We observe similar trends for the other models with the baseline subverses scoring always higher than /v/GreatAwakening. Overall, 33.6% and 36% of the baseline subverses’ posts have an *obscene* and *insult* score greater than 0.5, respectively (Figure 8(b)), and 33.6% for *profanity* and 46% for *inflammatory* (Figure 8(c)). For all six models, the percentage of the QAnon posts that have perspective score greater than 0.5, was at least 10% *smaller* than the general discussion posts. Last, we use two-sample KS test to check for statistically significant differences between all the distributions in Figure 8 and find the p-value on each pair ( $p < 0.01$ ).

**Remarks.** Although the content of the QAnon community exhibits some levels of toxicity, the movement is not as toxic as other discussions on the platform. We believe this not to be entirely surprising as the community seems to be more focused on the conspiracy aspects of world events, politics, and President Trump, while racist and/or hateful agendas might more vigorously characterize Voat as a whole, or at least the popular general-discussion subverses in our baseline. In other words, toxicity in the discussions seem to be targeted towards the so called “deep-state,” the puppet masters, and the pedophile ring members. Whereas, baseline subverses like /v/news and /v/politics are likely to include inflammatory discussions between users with contradicting opinions or comment on world events from a racist/hateful standpoints.

Interestingly, the level of toxicity in the baseline subverses



**Figure 8:** CDF of the Perspective Scores related to how toxic, severely toxic, obscene, insulting, profane, or inflammatory a post is for the /v/GreatAwakening (Q) and baseline (B) subverses.

appear to be similar to that of 4chan’s /pol/, as presented in [47]. In particular, we find that the percentage of posts that get scores above 0.5, across all models, are very similar on /pol/ and our four baseline subverses. Considering that /pol/ is broadly considered to be a highly toxic place [27], this suggests that Voat is too.

## 7 Related Work

In this section, we review previous work on QAnon and Voat.

**Qualitative work around QAnon.** Prooijen [28] studies why people tend to believe in conspiracy theories like QAnon, arguing that their beliefs are not necessarily pathological or novel, and can be followed by individuals who behave relatively normally. The author explains that, typically, individuals follow more than one conspiracy theory, as also discussed by Goertzel [25], and that they believe that nothing happens coincidentally. At their core, conspiracy theories reinforce the idea that hostile or secret machinations permeate all social layers, thus forging an appealing account of events for the individuals that seek “explanations.” Finally, followers are likely to experience anxiety and uncertainty, which often lead them to try to understand societal events that traumatized them.

Sternisko et al. [64] argue that conspiracy theories, including QAnon, pose a real threat to democracies, as government officials and media might start or amplify them to benefit their political agendas and interests. Schabes [61] stresses that social networks help conspiracy theories spread faster, which in turn threatens individual autonomy and public safety, enforces political polarization, and harms trust in government and media. Rutschman [59] studies misinformation spread by the QAnon movement on the Web, e.g., claiming that Bill Gates orchestrated the COVID-19 outbreak and claiming that drinking “Miracle Mineral Supplement,” commonly known as chlorine dioxide, prevents infections. Thomas and Zhang [67] explain that small groups of engaged conspiracists, like QAnon followers, can potentially influence recommendation algorithms to expose new, unsuspecting users to their beliefs. The same study notes that conspiracy theories often include information from legitimate sources or official documents framed with misleading and conspiratorial expla-

nations to events. This creates an illusion of an explanation and further complicates moderation efforts against conspiratorial content.

**Quantitative work on QAnon.** McQuillan et al. [38] collect 81M tweets related to COVID-19 between January and May 2020, finding that the QAnon movement not only has grown throughout the pandemic, but also that its content has reached more mainstream groups. In fact, the Twitter QAnon community almost doubled in size within two months. Darwish [20] gather 23M tweets related to US Supreme Court judge Brett Kavanaugh for 3 days and 4 days in September and October 2018, respectively. They find that the hashtags #QAnon and #WWGIWGA (Where We Go One We Go All) are in the top 6 hashtags in their dataset. Chowdhury et al. [18] identify 2.4M accounts suspended from Twitter and collect 1M of their tweets, performing a retrospective analysis to characterize the accounts and their behavioral activities. Among other things, they observe that politically motivated users consistently and successfully spread controversial and political conspiracies over time, including the QAnon conspiracy.

Faddoul et al. [24] collect the top-recommended YouTube videos from 1,080 YouTube channels between October 2018 and February 2020. In total, they analyze more than 8M recommendations from YouTube’s watch-next algorithm and use 500 videos labeled as “conspiratory” to train a classifier to detect conspiracy-related videos with 78% precision. Using TF-IDF, they also find that, within the top 15 discriminating words in the snippet of the videos of the training set, the term “qanon” ranks third. Also, QAnon-related videos belong to one out of the three top topics identified by an unsupervised topic modeling algorithm. The authors conclude that YouTube’s recommendation engine might operate as a “filter bubble.”

**Voat.** Chandrasekharan et al. [17] detect abusive content using data from 4chan, Reddit, MetaFilter, and Voat, and relying on a novel approach called Bag of Communities (BoC). Part of the Voat data collected for their work originate from /v/CoonTown, /v/Nigger, and /v/fatpeoplehate: three communities focused on hate towards groups of individuals with specific body or race characteristics. These subverses were created in Voat after Reddit banned the original /r/CoonTown, /r/fatpeoplehate, and /r/nigger subreddits in

2015 [57, 55, 52]. Similarly, Salim et al. [58] use Reddit comments to train a classifier to detect hateful speech including on Voat’s /v/CoonTown, /v/fatpeoplehate, and /v/TheRedPill. Khalid and Srinivasan [34] collect 872K comments from /v/politics, /v/television, and /v/travel in an attempt to detect distinguishable linguistic style across various communities; more specifically, they compare the features of Voat comments to Reddit and 4chan comments and train a classifier to predict the origin of the comments based on its style and content. Finally, Popova [49] uses data from Voat’s /v/DeepFake and the site mrdeepfakes.com, finding pornographic deep-fakes created for circulation and enjoyment within the community. Note that both the mrdeepfakes.com and the subverse /v/DeepFake were created after Reddit banned the subreddit /r/DeepFakes in 2018 [53, 26].

**Remarks.** Previous quantitative work related to QAnon has mostly focused on Twitter [18, 38], while ours does so on Voat. Overall, our paper presents, to the best of our knowledge, the first characterization of the QAnon community on Voat. Some of our findings are, to some extent, aligned with those from previous studies; in particular, we too observe a steady increase in posting activity on /v/GreatAwakening, somewhat similar to [38], which finds that the QAnon movement on Twitter increased in size over their collection period. Overall, this study is the first to collect and characterize the QAnon movement on Voat.

## 8 Conclusion

This work presented a first characterization of the QAnon movement on the social media aggregator site Voat. We collected over 510K posts from five subverses: /v/GreatAwakening, the largest QAnon-related subverse, as well as a baseline consisting of the four most active subverses, /v/news, /v/politics, /v/funny, and /v/AskVoat.

We showed that users on both the QAnon and baseline subverses tend to be engaged, but the audience of /v/GreatAwakening (20K subscribers) consumes data from just a handful of content creators who are responsible for over 72.8% of the total submissions in the community. In addition, we found that /v/GreatAwakening users had a peak in registration activity shortly after Reddit banned QAnon related communities in September 2018. Using topic modeling techniques, we showed that conversations focus on world events, US politics, and President Trump. We also trained a word2vec model to illustrate the connection of different terms to closely related words, finding that the terms “qanon” and “q” are closely related to other conspiracy theories like Pizzagate, other social networking platforms, the so-called deepstate, and “research” activities the community performs to decode Q’s cryptic posts. Finally, toxicity scores from Google’s Perspective API shows that posts in /v/GreatAwakening are *less* toxic than those on popular general-discussion (baseline) subverses.

Although this paper represents the first large-scale study of the QAnon movement on social media, it is far from com-

prehensive, and numerous questions about the movement remain, leaving several directions for future work. First, while this paper focused on Voat, the QAnon movement is decidedly multi-platform, and thus we encourage work that examines it from a cross-platform perspective. Next, even though it has only recently entered mainstream discourse, QAnon has a long and still somewhat muddled evolution. This calls for longitudinal studies that cover a much longer period than that in the present work to get a firm grasp on how the movement has evolved, both in terms of components of the conspiracy as well as user engagement and discussion (e.g., how do adherents react when the predictions in a q-drop do not come to pass). Finally, we believe that while understanding the movement itself is important, there are real indications that it exhibits cult-like characteristics, e.g., recovery stories from former adherents [50, 36] and communities devoted to emotional support for people whose loved ones have become adherents [1], it is crucial to understand more about the QAnon *counter-movement* which might provide insights into the real-world impact of the spread of this and other dangerous conspiracy theories as well as devising mitigation strategies.

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