The Gospel According to Q: Understanding the QAnon Conspiracy from the Perspective of Canonical Information

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Abstract

The QAnon conspiracy theory claims that a cabal of (literally) blood thirsty politicians and media personalities are engaged in a war to destroy society. By interpreting cryptic "drops" of information from an anonymous insider calling themselves Q, adherents of the conspiracy theory believe that they are being led by Donald Trump in an active fight against this cabal. QAnon has been covered extensively by the media, as its adherents have been involved in multiple violent acts, including the January 6th, 2021 seditious storming of the US Capitol building. Nevertheless, we still have relatively little understanding of how the theory evolved and was spread on the Web, and the role played in that by multiple platforms.

To address this gap, in this paper we study QAnon from the perspective of "Q" themself. Specifically, we build a dataset of 4,949 canonical Q drops collected from six "aggregation sites," which curate and archive them from their original posting to anonymous and ephemeral image boards. We expose that these sites have relatively low (overall) agreement, and thus at least some Q drops should probably be considered apocryphal. We then analyze the contents of the Q drops themselves, identifying topics of discussion, as well as finding statistically significant indications that drops were not authored by a single individual. Finally, we look at how posts on Reddit are used to disseminate Q drops to a wider audience. We find that dissemination was (originally) limited to a few sub-communities and that, while heavy-handed content moderation decisions have reduced the overall issue, the "gospel" of Q persists on Web communities.

1 Introduction

While ubiquitous social media has helped foster new relationships and the dissemination of information, not everything is beneficial to society. Over the past decade, a few conspiracy theories have emerged, often blaming secret organizations, governments, or cabals for world-changing events [6], which the Web has help spread and evolve. E.g., conspiracy theorists claim that Bill Gates created the COVID-19 pandemic to implant microchips in people via the world-wide administration of a vaccine [50]. Some of these theories can threaten democracy itself [43, 46]; e.g., *Pizzagate* emerged during the 2016 US Presidential elections and claimed that Hillary Clinton was involved in a pedophile ring [47].

A specific example of the negative consequences social media can have is the QAnon conspiracy theory. It originated on the Politically Incorrect Board (/pol/) of the anonymous image board 4chan, via a series of posts from a user going by the nickname Q. Claiming to be a US government official with Q level security clearance, Q described a vast conspiracy of actors heavily embedded within the US and governments worldwide waging a war against freedom and decency with another set of actors, led by Donald Trump, actively fighting back [51]. Since its inception in 2017, it has grown to encompass numerous previously existing conspiracies, including Pizzagate [49].

QAnon has long ceased to be a kooky, but ultimately inconsequential conspiracy theory confined to the Internet's dark corners. The recent events of January 6th, 2021, when a violent pro-Trump mob rushed the US Capitol and resulted in five deaths, including one police officer [17], demonstrates how deeply entrenched QAnon is in violent, far-right calls to extremist actions. In the aftermath of the insurrection, it became clear that many of the people involved were QAnon followers, including law enforcement officers, former military, and Internet personalities [22]. Even prior to that, QAnon supporters have been linked to various crimes, including an attempt to blow up a statue in Illinois, kidnapping children to "save them from the pedophiles," etc. [5].

Overall, conspiracy theories can pose very concrete risks to democratic societies, e.g., when used to benefit political agendas and interests [43]. QAnon has proven this to great effect, as at least 25 US Congressional candidates with direct links to QAnon appeared on ballots during 2020 US Presidential Election [1], and at least two elected US House Representatives publicly supported the movement [10].

Although having received substantial media coverage, we still lack an understanding on how QAnon works, making

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it difficult to not only develop mitigation techniques for future conspiracies, but also to directly address QAnon. A primary challenge here is directly related to QAnon's origin and evolution on image boards like 4chan and 8chan/8kun. Image boards are ephemeral and anonymous, with the only method of persistent identification across posts being a fallible system known as *tripcodes*. Interestingly, QAnon adherents themselves have faced these same issues of anonymity and ephemerality and developed a set of sites that aggregate and "authenticate" messages posted by Q, known as *Q drops*. These Q drops are discussed on image boards, collected on these aggregation sites for ease of access, and later discussed on other Web communities.

Research Questions. We aim to understand how the QAnon conspiracy theory evolved over time, studying how Q drops were posted and catalogued on aggregation sites, and then discussed on QAnon-focused Web communities. Specifically, our work is driven by the following research questions:

RQ1 How does the canonicalization process of the QAnon conspiracy work?

RQ2 What topics are discussed in, and the canonical Q content is likely to be perceived?

RQ3 How and where is the canonical Q content shared on social media?

Methodology. We collect and analyze 30,320 Q drops (4,961 unique) from six aggregation sites, and the corresponding 4chan and 8chan/8kun threads that Q posted in, over 846K tweets that link to one of our six aggregation sites, and 1.4M and 546K posts from Reddit and Voat.

To answer our RQ1, we measure the agreement across all aggregation sites using Fleiss' kappa score [16] and calculate the set of overlapping drops across aggregation sites to find a canonical set. In addition, we employ basic stylometric techniques to measure the similarity of posts across tripcodes. Then, for RQ2, we use word embeddings, graph analysis and visualization techniques, as well as Google's Perspective API [35], to analyze how different words are used in the Q drops, how they are interconnected together, what are the various topics of interest, and how toxic, inflammatory, and coherent is the content created by the Q persona. Finally, to answer RQ3, we study how aggregation links are mentioned on Reddit.

Main findings. Overall, we make the following findings:

- The six aggregation sites devoted to archiving Q drops have very low agreement scores between them. We detect significant differences regarding the writing habits of the five most used tripcodes. Overall, this suggests there is no single canonical Q.
- Q discusses, among other things, the "usurpation" of the government. Q drops are also extremely incoherent, a likely explanation for the decoding/interpretation efforts of adherents. Although adherents have been involved in violence, Q drops are not particularly toxic or threatening. This questions whether by themselves they may be considered high risk, at least by automated moderation tools; rather, toxicity and calls for violence stem from the interpretations of the communities built around the conspiracy and the actors with vested interests that weaponize it.
- We find that the aggregation links were disseminated across Reddit from a handful of users. Also, although Reddit banned QAnon related subreddits, other subreddits, e.g., r/conspiracy, still share and discuss Q drops.

2 Background and Related Work

In this section, we provide background information on the history and main beliefs of the QAnon movement, as well as on the Web communities that are part of our datasets. Finally, we review relevant previous work.

2.1 QAnon

On October 28, 2017, an anonymous user with the nickname "Q" posted a new thread on 4chan's Politically Incorrect board (/pol/), titled "Calm before the Storm," claiming to be a government insider with "Q level" security clearance.[1] Q claimed to have got ahold of documents proving the existence of a satan-worshiping pedophile cabal of highly influential and powerful people that secretly controls governments world wide [52]. Among other things, Q swears allegiance to an alleged noble crusade that Donald Trump has been leading to bring this satanic cabal to justice.

Q drops. The posts that Q made on 4chan, and later 8chan/8kun, since 2017 are known as "drops." QAnon followers devote themselves to decoding Q drops in an attempt to understand and expose the actions of the "deep state." The movement has since grown substantially on mainstream social networks like Facebook, Reddit, and Twitter. The conspiracy has even spread to countries other than the US, where QAnon adherents have staged protests [4].

QAnon Aggregation Sites are platforms dedicated to providing a collective index of information about the conspiracy. They are created, developed, and funded by Q supporters to aggregate the posts that Q drops across the image boards, and to help others find information about the conspiracy. The decision of which post is indeed a Q drop falls, to some extent, to the operators themselves. Perhaps the most popular aggregation site is qmap.pub, which was shut down in September 2020 after an investigation led to the identification of its owner and host [21]. Overall, aggregation sites are crucial data points for this study, as they provide insight into sources which report on and discuss the conspiracy. As detailed later, we focus on six of them: qmap.pub, qagg.news, qanon.pub, qalerts.app, qanon.news, and operationq.pub.

QAnon on the Web. As a conspiracy theory born out of the Web, it is not surprising that social networks have played a big role in QAnon's evolution. Active and fast-growing QAnon-related communities have emerged not only on fringe platforms, but also on mainstream ones [29]. In fact, most of the

[1]The top-secret clearance for the US Department of Energy.

latter have banned QAnon-linked groups and content—Reddit in 2018, and Twitter, Facebook, and YouTube in 2020 [53]. However, these deplatformed QAnon communities resurface on other fringe platforms like Voat, and discussion on 4chan and 8chan/8kun remains active [33, 38].

2.2 Web Communities

4chan and 8chan/8kun. As detailed later, we collect and analyze data from 4chan and 8chan/8kun. These are image boards, a type of anonymous and ephemeral social media with a focus on images being posted along side textual content, organized in boards devoted to specific themes, e.g., sports, science, politics, etc. Typically, users create a thread by posting an image and/or description, and others then can post on that thread with or without images.

We focus on 4chan and 8chan/8kun as the conspiracy started on 4chan's /pol/, before moving to 8chan in December 2018 [14]. 8chan was shut down in August 2019 [31], resurfacing in November 2019 as 8kun. For simplicity, in the rest of this paper, we refer to both 8chan/8kun as 8kun.

Posting on 4chan and 8kun is ephemeral (i.e., all posts and threads are deleted after some time) and, by default, anonymous, i.e., there are no user accounts and anyone can post (after solving a CAPTCHA). Posts are displayed under the generic username Anonymous, and users typically call each other as Anons—this is where 'QAnon' comes from to refer to 'Q'. However, users can choose a unique, linkable username for themselves using so-called *"tripcodes."* Although 4chan and 8kun have different technical implementations, tripcodes are basically hashed passwords. This allows a user with the correct password to post under a username that makes them recognizable across threads [18].

Voat. Voat was a news aggregation site, somewhat similar to Reddit, launched in April 2014 and shut down in December 2020 [39]. Voat often attracted users that had their hateful communities banned, e.g., r/CoonTown [15]. It also reportedly hosted QAnon-related communities banned from Reddit, like r/GreatAwakening [38]. The Voat equivalent of a subreddit is called "subverse." Initially, users could create new subverses, but that was disabled in June 2020. Also note that Voat limited the number of subverses a user may own or moderate.

2.3 Related Work

Papasavva et al. [33] search Voat for subverses named after banned QAnon-related subreddits, and collect over 150K posts from 5K users between May and October 2020. They find that the QAnon community on Voat grew shortly after the Reddit bans. They also show that conversations focus on world events, US politics, and Trump, while terms like QAnon and Q are closely related to Pizzagate.

Mcquillan et al. [28] study QAnon on Twitter, finding that QAnon-related hashtags are associated to COVID-19; in fact, the Twitter QAnon community almost doubled in size between January and May 2020. Also, Darwish [13] study 23M tweets related to the US Supreme Court judge Brett Kavanaugh, finding that the hashtags #QAnon and #WWG1WGA[2] are in the top six in their dataset. Chowdhury et al. [12] collect 1M tweets from 2.4M suspended Twitter accounts, finding that politically motivated users consistently spread conspiracies including QAnon. Finally, [48] studies "follow trains" (long lists of like-minded accounts that are mentioned for others to follow) on 5.5K Twitter accounts aiming to analyze political echo-chambers, finding that Republican users tweet QAnon-related hashtags often.

Aliapoulios et al. [2] collect 120M posts from 2.1M users posted between 2018 and 2020 on Parler, an alternative social network that gained popularity after the 2020 US Elections and several conservative figures were banned from Twitter and Facebook. Among other things, they find that Parler's user base mainly consists of Trump supporters that are heavily discussing the QAnon conspiracy theory.

Overall, this line of research focuses on single communities (Twitter, Voat, Parler), whereas, our work provides a multi-platform analysis of QAnon along several axes. Furthermore, we do not only look at social network discussions, but at Q drops and aggregation sites as well.

OrphAnalytics [32] analyze 4,952 Q drops collected from a single aggregation site (qresear.ch). Using a (patented and undisclosed) unsupervised machine learning algorithm, they identify two individual signals, positing that drops were written by two different authors. Our stylometric analysis (see Section 4.1) also suggests that the content written by the most used tripcodes originates from two different authors.

Perhaps closer to our work is the study by Zeeuw et al. [14], who collect QAnon-related data between October 2017 and November 2018 from 4chan's /pol/, 8chan's /qresearch/, Reddit, Twitter, YouTube, and online press articles and comments. Their goal is analyze the evolution of the conspiracy theory from fringe communities to mainstream social networks and news. They show that /pol/ was the original board used by Q before it moved to /qresearch/. Around the same time, Reddit and YouTube users started mentioning the conspiracy increasingly often, while online press started covering it in depth only after r/CBTS_Sream got banned.

Our work differs from previous research in that we approach the problem from the perspective of Q drops themselves. We are interested in understanding how Q drops are disseminated as well as their canonicalization process, comparing data across six aggregation sites and data from three social networks. While other work has examined discussions and communities related to the conspiracy theory, there has been no systematic exploration of the "source material," in terms of high-level topic and toxicity detection. Furthermore, to the best of our knowledge, our multi-platform dataset is the largest and most complete to date.

3 Datasets

We now describe the data we collect and use in this work.

Q Drops. Using a custom crawler, we collect Q drops that were posted on six different QAnon aggregation sites between

[2]Where we go one we go all, a popular QAnon motto.

Aggregation Site	#Drops
qagg	4,954
qalerts	4,953
operationq	4,953
qanon.news	4,952
qanon.pub	4,854
qmap.pub	4,650
Total (unique)	4,961

Table 1: Counts of collected drops across aggregation sites. NB: A unique drop is with respect to the post ID and board it appeared.

Board	Site	#Posts	#Threads
pol	4chan	141,722,957	3,297,289
qresearch	8kun	10,661,799	16,729
pol	8kun	3,931,616	47,680
cbts	8kun	163,745	453
thestorm	8kun	35,828	124
patriotsfight	8kun	248	3
projectdcomms	8kun	11	1
greatawakening	8kun	9	2

Table 2: Post and thread count across all QAnon related boards.

2017 and 2020. Table 1 reports the number of Q drops per aggregation site; a drop is considered unique by its post ID and the specific board that it is posted on.

4chan and 8kun. We use a custom crawler, following the same methodology of previous work on 4chan [18], to collect threads and posts from 4chan and 8kun. We focus on eight distinct boards that the aggregation sites note as containing posts from Q. For each board, we collect all threads and posts made between June 2016 to November 2020. Table 2 reports the number of threads and posts we collect for each board.

There are some gaps in our 4chan and 8kun datasets; this is mostly due to infrastructure failures (recall that these platforms are ephemeral) and periods of sporadic availability when 8chan rebranded as 8kun. We thus use data archived on archive.org to backfill as many gaps as possible. Specifically, we collect 435,668 posts and 1,909 threads from archive.org, using the domain and thread IDs from 4,961 unique Q drop links on the aggregation sites. Of the 4,961 drops, our crawlers are able to retrieve 4,415 (88.99%). We assume that the missing 546 drops are also due crawling related issues, and are able to retrieve 99 of them from archive.org. Finally, from the 1,936 total (unique) threads that aggregation sites claim drops were posted in, our crawlers retrieve 1,858 (95.97%); using the data from archive.org, we are able to collect 67 of the missing threads. Note that Table 2 includes the number of posts/threads obtained from archive.org.

Twitter. Although Q drops did not happen on it, Twitter certainly serves as a mainstream mechanism of disseminating the QAnon theory. Thus, from tweets made available via the 1% Streaming API between Sept 2019 and Sept 2020, we extract the 846,339 tweets from 92,307 users that contained a direct link to a drop or to an aggregation site. We begin with a set of a 1% feed of all data posted on Twitter for a year from September 2019 until September 2020.

Subreddit	#Posts	#Comments
greatawakening	79,952	926,676
CBTS_Stream	30,176	267,744
Qult_Headquarters	7,465	101,776
The_GreatAwakening	1,479	0
eyethespyzone	1,292	1,398
AFTERTHESTQRM	648	1,544
TheGreatAwakening	343	15
BiblicalQ	274	551
WakeAmericaGreatAgain	124	135
QAnon	122	339
QProofs	76	254
CalmBeforeTheStorm	5	3
Aggregation filtering	714	6,344
Total (unique)	121,956	1,304,523

Table 3: Comments and posts collected from Reddit. All posts and comments crawled using aggregation link filtering are grouped.

Reddit. We start from all the data collected by Pushshift [3], between November 2017 and April 2020, then, we extract the 6,344 comments and 712 posts that contain a direct link to a drop or to an aggregation site. We complement our Reddit dataset with all posts made on QAnon-related subreddits. To find QAnon-related subreddits, we search the Pushshift archive for subreddits with names similar to the ones reported by previous work [33] and online press related to QAnon [38, 54]. Overall, we collect 121,956 posts and 1,304,523 comments shared on Reddit between November 2017 and April 2020 (see Table 3).

Voat. We use the methodology of [33] to collect submissions and comments from the /v/GreatAwakening and /v/news subverses, between May 28 and December 10, 2020. Overall, we collect 21,668 submissions and 196,673 comments from /v/GreatAwakening, and 141,177 submissions and 186,595 comments from /v/news. We use the data from the latter as a baseline dataset for later analyses.

Ethical considerations. We confirm that we only collect publicly available data, following standard ethical guidelines [37]. Importantly, we do not attempt to identify users or link profiles across platforms. Moreover, the collection of data analyzed in this study does not violate any of the social networks' Terms of Service.

4 Canonicalization of QAnon

In this section, we compare the Q drops collected across six aggregation sites; we shed light on which drops these sites consider to be canonical, and what is the agreement between them. Then, we present a stylometric analysis of Q's posts using different tripcodes.

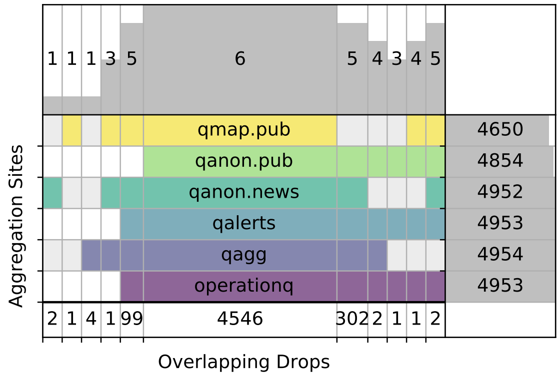


Figure 1: A Venn diagram-esque visualization of discrepancies between Q drops included by different aggregation sites.

Label	Tripcode	#Posts
A	!!mG7VJxZNCI	1,796
B	!!Hs1Jq13jV6	1,315
C	!UW.yye1fxo	583
D	!CbboFOtcZs	399
E	!xowAT4Z3VQ	351
F	!ITPb.qbhqo	223
G	*no tripcode*	163
H	!4pRcUA0lBE	94
I	!A6yxsPKia.	16
J	!2jsTvXXmXs	9
Total		4,949

Table 4: Tripcodes and the number of posts they made.

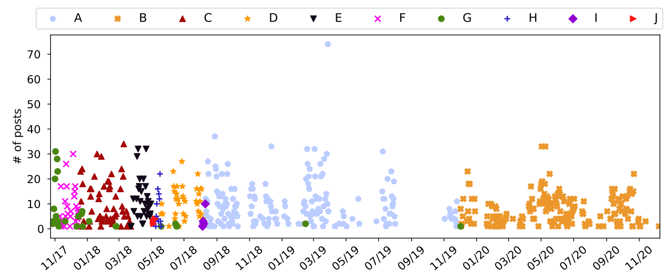


Figure 2: Posts per day per tripcode.

4.1 Is there a canonical set of Q drops?

The first question we set out to answer is to what degree different aggregation sites agree on what constitutes a canonical Q drop. This is important because aggregation sites serve not only as an archival system for ephemeral data, but also because, over time, Q migrated from 4chan to 8chan, and 8chan later became 8kun. Even assuming a perfectly secure system, which tripcodes are not, this presents opportunity for apocryphal drops to be introduced.

We begin by using a standard statistical measure of agreement quality, the Fleiss' kappa score [16]. This is typically used to measure the agreement between multiple annotators on a classification task. For our purposes, we are treating each aggregation site as an annotator classifying whether or not a given Q drop (uniquely identified by the post ID and the board it appeared on) is canonical.

When computed across all Q drops in our dataset, we find *poor* agreement ($\kappa < 0$) as per [24]. One of the major reasons for this is that qmap.pub was shut down in September 2020 and thus did not archive the several hundred Q drops that occurred later in 2020. When we remove qmap.pub from the dataset, the Fleiss score increases ($\kappa = 0.24$). While this is considered *fair* agreement, there is enough discrepancy to warrant a deeper look.

In Figure 1, we visualize the discrepancies in Q drops across our six aggregation sites. The figure can be read as a Venn diagram, where a cell is shaded for each drop that a given site includes. Along the bottom of the figure, we show the number of drops unique to the intersection of aggregation sites that are shaded. Along the top of the figure, we show the number of sites that agreed about the given set of drops. For example, in the middle of the figure is the set of 4,546 Q drops that all six sites included.

Exploring the discrepancies in this manner reveals a few things. First, directly to the right of the block of 4,546 drops that all sites include, we find the 302 that all sites except qmap.pub include. While the majority of these drops (300) were posted after qmap.pub was shut down, two were not. As we will show later (see Section 5.4), qmap.pub was the most linked aggregation site on social media. Although these two Q drops were posted in 2018, well before qmap.pub went offline, manual examination offered no explanation for why they are not included by qmap.pub.

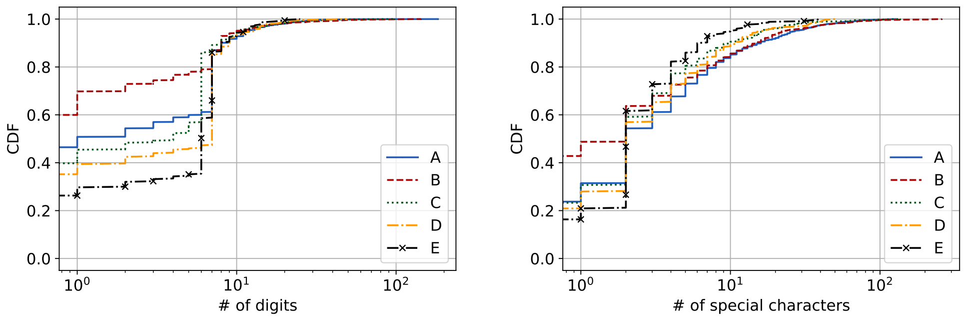
To the left of this block is the 99 Q drops that five sites, all except qanon.pub, included. One possibility for these not being included is that they might have been improperly attributed to a different board or post ID, however, manual examination reveals this not to be the case: these 99 drops do not appear on qanon.pub in any fashion. As discussed later (Section 5.4), qanon.pub was, by far, the most popular aggregation site in the early days of QAnon spreading to the mainstream via Reddit, and so the absence of these drops has serious implications with respect to the evolution and current state of the conspiracy theory.

Overall, our analysis shows that even which *source material* QAnon is derived from is not a clear cut conclusion. In part, it relies on the interpretation of aggregation site operators. **NB:** With this caveat, in the rest of the paper, we treat the set of Q drops included in at least *five* aggregation sites as the canonical set of Q drops.

4.2 Is there a canonical Q?

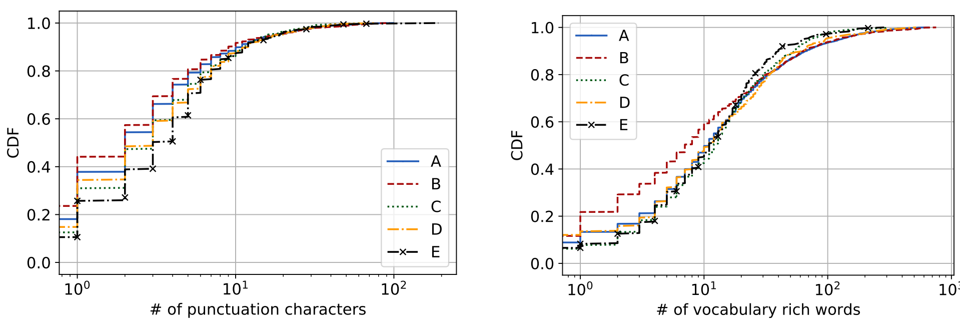
Considering the murky nature of Q in general, we now explore Q's behavior over time. We compare the posts made by the different tripcodes that have been deemed canonical by at least 5 aggregation sites. Table 4 lists all tripcodes, along with the number of posts they made. We further label each tripcode for visualization purposes in the following analysis.

Q drops by tripcode. In Figure 2, we plot the number of posts per day by the different tripcodes attributed to Q. The majority of them are used within the first nine months since the beginning of the QAnon conspiracy theory. Interestingly,



(a) (b)

Figure 3: CDF of the number of (a) digits and (b) special characters per post for each tripcode.



(a) (b)

Figure 4: CDF of the number of (a) punctuation characters and (b) vocabulary rich words per post for each tripcode.

this is also the time period where the most overlap between tripcodes occur – in the first nine months, the tripcode attributed to Q changed six times, and there are several time periods where drops with no tripcodes (i.e, G in Figure 2) overlap with other drops.

The question around authentication/authenticity of Q and the posts they made is central to understanding the conspiracy theory in general. Simply put, if Q was not the same person across time, it would, for all intents and purposes, be a meaningful blow to the sustained narrative. Indeed, the overlap in Figure 2 indicates that additional attempts to disambiguate potentially different authors of Q drops warrants further exploration.

Q's writing habits. One way of exploring the question of whether or not Q is one person is to use stylometry. In other words, can we identify differences in the way that different tripcodes write? To do so, we start by measuring two simple stylometrics: the number of words and the number of characters used across the top five tripcodes (each accounting for at least 300 posts). We find that one tripcode in particular, B, exhibits a significantly different number of words and character. We reject the null hypothesis of the 2-sample Kolmogorov-Smirnov test [27] that the distributions are drawn from the same parent distribution ($p < 0.001$). Interestingly, we test the distributions of the #words and #characters per post, and are unable to reject the null hypothesis when looking at the pairs of tripcode A vs C, D, and E; for C vs D, and E; and for D vs E.

Figure 3 reports stylometrics related to the use of digits and special characters. Here, we are able to reject the null hypothesis for the use of digits (Figure 3(a), $p < 0.01$ for all comparisons). However, for the use of special characters (Figure 3(b)), we are unable to reject the null hypothesis when comparing tripcode D to C ($p = 0.72$) as well as D to A ($p = 0.33$). As before, we reject the null hypothesis for tripcode B vs the other four top tripcodes. Finally, in Figure 4, we plot the CDF of punctuation and vocabulary richness of Q drops per tripcode. Here, we are unable to reject the null hypothesis for tripcode C vs D for punctuation ($p = 0.92$), while, for vocabulary richness, when comparing tripcodes A vs D ($p = 0.83$), C vs D ($p = 0.37$), as well as E vs D ($p = 0.60$). Again, we reject the null hypothesis for B vs the other four tripcodes.

4.3 Take Aways

Our analysis indicates that the six aggregation sites we focus on do not exhibit high agreement scores for what is considered to be a Q drop. Moreover, stylometric analysis shows that there are reasons to question whether the canonical posts from Q have had different authors over time. In fact, at the very least, the characteristics of the B tripcodes are quite different (and in a statistically significant way) from the other top four tripcodes. Also note that tripcode B only start posting when QAnon moved to 8kun (November 2019).

Overall, our analysis provides a strong indication that the Q persona was adopted by more than one person, interested in sharing their own beliefs within these forums, using a signature that everyone would notice.

5 Q Conspiracy Analysis

In this section, we analyze the content of the Q drops, exploring the topics discussed, and investigating the nature of the content, such as its toxicity, coherence, etc.

5.1 What does Q discuss?

Considering the prominent nature of QAnon in real-world events, understanding what Q actually talks about is particularly relevant, and so is discovering the topics a cult of adherents has formed around.

Word Embeddings. To assess how different words are interconnected within the Q drops, we use word2vec, a two-layer neural network that generates word representations as embedded vectors [30]. This model takes as input a corpus of text and maps each word in the corpus to a multi-dimensional vector in a linear space. In a nutshell, this means that words used in similar contexts tend to have similar ("close") vectors.

We remove all formatting characters, e.g., \n, \t, and URLs from each Q drop. We also remove Q's "signature" at the end of the drops since it holds no value for our purposes, as well as all numbers, with the exception of numbers included in words (e.g., "wwg1wga"). Finally, we tokenize every post and remove stop words. In the end, we build a corpus of 3.7K drops consisting of 77.8K tokens. We train our model using a context window (which defines the maximum distance between the current word and predicted words when generating the embedding) of five, as previous work suggests it is commonly used to capture broad topical content [25]. Finally, we limit our vocabulary to words that appear at least ten times because of the small size of our dataset, which yields a vocabulary of 1,673 words in the trained models.

Discovering important phrases. To identify the most important words in our vector space, we look at the top ten words closest to the *centroid* in the embedding's vector space. We do so as words closest to the centroid vector tend to be related to the main topics of the corpus; see [41].

The ten most words closest to the centroid, along with the computed similarity score of the words and centroid embeddings, are: throw (0.737), laying (0.705), jim (0.703), despotism (0.649), priestap (0.648), importance (0.640), judiciary (0.634), heavenly (0.626), independent (0.625), evinces (0.615).A manual examination of the Q drops indicates that these are indeed common topics of discussion. For instance, Q promotes the over-*throw* of the government, which is allegedly run by despots, and the institution of a new one. Also, Q speaks often about law enforcement and criminal justice figures like E. W. Priestap (an attorney) and Jim Rybicki (formerly at the US Dept. of Justice).

Word visualization and topics. We visualize broader topics using the methodology of [57], transforming the embeddings

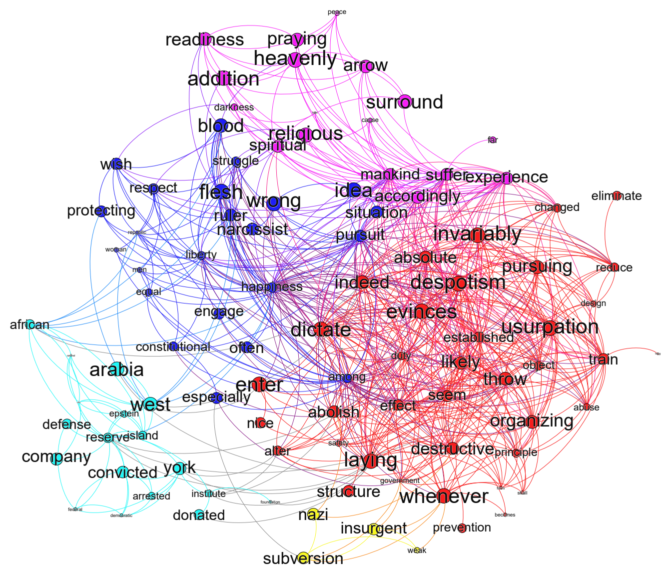
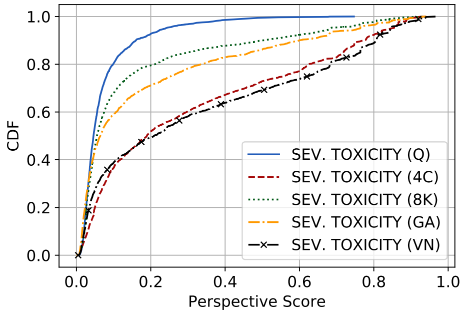


Figure 5: Graph representation of the two-hop ego network, starting from the keyword "throw."

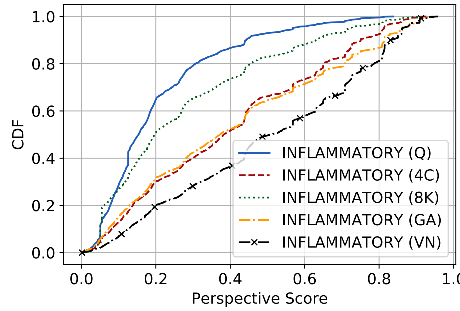
into a graph, where nodes are words and edges are weighted by their cosine similarity to other words. This requires removing edges from the graph that are below a certain threshold of similarity (i.e., we prune low similarity edges). We use a threshold of 0.6 based on the distribution of pair-wise vector similarities from our embeddings (we omit the figure due to space constraints) and for visualization purposes. Finally, we perform community detection using the Louvain method [8] on the resulting graph to provide insights into the high-level topics that individual words form.

Insurgent Communities. Figure 5 shows the two-hop ego network around the most similar word to the centroid, i.e., "throw". Nodes in the figure are colored by the community they form and the graph is laid out using ForceAtlas2 [20], which positions nodes in the two-dimensional space based on the weight of edges between them (i.e., more similar words are closer together in the figure). The community that "throw" belongs to (in red on the right side of the figure) is related to governments, the alleged despotism they are engaging in, and the supposed duty that patriotic citizens have in addressing these issues. For instance, "government," "usurpation," "duty," and "abolish" all appear in this community. The small yellow community close to "government" specifically discusses "subversion" and "insurgency."

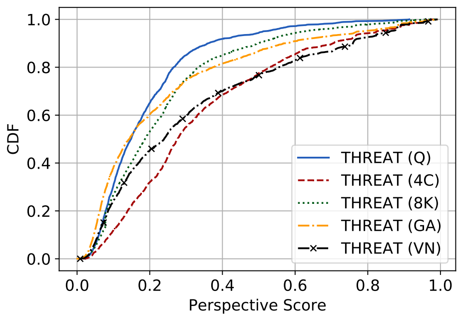
Religion. The magenta community at the top of the figure is related to "religion" and "spirituality." Interestingly, beneath the "religion" community, we find a blue community which discusses "narcissist" "rulers," along with "struggle," "blood," and "flesh." These two communities are interconnected as the movement believes that the rulers of the so-called deep-state drink the blood of children in satanic religious rituals. Finally, the turquoise community at the bottom left of the figure seems to be discussing Epstein and his island, as well as companies and institutions.



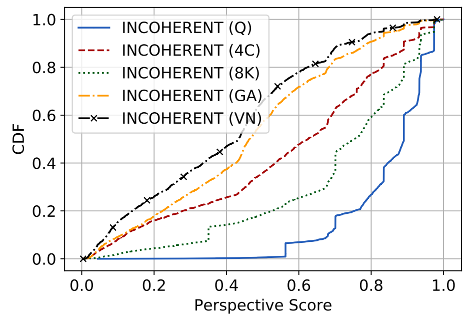
(a) toxicity



(b) inflammatory



(c) threatening



(d) incoherent

Figure 6: CDF of the Perspective API scores. "Q" stands for Q drops, "4C" for 4chan /pol/, "8K" for 8kun /qresearch/, and "GA" and "VN" for Voat /v/GreatAwakening and /v/news, respectively.

5.2 Who does Q mention?

Next, we dig deeper into the Q drop narrative analysis, and attempt to detect the most popular named entities that Q mentions in their drops. We do so to provide a better picture of the entities that the conspiracy revolves around.

To detect the most popular named entities, e.g., people, companies, etc., we use the Python spaCy library, and specifically the *en_core_web_lg* model. We choose this model as it is the fastest and its accuracy is within 1% of the best available [11]. It detects named entities, along with their entity labels, e.g., Donald Trump is a PERSON, The Avengers is WORK_OF_ART, and 01 January 2021 is a DATE.[3]

We feed the Q drops to the model and only get named entities for 58.6% (2.9K) drops. This is due to many Q drops only including a link, referring to other posts of the thread, not mentioning any named entities, or not having any text at all (i.e., they only include an image). In Table 5, we list the top 10 most popular named entities and entity labels mentioned in the Q drops. We also note the percentage of frequency, based on the 2.9K drops that include named entities.

We find that the US is the most mentioned named entity, followed by FBI. We also find "Hussein" included in the most popular named entities, which is the middle name of Barack Obama and is known to be used by 4chan users to refer to the president [40]. Then, we also find China, which is probably due to conspiracy theories around the COVID-19 pandemic, followed by Senate and House. Interestingly, companies, agencies, and institutions label (ORG) are the most popular named entity label mentioned in the Qdrops, followed by real people and dates. Also, countries and cities (GPE) are mentioned frequently, along with nationalities and religious groups (NORP).

Overall, our named entity detection analysis shows that Q drops refer to political matters as we detect words like the US, Hussein, the Senate, and House mentioned frequently. Also, it is evident that Q drops focus on agencies and institutions with almost 50% of the Q drops mentioning at least one. This is not surprising as the conspiracy theory discusses how agencies are controlled by the so-called deep-state and infiltrate the government to affect policy.

5.3 Perspective Analysis

Since QAnon has been linked to radicalization, and inspired believers to commit violent acts, we set out to investigate the perceived impact that text in Q drops might have on a conversation. More specifically, we use four models made available via Google's Perspective API [35]: 1) *severe toxicity,* 2) *inflammatory,* 3) *threatening,* and 4) *incoherent* language.[4]

These return a score between 0 and 1 and work on text only. About 25.1% (1.2K) of our Q drops either include no text or only have links and/or images. We compare the scores of the remaining 3.7K Q drops to those of an equal number of ran-

[3]For the full list of named entity labels, see https://spacy.io/api/annotation#named-entities.

[4]For more details, see https://github.com/conversationai/perspectiveapi/blob/master/2-api/model-cards/English/toxicity.md

Named Entity	#Posts	(%)	Entity Label	#Posts	(%)
US	126	4.21	ORG	1,482	49.57
FBI	107	3.58	PERSON	946	31.63
today	76	2.54	DATE	903	30.20
one	57	1.90	CARDINAL	881	29.46
Hussein	56	1.87	GPE	611	20.43
1	53	1.77	NORP	282	9.43
2	53	1.77	PRODUCT	254	8.49
China	45	1.50	WORK_OF_ART	165	5.52
Senate	44	1.47	ORDINAL	77	2.57
House	43	1.44	MONEY	69	2.31

Table 5: Top 10 named entities and entity labels that appear in Q drops.

domly selected posts from 4chan's /pol/, 8kun's /qresearch/, and Voat's /v/GreatAwakening and /v/news.

We acknowledge that the use of Perspective API is not without limitations. Specifically, previous work has shown that users can evade toxicity detection via simple deception techniques [19], while [42] note that the API is biased against posts written in African-American English. However, we do not take the scores at face value, but rather use them to compare Q drops to text written by other relevant communities. We are also faced with a lack of alternatives; in fact, [56] find that the "severe toxicity" model outperforms other tools like HateSonar [56], while [36] show that the "toxicity" model of the API yields comparable performance as manually annotated Reddit data.

In Figure 6, we plot the CDFs of the scores for each model. The Q drops do not seem to be severely toxic (Figure 6(a)), with a median value (0.04), similar to /v/GreatAwakening (0.06) and /qresearch/ (0.05), but lower than /v/news and /pol/ (0.2 and 0.19, respectively). We observe similar trends for the inflammatory model (Figure 6(b)), with the Q drops having the lowest median score overall (0.15). Q drops seem to score similar threat median scores (Figure 6(c)) as Voat's /v/GreatAwakening (0.14), but much lower than /pol/ and /v/news (0.27 and 0.24, respectively). Considering what discussed in Section 5.1 related to government overthrow, one would expect the scores of the "threat" model to be higher. Thus, we manually inspect our dataset and find that Q does not tend to directly threaten to harm individuals or groups, which is what the model detects.

Last but not least, Q drops seem to be incoherent, much more so than /pol/, /qresearch/, and /v/GreatAwakening posts (Figure 6(d)). Specifically, 99% of the Q drops receive incoherent scores greater than 0.5; as discussed in Section 5.5, incoherence is noticeable upon manual examination. Note that we also test for significant statistical differences across all five distributions for all four models, and reject the null hypothesis for all distributions ($p < 0.001$).

5.4 Conspiracy Spread

The prevailing thought on how QAnon gained widespread adherents was that several actors were responsible for spreading it from fringe image boards to the mainstream Web, creating

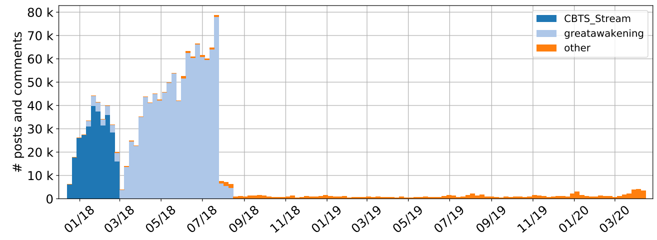


Figure 7: Unique number of posts and comments per week across QAnon related subreddits.

accounts and curating communities endorsing and promoting the conspiracy theory on Reddit, YouTube, and Twitter [45]. In particular, anecdotal evidence suggests that Reddit played an important role in QAnon's transition to mainstream adoption [55], although it was also the first to exercise related content moderation policies [15].

This prompts us to examine the activity in QAnon-focused subreddits to understand how QAnon content spread on Reddit. We also analyze our datasets across several axes to shed light on how QAnon was disseminated overall.

Reddit Activity. In Figure 7, we plot the total content (submissions and comments) for r/CBTS_Stream and r/greatawakening, created in November 2017 and January 2018, respectively, as well as for the remaining 11 QAnon related subreddits in our dataset combined ("other" in the figure). Note that r/CBTS_Stream was the first major subreddit focused on QAnon, which saw an explosive growth in content in late 2017. The activity starts to decline in February 2018, and eventually ceases on March 14th 2018, when it was banned by Reddit for inciting violence [54].

Although there was some content posted in r/greatawakening, this subreddit was essentially unused until r/CBTS_Stream was banned, at which point, over the course of 7 weeks, it exceeded its volume. At its peak, right before it was banned in early September 2018, r/greatawakening had reached twice the volume of the r/CBTS_Stream peak.

Since the banning of these two subreddits, QAnon related activity on Reddit is greatly reduced; the combined activity of the remaining 11 subreddits is minuscule in comparison. In fact, the only regularly active subreddit is currently r/Qult_Headquarters, a community focused on *debunking* QAnon. This follows the general trend suggesting that hard moderation of troubling communities does manage to clean up the platform when appropriate action is taken, however, banned users will probably migrate to other communities [23]. However, because of its super conspiracy nature and close relationship to extremist ideology, Q drops may of course still be disseminated.

Links. We then look at the occurrences of links to Q drop sites on Reddit. When looking at the individual aggregation sites that are linked to (Figure 8), we notice that r/CBTS_Stream was not responsible for disseminating any Q drop links, as it was banned before the first appearance of a link to an aggregation site. Domain registration information shows

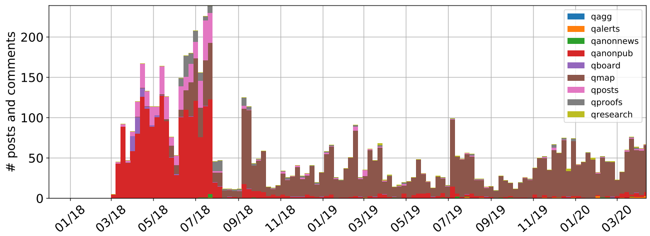


Figure 8: Number of posts and comments mentioning the different aggregation sites across all of Reddit.

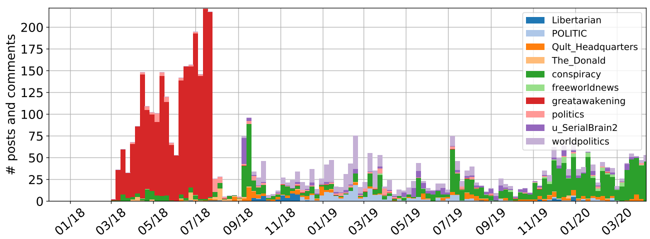


Figure 9: Aggregate site mentions on Reddit broken up by the top 10 subreddits.

Hashtag	Tweets	Hashtag	Tweets
qanon	213,104	unitednotdivided	196,902
wwg1wga	205,826	wakeupamerica	196,878
wearethenewsnow	200,790	saveamerica	196,360
greatawakening	197,736	q	3,639
factsmatter	197,415	thegreatawakening	2,441

Table 6: Top 10 hashtags mentioned in tweets containing aggregation site links.

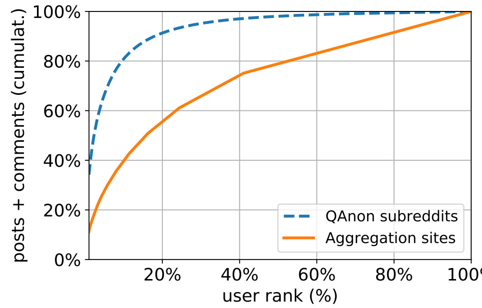


Figure 10: Rank plot showing the percent of Reddit comments made by percent of users.

that qanon.news was registered in December 2017, and was the only aggregation site existing prior to r/CBTS_Stream ban. Considering that links to aggregation sites began to appear as soon as r/greatawakening received the traffic of r/CBTS_Stream, we speculate that these sites were created as a response to r/CBTS_Stream's ban. Next, although there is diversity in the use of different aggregation sites, the majority of links are to qanon.pub and qmap.pub. The former was mostly used during the period that r/greatawakening was active, but since then, the latter became the favored aggregation site until it was eventually shut down. We believe that qmap.pub's rise in popularity was, in large part, due to a dedicated mobile app and bits of content (e.g., QAnon related definitions and news) that other aggregation sites do not have.

We also zero in on the top ten subreddits that links were posted to (Figure 9) and find similar levels of diversity: not only QAnon related subreddits engage in sharing aggregation links. While dominated by r/greatawakening, r/conspiracy has consistently posted links to Q drops, and this trend is increasing towards the end of our dataset. Next, although r/Qult_Headquarters is the most active QAnon oriented subreddit remaining, it has relatively few Q drops linked. Our understanding is that links to Q drops are primarily used by r/Qult_Headquarters users to point out contradictions or help untangle interpretations by adherents. Finally, we note the appearance of the left-leaning r/politics in stark contrast to the remaining subreddits which are largely right-wing subreddits known for extremism and racist ideology [7, 9].

Users. Finally, Figure 10 provides a rank plot with the percentage of the user base making a corresponding percentage of the comments. For example, we find that 20% of users made over 90% of the comments on QAnon subreddits, suggesting that a few main individuals control the conversation. This is similar to Voat, as submissions in /v/GreatAwakening are made by only 346 users out of the 20K subscribers [33]. Over 90% of users made ten or less comments mentioning aggregation sites, which, considering the volume of comments in Figure 9, is a clear indication that aggregation site postings was done by a select few users. In fact, the most prolific user shared links over one thousand times; more than six times the next highest account.

Twitter. Twitter activity around aggregation sites appeared more similar to activity on Q subreddits in that a small number of users accounted for a disproportionate amount of the activity. Over 90% of users had only 10 tweets or less that shared aggregation site links, while the most active users had thousands. However, the scale of link sharing on Twitter dwarfs Reddit activity. Aggregation site links were shared by over 90,000 unique accounts, as opposed to just 1,900 accounts on Reddit.

The hashtags of shared tweets revolved mostly around Q slogans, such as "wwg1wga" (where we go one we go all), and "wakeupamerica." For tweets that included hashtags, the overwhelming majority included 8 hashtags, more than ten times as much as tweets with just one. Coupled with Table 6, where the 8 most frequent hashtags occur over 50 times as much as the next most, it is clear that users employ combinations of hashtags to gain visibility and signal participation in the movement. The coordinated use of hashtags appears to be an important signal of support for the movement, and contributes to their spread across Twitter.

4chan and 8kun. We then measure Q-related activity on the image boards between October 2017 and December 2020. Several major events occurred on them which impacted the conspiracy, e.g., 8chan shutting down and resurfacing as 8kun. We outline the events impacting the activity in Table 7 and use these to annotate the longitudinal activity of QAnon

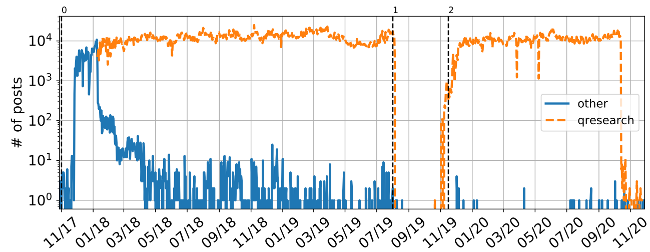


Figure 11: Number of daily posts on /pol/ threads Q posted in plus all daily posts from 8kun's QAnon-related boards (labeled as "other"), as well as all daily posts from /qresearch/.

Event ID	Description	Date
0	Q started posting on 8chan [26].	2017-11
1	8chan went offline [31].	2019-08
2	8kun replaced 8chan [44].	2019-11

Table 7: Events depicted in Figure 11.

image boards in Figure 11. Posting activity on /qresearch/ grew since November 2017, reaching above 10,000 posts per day in January 2018. After, /qresearch/ almost always saw 10,000 posts per day, except for some days in June and December 2018, and May and June 2019. Note that /qresearch/ was the main QAnon discussion community with orders of magnitude more activity than all the other boards combined.

We also calculate the number of posts per thread across all /qresearch/ threads in Figure 12. This shows that not only are /qresearch/ threads the largest, but they are also significantly larger than /pol/ ones [34].

5.5 Take Aways

Overall, we find that Q discusses, among other things, governments controlled by despots and the duty of the people to revolt against it, often using the same language as the US Founding Fathers. Also, Q drops are extremely cryptic and incoherent. Manual inspection of the Q drops sheds further light on the Perspective scores, as we find that Q does not tend to include threatening content in the drops and that these are very often extremely incoherent, consisting of short sentences, definitions, and various random excerpts from movies and official documents.

This highlights how it is not the Q drops to be openly toxic/threatening, or calling for violence, but rather the interpretations of the communities built around the conspiracy and the actors with vested interests that weaponize it.

We also demonstrate that bans on one platform or community are not enough to stop the spread of the conspiracy. After Reddit banned the largest Q-focused subreddits, the majority of other Q-focused subreddits essentially died out. However, the sharing of Q drops continued and spread to other subreddits.

Across Reddit and Voat, activity is driven by a small number of accounts, while on Twitter it is more widespread. However, even the accounts on Reddit which posted less remained

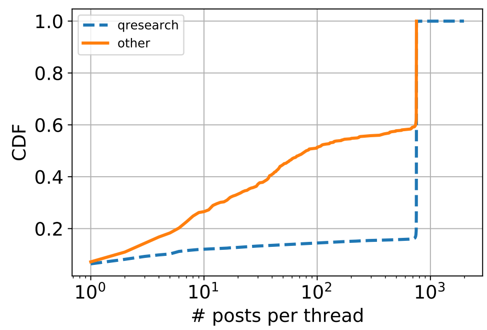


Figure 12: CDF of #posts per thread on qresearch and other boards.

active and participated in discussion.

In addition, Twitter activity suggests that banned communities can find a home for their content on other mainstream platforms. The scale of activity on Twitter dwarfs that of Reddit, showing that bans on one platform do little to slow growth on other platforms. It may even increase activity on differing platforms as disaffected users try to find a new community.

6 Conclusion

This work presented a data-driven, multi-platform, multi-axes analysis of the QAnon conspiracy theory. Our study of 4,949 Q drops from six aggregation sites yielded several findings. First, there are meaningful discrepancies in what is considered a canonical drop by different aggregation sites. Next, we analyzed the content of Q drops, finding clear topics related to religion and calls to revolutionary action in the defense of freedom. We also found statistically significant stylometric differences in Q drops, indicating that they were not authored by a single person. Finally, we showed how even though Reddit banned the two QAnon subreddits credited with helping the conspiracy theory go mainstream, that links to Q drop aggregation sites still appear, primarily in right-wing oriented subreddits.

In addition to increasing our understanding of how QAnon has gained mainstream adoption, there are several other implications and directions for future work. For example, the adoption of drop aggregation sites raises questions as to how affective deplatforming actions might be in terms of preventing susceptible individuals from becoming adherents. Further, these aggregation sites hold substantial power; since drops originally appear on anonymous and ephemeral image boards, aggregation sites ultimately control what information adherents are left to interpret.

With this in mind, we believe there is a fruitful line of work that can build on our study. In particular, we encourage future work that explores how drops are interpreted, both from the perspective of what they "mean" to adherents, and also from the perspective of which set of drops are the most impactful to the evolution of the theory.

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