What happens on the fringes, stays on the fringes?

Information flows in the contemporary media system

Simon, M.

Publication date
2024

Chapter 2

Inside Dark Platforms

Information flows within the Dutch Telegrampshere

A version of this chapter is published as: Simon, M., Welbers, K., Kroon, A. C., & Trilling, D. (2023). Linked in the dark: A network approach to understanding information flows within the Dutch Telegramsphere. Information, Communication & Society, 26(15), 3056-3080. Routledge. https://doi.org/10.1080/1369118X.2022.2133549

Abstract

Recent studies have shown that the stricter content moderation policies imposed by mainstream social networking sites (SNSs) stimulated the growth of low-moderated but relatively open discussion platforms such as Telegram. Despite Telegram's growing popularity among (deplatformed) digital exiles, and high potential for news dissemination, information consumption, mobilization, and radicalization, little is known about information flows with respect to politically and socially relevant topics within the Telegramsphere. We scrutinize the Telegramsphere as an information-sharing ecosystem of current affairs by uncovering how information flows indicated by content-overlap and shared users influenced the structure of Telegram networks and shaped communities over time. Using state-of-the-art web-mining, neural topic modeling, and social network analysis techniques on a unique dataset that spans the full messaging history ($N = 2,033,661$) of 174 Dutch-language public Telegram chats/channels, we show that over time, conspiracy-themed, far-right activist, and COVID-19-sceptical communities dominated the Dutch Telegramsphere of current affairs. Our findings raise concerns with respect to Telegram's polarisation and radicalization capacity in the context of consuming socially and politically relevant information online.

keywords: Telegram, information flows, social network analysis, public sphere, alternative news sources, dark platform

Introduction

The information flows that shape our societal beliefs have shifted since the World Wide Web with large social networking sites (SNSs) greatly reduced the barrier of entry for alternative news sources (Zannettou et al., 2017). Recent indications of an interdependent relationship between the uptick of alternative SNSs, and the escalation of (far-right) extremism (Haller et al., 2019; Holt, 2018) have fueled a growing concern that *"secluded online spaces can function as laboratories that develop extremist talking points that then find entry into the mainstream"* (Lewandowsky, Smilie, et al., 2020, p. 6). On the other side of the same coin, the darker corners of the Web also offer an opportunity for disadvantaged and marginalized communities, to speak up, and take action (Lewandowsky, Smilie, et al., 2020).

One platform that deserves particular attention in this regard is Telegram, an instant messaging (IM) app that has grown exponentially in the wake of the recent mass "deplatforming" (Rogers, 2020) of extremist and anti-establishment users from mainstream SNSs (Rogers, 2020) and amid the COVID-19 pandemic[6]. There is considerable evidence that Telegram's lenient platform guidelines and privacy-focused affordances have been leveraged by extremist groups worldwide (see e.g., Gallagher & O'Connor, 2021; Urman & Katz, 2020) and marginalized communities in authoritarian regimes (Schectman, 2019; Walker, 2020).

Telegram, however, is more than a tool for political fringe groups (Urman et al., 2021). It has become an important instrument for news broadcasting, information consumption and deliberation (Lou et al., 2021). Still, the literature concerning information flows on Telegram predominantly conceptualizes Telegram as an obscure breeding ground for extremism (see e.g., Shehabat et al., 2017; Urman & Katz, 2020), even though the majority of its 500 million active users[7] are likely not extremist, but simply use it to get informed and engage in potentially socially and politically relevant discussions.

Building on Habermas (1991), Benkler (2006), and Bruns and Highfield (2015), we conceptualize the relatively open, but low moderated discussion arena catered by public Telegram chats/channels as the "Telegramsphere" (i.e., an information-sharing ecosystem of current affairs). This underlines the urgency of studying how the increasing popularity of more secluded online discussion arenas may foster the formation of like-minded communities through shared narratives, which may lead to polarization through transcending their own public sphericules, reaching less-involved broader audiences (Bruns & Highfield, 2015).

Therefore, we collected a unique dataset of over 2 million messages that spans the full messaging history (18-03-2017 – 18-06-2021) of 174 Dutch-language public Telegram channels ($n = 94$) and chats ($n = 80$) – identified via keywords related to current affairs. We performed neural topic modelling and social network analyses to examine how the evolution of the narrative structures formed by content-overlap networks and user-overlap networks may have furthered the aggregation of chats/channels into like-minded communities over time.

[6]https://www.geenstijl.nl/5157390/telegram-rellers-klaar-voor-weer-een-avondklok/
[7]https://www.businessofapps.com/data/telegram-statistics/

Theoretical Framework and Related Research

Telegram and its lax moderation policies

Telegram is the largest, cloud-based, hybrid IM application that can be accessed via smartphones, tablets or on a desktop (Dargahi Nobari et al., 2021). It has several privacy enhancing features[8] that are attractive to users who seek a platform that offers opportunities of publicity and mobilization while safeguarding their anonymity to avert possible legal repercussions (Urman & Katz, 2020). End-to-end message encryption, secret chats, private group chats/channels, anonymous forwarding, and the unsend feature all tend to the needs of users who wish to stay completely under the radar.

Therefore, others have referred to Telegram as an example of *dark social media* characterized by private and semi-private end-to-end encrypted messaging spaces, which are difficult to access and retrieve data from (Al-Rawi, 2019). While Telegram certainly can be defined as dark social media if we refer to its private spaces alone, it also has a large public space, which is less hidden, easily accessible, yet weakly moderated. This makes it a particularly interesting medium to study in the wake of stricter content moderation policies imposed by mainstream SNSs.

There are two means to converse on Telegram: *Channels* primarily enable one-sided communication toward an unlimited number of followers, whereas *group chats* can host mass discussions among a maximum of 200,000 members. While chats/channels facilitate different kinds of user engagement, we argue that studying both features together is crucial to investigate information flows on Telegram. Although users cannot directly react to ideas disseminated by the administrators of public channels, these messages can be forwarded to group chats, where users can freely dissect and discuss the original idea among like-minded others. Likewise, administrators of channels can leverage the message forwarding feature to amplify messages of other chats/channels among their own subscribers.

Telegram's low threshold public space has recently become popular among individuals who feel censored by the stricter moderation policies of mainstream SNSs such as Twitter and Facebook (Rogers, 2020). We propose that Telegram's public space fits the mold of *dark platforms*, which are digital spaces characterized by (1) *content liberation*, (2) *exile congregation*, (3) and *infrastructure ostracization* (i.e., cutting ties with established infrastructure), which *"can be used for hosting content and content creators that may not be tolerated by their more mainstream counterparts"* (Zeng & Schäfer, 2021, p. 1).

[8] https://telegram.org/faq

The *darkness* of a platform can be viewed both positively and negatively. Telegram is a prime example of a dark platform precisely because it has received media and scholarly attention both as a platform that liberates marginalized communities and a platform that has the potential to radicalize users who are exposed to extremist content. Accordingly, Telegram promotes "content liberation" (Zeng & Schäfer, 2021) by deliberately positioning itself as a platform of free expression and privacy protection[9]. It fosters exile congregation by becoming an attractive refuge for (deplatformed) digital exiles due to its lenient platform governance (Rogers, 2020), and facilitates infrastructure ostracization by, for example, offering unlimited in-platform video hosting and live streams[10] that can be leveraged to host and spread content that bypasses the moderation policies of platforms such as YouTube. All in all, conceptualizing Telegram as a dark platform aims to highlight the obscurity and often hidden nature of secluded online spaces that are different from their mainstream counterparts (Zeng & Schäfer, 2021).

To illustrate, Telegram's lax moderation policies (Molla, 2021) and content liberation have been weaponized by such extremist groups as ISIS for recruitment, radicalization, and planning purposes[11], Irish ethnonationalists for spreading false information [12], white supremacists[13], and an increasing amount of far-right extremists (Urman & Katz, 2020) to discredit mainstream media, and spread disinformation and conspiracy theories (Walther & McCoy, 2021). On the other side of the same coin, Telegram has previously empowered and mobilized oppressed communities of authoritative regimes in Hong Kong (Urman et al., 2021), and Belarus[14]. Furthermore, Telegram represents an increasingly popular medium to both disseminate news and get informed about current affairs (Lou et al., 2021).

The Telegramsphere

According to Bruns and Highfield (2015), the ever-evolving social media ecology and mediasphere has brought on the need to revisit the Habermasian public sphere theory (Habermas, 1962; Habermas, 1991), which argued that public debate is driven by the hegemony of mass print and broadcast media. This view ignores the complexity and dynamic nature of the current (social) media ecology, that has changed tremendously since Habermas (1962) first established the framework of 'the public sphere'.

[9] https://telegram.org/faq
[10] https://telegram.org/blog/live-streams-forwarding-next-channel
[11] https://minerva.defense.gov/Owl-In-the-Olive-Tree/Owl_View/Article/1859857/telegram-and-online-addiction-to-terrorist-propaganda/
[12] https://www.vice.com/en/article/93yw4p/telegram-is-the-far-rights-weapon-of-choice-in-ireland, https://www.isdglobal.org/wp-content/uploads/2021/04/Layers-of-Lies.pdf
[13] https://www.isdglobal.org/wp-content/uploads/2020/06/A-Safe-Space-to-Hate2.pdf
[14] https://www.theguardian.com/media/2020/nov/07/nobody-can-block-it-how-telegram-app-fuels-global-protest

Specifically, the dawn of the digital media and the rise of SNSs led to a decline of longstanding opportunity structures that used to favor the elite (Jungherr, Schroeder, & Stier, 2019). Social media platforms enable ordinary members of the public to create their own channels of public communication leading to several different technology-driven public spheres (Cunningham, 2001) rather than one single elite-driven public sphere (Bruns & Highfield, 2015). Consequently, the information flows that citizens base their beliefs on with regard to societal topics are continuously shifting in a world of direct access to primary sources within various public spheres that are largely unaffected by institutional and journalistic gatekeeping in the traditional sense.

The emergence of new online communication platforms, such as Telegram, that increasingly blur the lines between public, semi-public, and private communication further reinforce the notion that the framework of the public sphere can no longer capture the complex, dynamic, and fluctuating media ecology (Bruns & Highfield, 2015). We argue that Telegram's affordances foster a technologically-driven, platform-specific "networked public sphere" (Benkler, 2006), which we refer to as *Telegramsphere* henceforth.

The idea of the Telegramsphere is comparable to the "Twittersphere" that enables the *"wild flow of information beyond the mainstream"* (Bruns & Highfield, 2015, p. 62). These platform-specific public spheres host so-called "public sphericules" (Cunningham, 2001) that do not necessarily reflect the agenda of the entire domain or society at large, but rather they address specific themes and issues that are present within or across multiple domains that only a smaller group of individuals are interested in (Bruns & Highfield, 2015).

Some argued that this new media ecosystem fosters the formation of like-minded communities or so called "echo-chambers" (Sunstein, 2007) on social media (Cinelli et al., 2020) given that *"the wide availability of user-provided content in online social media facilitates the aggregation of people around common interests, worldviews, and narratives."* (Vicario et al., 2016, p. 554). There are also indications that the information spreading in like-minded clusters of people is often misleading (see e.g., Bessi et al., 2015; Vicario et al., 2016) and can be leveraged for political manipulation (Bovet & Makse, 2019).

The Telegramsphere

According to Bruns and Highfield (2015), the ever-evolving social media ecology and mediasphere has brought on the need to revisit the Habermasian public sphere theory (Habermas, 1962), which argued that public debate is driven by the hegemony of mass print and broadcast media. This view ignores the complexity and dynamic nature of the current (social) media ecology, that has changed tremendously since Habermas (1962) first established the framework of 'the public sphere'.

Specifically, the dawn of the digital media and the rise of SNSs led to a decline of longstanding opportunity structures that used to favor the elite (Jungherr, Schroeder, & Stier, 2019). Social media platforms enable ordinary members of the public to create their own channels of public communication leading to several different technology-driven public spheres (Cunningham, 2001) rather than one single elite-driven public sphere (Bruns & Highfield, 2015). Consequently, the information flows that citizens base their beliefs on with regard to societal topics are continuously shifting in a world of direct access to primary sources within various public spheres that are largely unaffected by institutional and journalistic gatekeeping in the traditional sense.

The emergence of new online communication platforms, such as Telegram, that increasingly blur the lines between public, semi-public, and private communication further reinforce the notion that the framework of the public sphere can no longer capture the complex, dynamic, and fluctuating media ecology (Bruns & Highfield, 2015). We argue that Telegram's affordances foster a technologically-driven, platform-specific "networked public sphere" (Benkler, 2006), which we refer to as *Telegramsphere* henceforth.

The idea of the Telegramsphere is comparable to the "Twittersphere" that enables the *"wild flow of information beyond the mainstream"* (Bruns & Highfield, 2015, p. 62). These platform-specific public spheres host so-called "public sphericules" (Cunningham, 2001) that do not necessarily reflect the agenda of the entire domain or society at large, but rather they address specific themes and issues that are present within or across multiple domains that only a smaller group of individuals are interested in (Bruns & Highfield, 2015).

Some argued that this new media ecosystem fosters the formation of like-minded communities or so called "echo-chambers" (Sunstein, 2007) on social media (Cinelli et al., 2020) given that *"the wide availability of user-provided content in online social media facilitates the aggregation of people around common interests, worldviews, and narratives."* (Vicario et al., 2016, p. 554). There are also indications that the information spreading in like-minded clusters of people is often misleading (see e.g., Bessi et al., 2015; Vicario et al., 2016) and can be leveraged for political manipulation (Bovet & Makse, 2019).

Conversely, an emerging body of literature argues that the presence of echo chambers (and filter bubbles) is at best questionable (Zuiderveen Borgesius et al., 2016) but may even be completely wrong. Bruns (2019) maintains that not only echo chambers and filter bubbles do not exist, but extremists exploit their very absence to disseminate messages beyond partisan in-groups, given that debates that take place within particular public spheres and sphericules are not isolated to the platform that hosts these forms of communication. Instead, these narratives that often circle around particular topics and issues, form so called "issue publics" that may transcend their public sphericule and reach a broader less involved audience (Bruns & Highfield, 2015). Although the existence of echo-chambers on mainstream SNSs remains debatable, scholars who studied the formation of like-minded communities on social media appear to agree that content has the ability to pull like-minded people together (see e.g., Bessi, Petroni, et al., 2016; Bessi, Zollo, et al., 2016; Vicario et al., 2016) and that users who are closer to each other in a social network have similar interests (Aiello et al., 2012). But despite an increasing shift towards more private spaces (such as WhatsApp, WeChat, and Telegram) for news consumption and discussion (N. Newman, 2019), less is known about how more secluded online spaces may foster the formation of like-minded communities.

Research context and research questions

We argue that Telegram's increasingly popular public sphere (i.e., Telegramsphere) can be understood as an information-sharing ecosystem of current affairs where large groups of people can come together to discuss socially and politically relevant ideas in a low moderated but public medium. Following Y. Zhang (2020) who discerned that studying the connections between individuals can be leveraged to understand their actions, and exploring individuals' actions can be used to understand their connections, we adopted a network approach to explore information flows in the Telegramsphere.

In our view, there are two fundamental ways to measure the extent to which like-minded communities can emerge across different chats/channels within the Telegramsphere. The most basic proxy of capturing the aggregation of people around common grounds on Telegram would be to study user overlap across different chats/channels. If a large share of users are active in multiple different chats/channels, this would indicate that there may be shared perspectives across chats/channels that coincide with users views, given that people have the tendency to engage with like-minded information but disregard contradictory information (Garrett, 2009; Klapper, 1960).

A higher-order indicator of user aggregation around common grounds on Telegram would be to study shared narratives across chats/channels via content overlap. By assessing content overlap we could get a glimpse of how the common views captured by the content shared and topics discussed may pull different chats/channels together.

We studied the Dutch language Telegramsphere because Telegram usage in The Netherlands received increased media attention and some scholarly attention in the recent past with respect to riots and mass protests[15], anti-establishment sentiments and behaviour[16]. Problematic Telegram usage in The Netherlands recently led to the suspension of three public conspiracy chats/channels, and arrests of their administrators due to the posting of threatening and inflammatory content[17]. Anecdotal evidence also suggests that Telegram may have played a role in the mobilization of voters during the 2021 Dutch General Election campaign. To illustrate, Forum voor Democratie (FvD – Forum for Democracy), one of the most successful far-right parties of the elections, explicitly and regularly encouraged their Twitter followers to follow their Telegram channel (see Appendix B). Using party communication to draw voters to the darker corners of the web during the campaign period was unprecedented before in Dutch politics to the best our knowledge. In fact, one of the recently banned Telegram groups that propagated inflammatory and violent content towards the establishment bore the name of "FvDgeluiden" (i.e., FvD voices) which arguably proposes a direct connection between the increasingly extremist far-right party and criminal behavior encouraged on the Telegramsphere. These early findings and concerns suggest that the low-moderated Telegramsphere plays an important role in information dissemination and community building in The Netherlands. Therefore we ask:

RQ1: *Which major communities comprise the Dutch Telegramsphere with regard to (a) overlapping users and (b) overlapping content?*

RQ2: *How have Dutch public Telegram networks developed over time with regard to (a) overlapping users and (b) overlapping content?*

[15] https://www.parool.nl/gs-bbd03bbee
[16] https://www.groene.nl/artikel/kijk-op-facebook-niet-naar-de-nos
[17] https://nos.nl/l/240124

Data and Methods

Data collection

We obtained the full text message history of 174 channels ($N = 94$) and chats ($N = 80$) by querying the Telegram's API via the Telethon Python library[18] from 18 March, 2017 until 18 June, 2021 ($\sim$ 4 years). To retrieve data from the Telegram API, channel and chat names are needed. In line with Semenzin and Bainotti (2020) and Walther and McCoy (2021) we adopted an in-platform approach of identifying public Telegram chats/channels via a list of queries that were as inclusive as possible. Specifically, we created a list of queries relating to a wide range of current affairs in The Netherlands such as all major party names, words related to (alternative) news, activism, conspiracy theories, health and wellness, and the COVID-19 pandemic (see Appendix A).

We used the Telegram Desktop app's search field to identify public chats/channels that corresponded to these queries[19]. The search queries were predominantly Dutch except a few internationally used phrases. The identification of the chats/channels was performed manually by the lead author. A chat/channel was included if their content was written (primarily) in Dutch [20], they had at least two posts, and a minimum of six subscribers. Left-leaning organizations and topics were hardly represented in the Dutch Telegramsphere, which resulted in a predominantly right-leaning collection of chats/channels.

We scraped the content of all chats/channels that met our inclusion criteria. After removing missing values, we obtained a dataset of 2,033,661 entries, which included user data, time of messages sent, message IDs, text messages, and the name of the chats/channels where the messages were posted. The obtained text messages were sent by 55,331 unique users across 174 chats/channels. The maximum member or follower size of a chat/channel was 26,346 users while the minimum size was 6 users ($M = 1628, SD = 4269$)[21].

Network analysis

Guided by previous research on group connections using social network analysis (see e.g., Urman & Katz, 2020; Y. Zhang, 2020) we examined which major communities comprised the Dutch Telegramsphere with regard to (a) overlapping users (b) and overlapping content (RQ1),

[18] https://docs.telethon.dev/en/stable/

[19] We tested the Telegram desktop search feature several times before data collection, using multiple keywords, and the search results appeared to be consistent over a short period of time (i.e., approximately 1 week).

[20] verified by human coder

[21] Mean chat/channel sizes were calculated on 166 chats/channels instead of 174 due to missing values.

and assessed the development of networks over time (RQ2). We conceptualized user overlap based on the number of common users who participated in discussions (i.e., sent text messages) in a given a chat or channel.

We conceptualized content-overlap using two complementary approaches. The first and more direct approach was measuring the extent to which the same URLs were shared in different chats/channels since they represent a prevalent and easily traceable element of messages sent on social media (i.e., URL-overlap network). This approach is in line with previous research that studied news-flows via URL-tracking (Zannettou et al., 2017).

The second, more indirect approach was measuring the extent to which topics shared across chats/channels were similar over time (i.e., topic-similarity network). To obtain topics, we performed dynamic topic modelling using BERTopic (Grootendorst, 2022), a state-of-the-art neural topic modelling method that employs sentence transformers to obtain and cluster document embeddings into coherent topic representations with minimal researcher input, with regard to textual preprocessing, choice of model parameters, and topic interpretation. It must be noted that conducting neural topic modelling via BERTopic merely represented a means to an end, and we refer to Grootendorst (2022) for a discussion of the merits of this method compared to older approaches such as Latent Dirichlet Allocation.

BERTopic enabled us to map Telegram messages onto a 384 dimensional dense vector space in order to cluster similar sentences together into topics based on their cosine similarity. Following best practices we obtained 125 topics via BERTopic, which we used as inputs for network analyses to gain insights into the narrative space between chats/channels that characterized the Dutch Telegramsphere.

Network graphs

Using the igraph R library (Csardi & Nepusz, 2006), we first created a single-snapshot user-overlap network graph. Then we created two separate network graphs for content-overlap: one URL-overlap network and one topic-similarity network across chats/channels (RQ1). Finally, we created a total of nine of such network graphs across three time slices to trace the evolution of the user-overlap network and the two types of content-overlap network over time (RQ2).

The resulting network graphs were undirected given that we assumed a bidirectional relationship when calculating intersections (i.e., edges) between nodes (i.e., chats/channels). Intersections were measured based on three incidence matrices: of chats/channels with users (i.e., user-overlap network), and chats/channels and with URLs and with topics (i.e., content-overlap networks). The edges between chats/channels were then calculated as the cosine similarity of chats/channels. As such, we obtained weighted edge lists as inputs for the generation of each network graph where the higher the edge weights (i.e., common users, URLs, and topics), the stronger the connection between two nodes was regarded.

Disparity filter

In addition to using weighted edges, it is common practice to remove unimportant edges from a network (also called edge pruning). Since large complex networks such as the ones studied here tend to be multi-scale in nature, we apply a disparity filter (i.e., backbone extractions) proposed by Gursoy and Badur (2021) and Serrano et al. (2009). This method is considered superior to the commonly applied frequency-based edge pruning approach, given that the disparity filter preserves edges that have statistically significant deviations compared to a null model without belittling nodes with smaller-scale interactions (Gursoy & Badur, 2021; Serrano et al., 2009).

Alpha levels between 0.01 and 0.5 are considered optimal with respect to maintaining the characteristics of the original network (Serrano et al., 2009). We opted for an identical alpha level ($\alpha = 0.01$) for the user-overlap network and the URL-overlap network, which ensured comparability of these two types of direct-overlap networks across the three time slices. Guided by the data, we used an α of 0.1 for the topic-similarity networks given that a lower α level would have been too restrictive with respect to identifying communities via the low number of unique topics ($n = 125$), which we used to calculate intersections between chats/channels.

Data preparation

First we describe our approach to preparing the data for the generation of the single snapshot user-overlap network. After removing entries that did not include any information about users ($n = 12,566$) we obtained a dataset of 2,021,095 entries. All messages in a given *channel* (as opposed to a chat) correspond to a single user ID, given that channels have a broadcasting function where only channel administrators can send messages.

To answer the second part of the first research question, we reorganized our full dataset by URLs and by topics derived via BERTopic. After removing missing values and resolving URLs we obtained a dataset with 362,837 entries, where each row represented a single URL. After conducting dynamic topic modelling and topic modelling per class with BERTopic we obtained two data frames. We merged these data frames by topic number, and removed outliers. Similar to the aforementioned process, we prepared our data to conduct one single-snapshot content-overlap network analysis based on URL-overlap and another one based on topic-similarity. Finally, we performed community detection using the Louvain algorithm (Blondel et al., 2008) to assess which communities comprised the user-overlap network and the content-overlap networks.

Time slices

To answer our second research question concerning the evolution of the studied networks, we created three snapshots of the data. Data slicing was guided by the course of the COVID-19 pandemic in The Netherlands (Rijksoverheid, 2020) given that this crisis is arguably the most significant global event in the recent past[22] that had a direct impact on the Dutch population, whose lives were governed by biweekly press conferences[23] and daily news about COVID-19 measures that were associated with social unrest[24] and increased (problematic) Telegram usage in The Netherlands during the investigated timeline (Bakker et al., 2020).

While there may be more exogenous events such as Donald Trump being banned from Twitter that may have contributed to changes in the use of alternative platforms, our focus on Dutch-language chats/channels from the Netherlands makes it reasonable to assume that such events are much less influential compared to the development of the COVID-19 pandemic that dominated the news cycle and political discourse in the Netherlands in that time frame.

The first time slice (T_1) comprised all messages sent before before COVID-19 was declared a global pandemic (11-03-2020). The second time slice (T_2) included all messages that were sent from the day COVID-19 was declared a pandemic (11-03-2020) until the day before The Netherlands introduced stricter corona-combating measures such as a curfew (19-01-2021). The third time slice (T_3) included all messages sent starting from the day the Dutch government introduced the hard lockdown (20-01-2021) until the day data collection was completed (18-06-2021).

T_1 spans over almost three years while the second and third over a couple of months. Still, only 2.7% of messages were sent before 2020-03-11 and the majority of the data points in our dataset fell within the time frame of the COVID-19 pandemic. The inclusion of user activity from T_1 provided us with insights about the Telegramsphere of current affairs when Telegram was less popular and before outbreak of the COVID-19 pandemic. T_2 and T_3 illustrated the highly precarious timeline of the first year of the pandemic, which coincided with an increased usage of Telegram[25]. We followed the previously outlined steps to perform network analyses on the three time slices of the user-overlap network and the content-overlap networks. We computed several metrics for each network graph (see Appendix E and F).

[22] https://www.who.int/emergencies/diseases/novel-coronavirus-2019

[23] https://nos.nl/artikel/2360729-kijkcijferrecord-voor-lockdownspeech-premier-rutte

[24] https://www.who.int/emergencies/diseases/novel-coronavirus-2019, https://www.who.int/emergencies/diseases/novel-coronavirus-2019

[25] https://www.businessofapps.com/data/telegram-statistics

Results

RQ1: Communities within the Telegramsphere

Our first aim was to examine which major communities comprised the Dutch Telegramsphere with regard to overlapping users and overlapping content (URL-overlap and topic-similarity). All of our results are reported after the application of the disparity filter and removal of isolates [26]. We exclude isolates given that the community detection algorithm as well as the vast majority of the network metrics we conducted do not take them into account. We report the number of isolates wherever relevant.

Single snapshot user-overlap network

The user-overlap network consisted of 89 nodes (85 isolates) and 287 edges. The edge density of the single snapshot user-overlap network illustrated that 1.90% of nodes were connected within the network. The transitivity of the network indicated a 27.6% probability that two chats/channels were connected when they had a chat/channel in common. Degree assortativity of the user-overlap network was low and negative (-0.061), illustrating that nodes with high degrees tended to connect to nodes with low degrees. We found a low level of centralization within the user-overlap network (0.251).

Community detection partitioned the user-overlap network into 12 clusters (84 isolates) with a modularity score of 0.627. This suggests a strong decentralized community structure. Figure 5 illustrates the network's community structure. The largest community (yellow) comprised of conspiracy-themed, freedom-activist, anti-establishment, and anti-lockdown chats/channels (nodes = 21, edges = 45). Another pronounced cluster (red) was dominated by chats/channels dedicated to the far-right parties Forum voor Democratie and Partij voor de Vrijheid –Freedom party).

Single snapshot URL-overlap network

The URL-overlap network consisted of 118 nodes (42 isolates) and 174 edges. The density scores indicated that 1.4% of nodes were connected within the network. The transitivity of the network showed a 35.8% chance that two chats/channels were connected if they had a chat/channel in common. Degree assortativity of the content-overlap network was low and positive (0.144), suggesting that nodes with similar degrees had a slight tendency to connect to one another. We found a low level of network centralization (0.140). The community detection

[26] nodes not connected to others within the network graphs

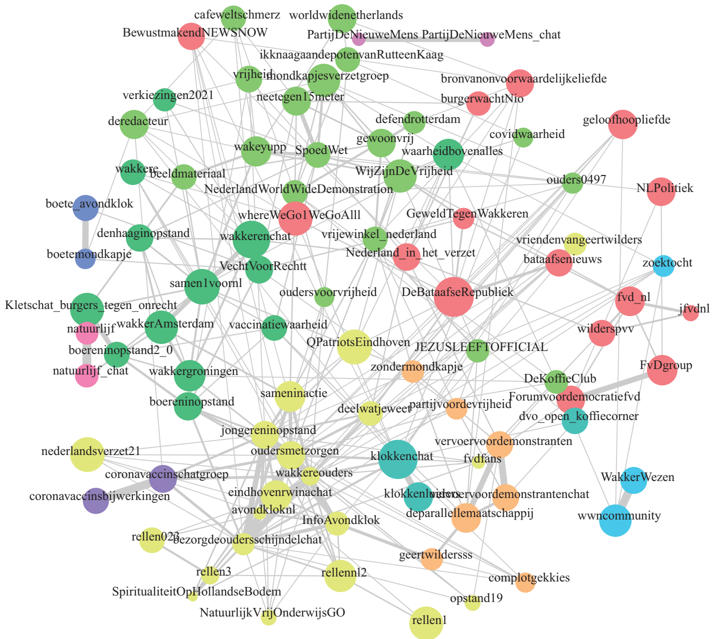


Figure 5: Single snapshot user-overlap network after the application of the disparity filter (α = 0.01) and removal of isolates ($n_{nodes} = 89$, $n_{edges} = 287$).

revealed 19 clusters (46 isolates) within the network, with a high modularity score of 0.710. Similar to the user-overlap network, the high modularity score revealed that the URL-overlap network was extraordinarily decentralized and had a distinct community structure.

The cluster of green nodes on Figure 6 illustrates the largest community of the network (nodes = 17, edges = 26). This community comprised of conspiracy-themed, spiritual, and anti-establishment chats/channels sharing the same URLs. Other clusters displayed more surprising patterns with respect to content-overlap. For instance, the light-green cluster on the bottom right of Figure 6 included chats/channels that can be roughly categorized as anti-COVID-19 measure activists and conspiracy theorists (see Appendix C and Appendix D for categories). but also farmers' protest groups. This corroborates recent findings showing that farmers and conspiracy theorists found common grounds on social media due to anti-establishment sentiments[27].

[27] https://www.groene.nl/artikel/kijk-op-facebook-niet-naar-de-nos

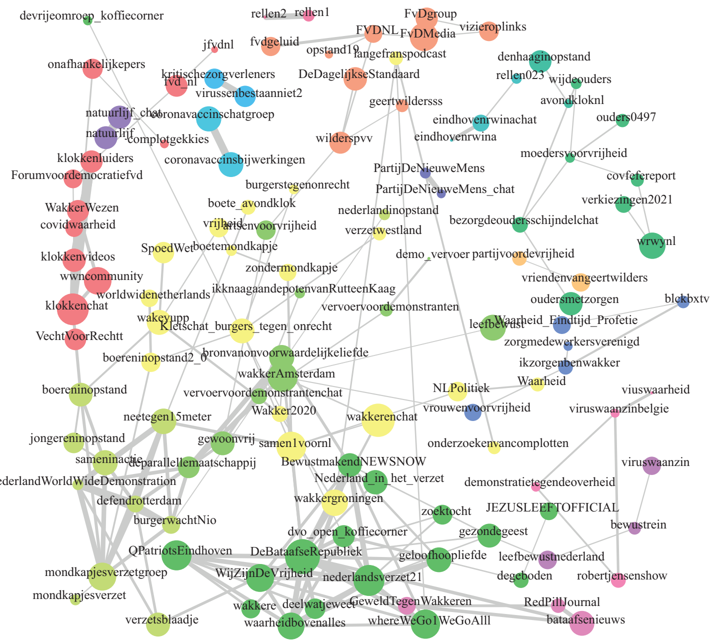


Figure 6: Single snapshot URL-overlap network after the application of the disparity filter ($\alpha = 0.01$) and removal of isolates ($n_{nodes} = 118$, $n_{edges} = 170$).

Single snapshot topic-similarity network

The topic-similarity network consisted of 112 nodes (56 isolates) and 306 edges. The density of the network indicated that 4.9% of nodes were connected. The network had a very high transitivity score, suggesting that there was a 54.7% chance that two nodes were connected if they had a neighbor in common. Degree assortativity was rather high and positive (0.453), revealing that nodes with similar degrees tended to connect to one another. Centralization in the topic-similarity network was low (0.133).

Community detection revealed 13 clusters (56 isolates) with a modularity score of 0.580, which suggests that the network had a weaker but still distinctive community structure in comparison with the URL-overlap network. The cluster of yellow nodes on Figure 7 illustrate the largest community within the network, which contained a great variety if chats/channels that shared similar topics, including a flat earthers and other conspiracy groups, anti-covid measure activists, right-wing politics as well as farmers' protest groups. These clusters are similar to the composition of the URL-overlap network as well as the user-overlap network. Taken together, we observed that in general Telegram users were active in and shared content across different communities.

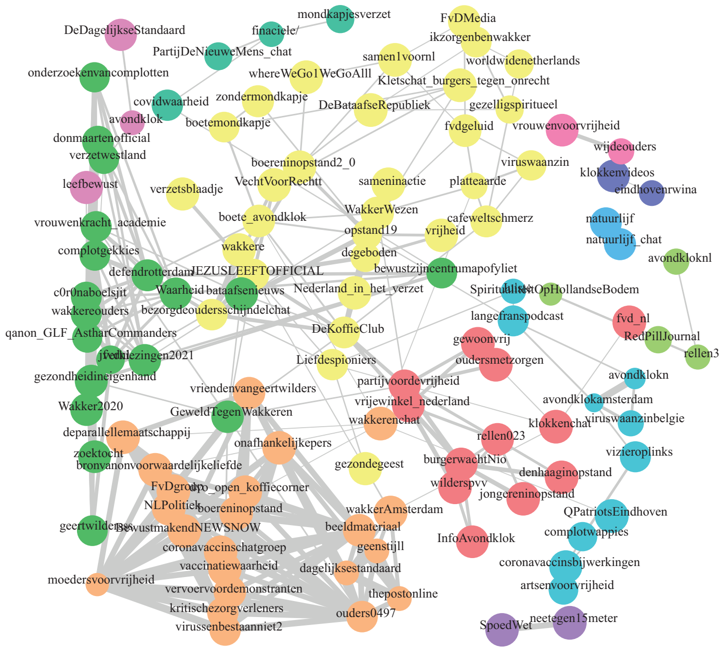


Figure 7: Single snapshot topic-similarity network after the application of the disparity filter (α = 0.1) and removal of isolates ($n_{nodes} = 112$, $n_{edges} = 306$).

RQ2: The evolution of the networks

Our second aim was to assess how have Dutch Telegram networks evolved over time with regard to (a) overlapping users and (b) content-overlap. We begin by assessing the temporal distribution of chat/channel activity to provide context to interpreting our subsequent findings.

Evolution of chat and channel activity

The bottom graph of Figure 8 depicts the overtime distribution of active chats/channels per time slice. In a nutshell, we observed a low amount of chat/channel activity during T_1. T_2 marked the time period when gradual increase of active chats/channels took place, which eventually escalated at T_3.

Evolution of user activity

Turning to temporal developments with regard to user activity (middle graph of Figure 4), T_1 was a generally quiet period with a low amount of users sending messages in chats/channels except

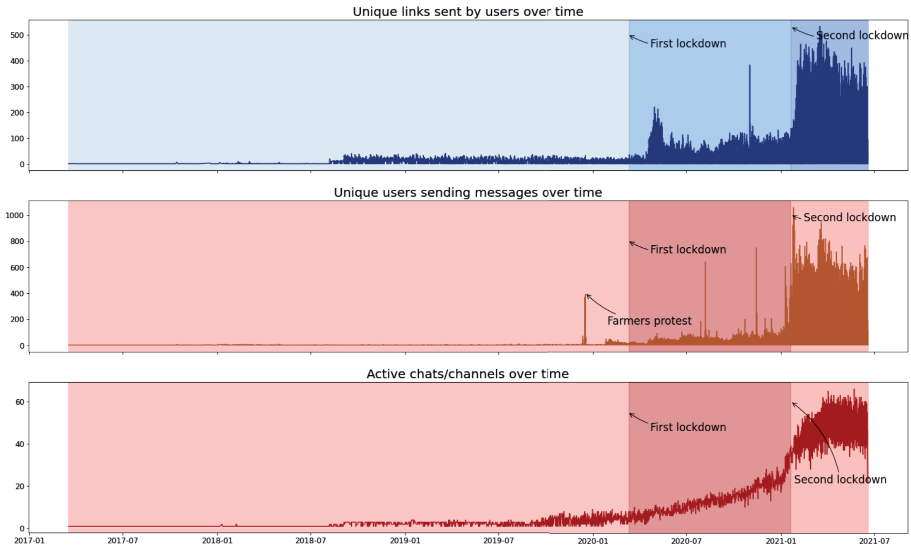


Figure 8: The top two graphs display unique link posting and unique user activity over time per chat/channel. The bottom graph displays active chats and channels over time.

for a spike around mid December 2019, which the result of heightened activity by a farmers' activist group (i.e., "beeldmateriaal") that organized a major protest in mid December 2019[28].

We observed four major spikes and more activity across the board at T_2 compared to T_1 with respect to user activity. These spikes were related to increased activity by users of a COVID-19 denier, conspiracy theory-propagating group (i.e., klokkenchat). We did not find major events other than an upswing in COVID-19 infections that would explain the increase in user activity on the days a particularly high number of unique users sent messages. T_3 represents a highly active period with a high amount of users sending messages in chats and channels. The first and biggest spike of the graph dates back to the time when the Dutch government introduced a curfew to combat COVID-19, which also represents roughly the first time point of T_3. Users have remained active throughout T_3 with some additional spikes around March 2021, when the Dutch general elections took place.

[28]https://www.rtlnieuws.nl/nieuws/nederland/artikel/4950316/boerenprotest-boerenacties-stikstofbeleid-supermarkt

Evolution of URL sharing

Apart from a slight increase during the second half of T_1, URL sharing at T_1 was not very prominent within the Telegramsphere. T_2 represents a more fruitful period of URL sharing with more activity in general and some spikes of activity in response to governmental measures imposed to combat COVID-19. Similar to the evolution of user activity, T_3 represents the most active period of URL sharing predominantly catered by one conspiracy group "DeBataafseRepubliek".

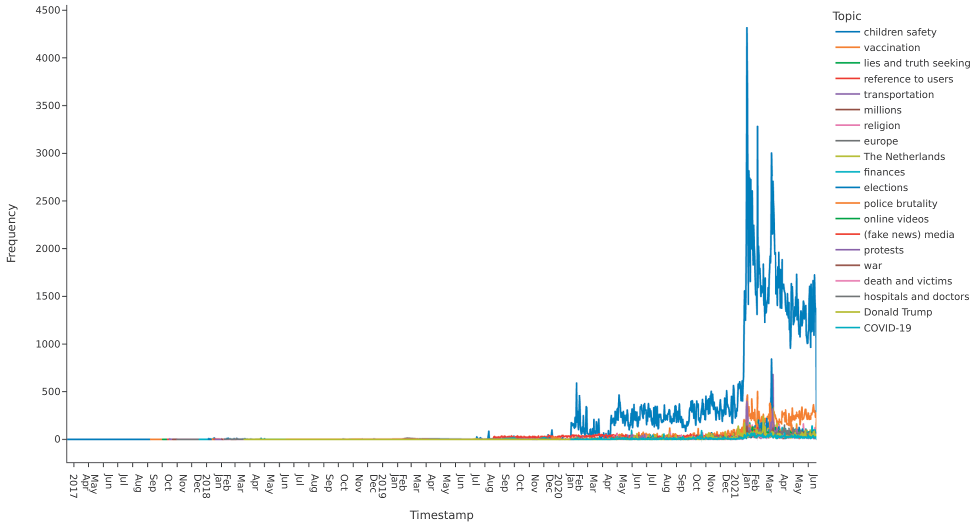


Figure 9: The top 20 topics overtime (18-03-2017 – 18-06-2021).

Evolution of Topics

Telegram chats/channels shared a wide variety of topics during the investigated time period (see Figure 9). The most prominent topic was children safety, which was present throughout the entire timeline and skyrocketed in early 2021. Although the climax of this topic may seem unusual at a glance, we believe that it could suggest two things. The first, more general explanation is related to an increase in concern with respect to children's safety during the pandemic. The second, more worrying explanation is that QAnon's central message "save the children" (Bracewell, 2021) may have permeated the Telegrampshere amid massive social unrest induced by the hard lockdown[29]. This is concerning as the topic of children safety was high on the agenda during

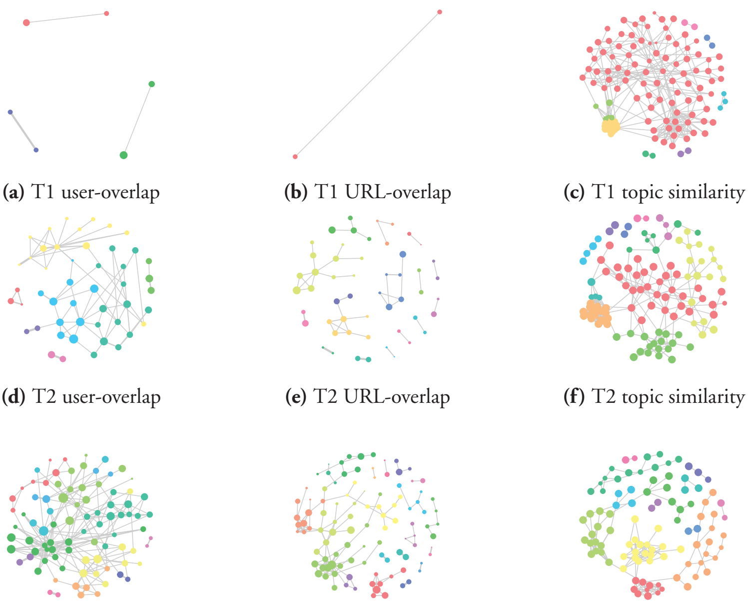
[29]https://www.ad.nl/tech/rellen-via-telegram-is-laagdrempelig-hip-en-effectief-je-kunt-veel-meer-mensen-mobiliseren~ab0c7c94

the pandemic, which may have represented a gateway to a conspiracy-infused, alternate reality to concerned parents where COVID-19 is a hoax and the real danger to children's safety is the deep-state (Bracewell, 2021).

Other prevalent topics shared by the chats/channels were related to contentious issues such as vaccination, lies and truth seeking, religion, elections, police brutality, (fake news) media, protests, war, Donald Trump, and COVID-19. These topics illustrate that the Dutch Telegramsphere was dominated by anti-establishment, anti-media, and anti-COVID narratives during the investigated timeline, and especially amid the pandemic when most of these themes emerged or escalated.

Evolution of networks: T_1

The following section reveals results with regard to temporal developments of the user-overlap network and content-overlap networks to answer RQ2



(a) T1 user-overlap **(b)** T1 URL-overlap **(c)** T1 topic similarity

(d) T2 user-overlap **(e)** T2 URL-overlap **(f)** T2 topic similarity

(g) T3 user-overlap **(h)** T3 URL-overlap **(i)** T3 topic similarity

Figure 10: User-overlap network, URL-overlap network and topic-similarity network over time after the application of disparity filter and removal of isolates.

Although T_1 covered almost 3 years worth of data, very few chats/channels were active during this time period within the user-overlap and URL-overlap networks. Conversely, the topic-similarity network had 122 nodes (46 isolates) at T_1, which is much higher than for the direct-overlap networks. Network density at this time period was low for all three networks despite the fact that the topic-similarity network had many more nodes and edges at T_1. Transitivity and assortativity metrics were not computed for the user-overlap and the URL-overlap networks due to the absense of nodes with at least two degrees. Contrarily, transitivity was very high for the topic-similarity network suggesting a high chance of topic spillover across connected chats/channels.

Table 1: Network metrics over time.

Network	Density	Transitivity	Assortativity	Centralization
Discussion network graphs				
T1 (2017-03-18 - 2020-03-10)	0.013	-	-	0.000
T2 (2020-03-11 - 2021-01-19)	0.016	0.283	-0.211	0.197
T3 (2021-01-20 - 2021-06-18)	0.015	0.304	0.098	0.180
Content overlap network graphs (URL-overlap)				
T1 (2017-03-18 - 2020-03-10)	0.005	-	-	-
T2 (2020-03-11 - 2021-01-19)	0.012	0.422	0.269	0.088
T3 (2021-01-20 - 2021-06-18)	0.013	0.470	0.224	0.132
Content overlap network graphs (Topic similarity)				
T1 (2017-03-18 - 2020-03-10)	0.033	0.712	0.528	0.121
T2 (2020-03-11 - 2021-01-19)	0.020	0.499	0.568	0.110
T3 (2021-01-20 - 2021-06-18)	0.013	0.501	0.457	0.086

Note: Properties calculated after backbone extraction and removal of isolates. Centralization scores are slightly higher when excluding isolates.

Similarly, centralization of the two direct overlap-based networks was either very close to 0 or not computed due to the low amount of nodes and edges at T_1. The centralization of the topic-similarity network was also very low. Thus, we can conclude that at T_1, we found no indication of the presence of influential nodes in either of the three networks. At T_1 community detection revealed low modularity scores for all three networks (see Table 2 suggesting that the studied networks comprised of weak and centralized communities at T_1 (see Figure 10 depicts the networks at T_1 based on the community detection. All in all, it appears that chat/channel presence related to the right wing party FvD, activism, and alternative news seemed to be strongest at T_1 with regard to user overlap and content-overlap. The topic-similarity network illustrated that at T_1, the majority of the chats/channels discussed a wide range of similar topics. In fact 121 out of the identified 125 topics were already present at this time. The most prevalent topics were related to the safety of children, The Netherlands, vaccines, coronavirus, and wind turbines and climate change.

Table 2: Network modularity over time

Network	Modularity	Clusters	Isolates
Discussion network graphs			
T1 (2017-03-18 - 2020-03-10)	0.121	3	16
T2 (2020-03-11 - 2021-01-19)	0.752	7	51
T3 (2021-01-20 - 2021-06-18)	0.637	12	75
Content overlap network graphs (URL-overlap)			
T1 (2017-03-18 - 2020-03-10)	0.000	1	18
T2 (2020-03-11 - 2021-01-19)	0.846	16	35
T3 (2021-01-20 - 2021-06-18)	0.760	20	44
Content overlap network graphs (Topic similarity)			
T1 (2017-03-18 - 2020-03-10)	0.160	8	46
T2 (2020-03-11 - 2021-01-19)	0.530	10	56
T3 (2021-01-20 - 2021-06-18)	0.730	13	69

Note: Properties calculated after backbone extraction ($\alpha = 0.01$).
For topic similarity: $\alpha = 0.1$.

Evolution of networks: T_2

Results revealed that the number of nodes in both direct-overlap networks increased substantially, with an eight-fold increase in the user-overlap network and a 25-fold increase in the URL-overlap network at T_2. Both networks became denser. Transitivity scores indicated a 28.3% chance that two nodes were connected in the user-overlap network if they had one node in common. There was a 42.2% likelihood for two nodes to be connected in the URL-overlap network if they had a common connection, suggesting a high chance of content spillover.

The degree assortativity of the user-overlap network was low but negative, illustrating that nodes with higher degrees tended to connect to nodes with lower degrees. This was corroborated by the substantially elevated normalized centralization score of the network. As opposed to the user-overlap network, the degree assortativity of the URL-overlap network was low but positive, while the normalized centralization score of the network slightly decreased.

The topic-similarity network displayed a slightly different trend. Between T_1 and T_2, the network had less nodes and edges, became less dense, and its transitivity remained rather high and stable suggesting a high chance for content spillover across connected chats/channels (see Table 1). The network's assortativity increased slightly, while its centralization decreased.

Modularity scores of all three graphs skyrocketed at T_2 (see Table 2). Such high modularity scores indicate strong and distinct community structures of divided clusters. The most distinctive communities at T_2 are illustrated by Figure 10. For instance, conspiracy, farmers' protest, and anti-COVID-19 measure activism chats/channels formed one of the communities of the user-overlap network. Similar clusters arose within the URL-overlap network and topic-similarity network.

Evolution of networks: T_3

Results revealed a further increase of the number of nodes within the direct overlap networks at T_3 reaching 88 nodes (76 isolates) within the user-overlap network, and 104 nodes (44 isolates) in URL-overlap network. In contrast, the number of nodes decreased within the topic-similarity network.

Density and transitivity scores slightly increased for the user-overlap and URL-overlap networks, while density decreased, and transitivity stayed roughly the the same within the topic-similarity network. The degree assortativity of the user-overlap network increased and became positive, while the degree assortativity of both content-overlap decreased slightly. The normalized centralization score of the user-overlap and topic-similarity networks slightly decreased, whereas the content-overlap network became slightly more centralized (see Table 1). Modularity scores decreased for the user-overlap and URL-overlap network, and increased for the topic-similarity network. The number of communities increased for all three networks at T_3 (see Table 2).

The user-overlap network indicated that at T_3 users who posted messages in groups related to FvD were also actively participating in conversations in groups dedicated to the organization of violent riots amid stricter lockdown measures in early 2021[30]. FvD-themed chats/channels clustered together with freedom activist, anti-establishment chats/channels, and a radical right, doxxing organization that stood behind intimidating left-wing politicians and academics[31] in the URL-overlap network, suggesting that these groups shared a large portion of the same content. The topic-similarity network showed that the official FvD youth organization clustered together with (QAnon) conspiracy, (con)spirituality and anti-covid chats/channels. Other FvD-related chats/channels clustered together with one another and anti-establishment chats/channels.

These findings corroborate what others found with respect to FvD's central role in conspiracy discussions within the Dutch Telegramsphere (Peeters & Willaert, 2022), and raise new questions with respect to the role and responsibility of FvD in fueling riots and inciting violence through the propagation of anti-establishment, anti-lockdown, and conspiratorial narratives.

[30] https://www.parool.nl/gs-bbd03bbee

[31] https://www.nu.nl/binnenland/6124046/dit-weten-we-nu-over-het-radicaal-rechtse-platform-vizier-op-links.html

Conclusion and Discussion

The current study investigated the Dutch Telegramsphere as an information sharing ecosystem of current affairs by exploring the communities that shaped this low-moderated but easily accessible medium across time. During data collection, we found that right-leaning groups were over-represented on the Dutch Telegramsphere when searching for chats/channels via keywords related to current affairs. This suggests that Telegram's affordances may align better with the agendas of (far-) right parties and groups in The Netherlands (Peeters & Willaert, 2022).

One political party that has made a greater use of the Telegramsphere than any other political party in The Netherlands was the far-right party FvD. At least 9 public Telegram chats/channels were explicitly FvD-themed, which included 3 official channels.

Their quest to "free the oppressed people from the elite's lies" and "unnecessary corona measures" resonates well with Telegram's content liberation policies that empower citizens who feel censored and "oppressed" by the mainstream media. Recent studies have found support for the emerge of such "digital pandemic populism" (Vieten, 2020) within the Dutch Telegramsphere that stimulated the fusion of the far-right with conspiracy groups (Peeters & Willaert, 2022) and mobilized them from the screens to the streets amid the COVID-19 lock-downs (Bakker et al., 2020; Vieten, 2020).

Having a predominantly right-leaning collection of chats/channels in our dataset, our findings should be comparable to what others observed regarding the structure of (far)-right networks on Telegram. In line with Urman and Katz (2020), all studied networks had strong and distinct community structures that resembled far-right networks on Twitter (Froio & Ganesh, 2019) and Facebook (Klein & Muis, 2019). However, unlike Urman and Katz (2020), the analyses presented here did not show a clear division along ideological lines concerning how chats/channels clustered together. Although we observed some communities that were ideologically more homogeneous, the most prominent communities in all networks included chats/channels related to a variety of themes and movements; including conspiracy thinking, far-right party politics, farmers' protests, freedom-activism, anti-establishment, and anti-lockdown groups.

One tentative explanation to the mixture of groups and topics within the most dominant communities was provided by our results regarding the temporal evolution of networks. Before the outbreak of the COVID-19 pandemic, active chats/channels formed an extremely sparse networks of a handful of weakly connected clusters, which indicated very little tendency for chats/channels to cluster around distinctive shared perspectives. However, after COVID-19 was declared a pandemic and especially since the Dutch government imposed a curfew at the beginning of 2021, chat/channel activity peaked and so did the number of identified communities within the studied networks. Although the connections between communities decreased indicating more division across chats/channels that belonged to different communities (i.e., less global spillover), high transitivity scores suggested more "local spillover" within the identified communities with respect to user-overlap, URL-overlap, and topic-similarity.

Another interesting phenomenon we observed was the sparsification of the topic similarity network and the simultaneous densification of the direct overlap networks illustrating that although the active users and the links they shared overlapped across communities, the main narratives that emerged within the identified communities became more distinctive – forming specific topic communities over the course of the pandemic. COVID-19 fostered the creation of new COVID-19 specific chats/channels and gradually drew them closer together into communities via user overlap and URL overlap across chats/channels. At the same time, the pandemic provided fertile ground for the cultivation of strong topic communities coalescing around shared perspectives in the Dutch Telegrampshere.

In our view, this phenomenon can be explained by *collective sensemaking* (Weick, 1995) – the process of gathering information, coming together and sharing theories about a threatening societal event to decipher how to best respond to the situation[32]. The uncertainty around the pandemic may have motivated Telegram users to look for information outside of their go-to sources, which would explain why we observed that from the time COVID-19 was declared a pandemic seemingly unrelated chats/channels clustered together to a great extent. This corroborates recent evidence suggesting that anti-establishment sentiments amid the COVID-19 pandemic united existing movements and communities such as farmers[33], conspiracy thinkers[34] and far-right groups (Peeters & Willaert, 2022).

Over time, the most activity regarding content sharing was produced by chats/channels that by definition propagated conspiracy theories and extremist views in the public Telegramsphere. The gradual dominance of extremist narratives was illustrated by the largely anti-establishment, anti-covid, and conspiratorial narratives we identified with topic modeling over time. We worry that users who self-selected into following initially more moderate chats/channels that resonated with their views, may have gradually adopted more radical perspectives as more extremist narratives seeped into their discussions; causing more societal division and political upheavals.

[32] https://onezero.medium.com/reflecting-on-the-covid-19-infodemic-as-a-crisis-informatics-researcher-ce0656fa4d0a

[33] The Netherlands has a long tradition of farmer movements organizing large-scale demonstrations. The movement grew so much that in 2019 a party called Farmer-Citizen Movement (BBB) received one seat during the 2021 Dutch Parliamentary elections.

[34] https://www.groene.nl/artikel/kijk-op-facebook-niet-naar-de-nos

Overall, our findings suggest that consuming socially and politically relevant information within the Telegramsphere exposes users to content spillover from extremist chats/channels especially in the wake of a crisis. The fact that more moderate and extremist chats/channels were *linked in the dark* raises concerns that the Dutch Telegramsphere has morphed into a "self-perceived corrective(s)" device (Holt, 2018, p. 49) against the "biased" views of established institutions. Our findings provide preliminary evidence for less visible and more complex processes of content spillover across chats/channels within the Telegramsphere.

Limitations and future research

As we primarily focused on collecting data on news, politics, activism, public health, and (con)spirituality, when scraping Telegram, our analysis did not include chats/channels concerning other current-affairs-related topics such as sports, arts, and culture. Future research should incorporate the latter types of chats/channels in order to expand the scope of studying information flows of public affairs on Telegram. This would allow us to gain further insights on how far a crisis can pull chats/channels dedicated to softer topics closer to politics and activism.

A large share of the queries used to identify chats/channels were more prominent throughout 2020 and 2021, which may offer an alternative explanation to the low amount of chats/channels in our dataset that were active before 2020. However, it is more likely that Telegram usage to discuss current affairs, and Telegram usage in general was less prevalent before 2020 in The Netherlands. Statistics show that global Telegram usage was still in its infancy in 2017 and only boomed around 2019[35].

Another data collection method we considered was exponential discriminative snowball sampling (Urman & Katz, 2020). However, this approach would have resulted in selecting on the dependent variable, since snowball sampling would not have allowed us to study intersections between chats/channels without prior assumptions of connectivity. Despite the fact that the Telegram search feature is rather nontransparent, to the best of our knowledge at present no better strategy exists to identify chats/channels via keywords and without prior expectations of connectivity.

Finally, future work could extend these findings by studying information flows dynamically to quantify the influence between chats/channels as well as the communities within networks in continuous time. This would allow us to gain a more granular understanding of the different drivers of information flows within the Telegrampshere zooming in on complex dynamics of content spillover.

[35] https://www.businessofapps.com/data/telegram-statistics/