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Ambient amplification: Memecry across platforms - Original research article

'Dark metrics' and the mainstreaming of political extremism on Dutch-speaking Telegram: A comparative reading of platform affordances

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Abstract

Telegram is a social media and messaging platform known for its hands-off approach to content moderation. This makes it both a popular 'mainstream' platform and an attractive medium for discourse less welcome on other platforms, such as those of politically extreme actors. Additionally, owing to its anonymity and prominence in Eastern Europe, it has been linked to campaigns of Foreign Information Manipulation and Interference (FIMI), particularly by Russian state actors. The objective of the present paper is to investigate how Telegram, through both user-curated and algorithmic recommendations, facilitates connections between channels pertaining to mainstream electoral politics and those propagating fringe political discourses. To this end, we analyse the Telegram environment surrounding the channels of two far-right political parties from the Netherlands and Belgium, respectively: Forum voor Democratie ('FVDNL') and Vlaams Belang ('vlbelang'). We specifically propose a comparative, 'centrifugal' reading of these channels, in which we trace outgoing connections to map the broader issue space to which they connect. On a methodological level, we argue that an analysis of the dataset based on outgoing links represented by forwarded messages – a popular method in Telegram research – is insufficient for a comprehensive understanding of this issue space and propose an approach centred around Telegram's new 'similar channels' feature. This under-researched algorithmic mode of amplification is to some extent based on shared audiences between channels, but the actual inner workings of this recommender engine remain largely opaque. Tracing these connections, we observe that both political seed channels exist in a context in which far-right, identitarian and conspiratorial discourse predominates. Moreover, channels concerned with geopolitical current events that propagate a pro-Russian narrative are present. We thereby conclude that Telegram's 'similar channels' feature affords new methodological opportunities that can enrich Telegram case studies by providing access to the platform's 'ambient' modes of amplification.

Keywords

Telegram, FIMI, far right, visual network analysis, semantic analysis, affordances, text mining

Introduction

Recent intelligence briefs from Belgium and the Netherlands foreground the role of the messaging platform Telegram in facilitating the radicalisation of local extremist actors (Koninkrijksrelaties Ministerie van Binnenlandse Zaken, 2024; VSSE, 2025). They describe Telegram as a digital 'rabbit hole' (VSSE, 2025: 25), quickly guiding users from seemingly innocuous channels to increasingly extreme content. Building on these assessments, this paper investigates Telegram's function as a gateway to fringe content, focusing on the platform affordances that enable these pathways and how they can be analysed. Our study examines the 'ambient', insidious amplification of potentially harmful content afforded by Telegram's channel discovery features.

Specifically, we compare the channels made discoverable through Telegram's established affordance of user-curated message-forwarding, with those rendered visible through the

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platform's newer, algorithmically curated 'similar channels' recommendations. Introduced in November 2023, this feature presents visitors with a selection of other channels that might fit their interests and to which they might subsequently wish to subscribe (see Figure 1). Unlike the manually curated channel discoverability feature of forwarded messages, the 'similar channels' lists are generated entirely by Telegram and thus fall outside of the users' control.

According to an official Telegram blog post, these lists are based on 'similarities in [the channels'] subscriber bases' (Telegram, 2023), although no further details on channel selection criteria or rankings are offered. Because these recommendations and their criteria are not made explicit in Telegram's documentation and communication to users, we conceptualise them as 'dark metrics'.

The 'dark' metaphor here refers to the opaque nature of Telegram's similar channels feature, which remains a 'black box' in contrast with the explicit, highly visible nature of Telegram's user-curated message-forwarding. Loosely inspired by Thorsten Quandt's concept of 'dark participation', the term further signals our interest in the 'evil flip side' of a platform already known for its antagonistic content and communities (Quandt, 2018: 37). As will follow, we specifically hypothesise that algorithmic amplification on the platform intensifies the propagation of politically extreme content.

We investigate this through an empirical case study of Dutch-speaking political channels from Belgium and the Netherlands, notably those of the parties Forum voor Democratie (t.me/FVDNL) and Vlaams Belang (t.me/vlbelang). By means of comparative visual network analyses and 'distant readings', we demonstrate how Telegram's discovery features connect electoral politics and official political communication with far-right discourse, conspiracy theories and instances of Kremlin-aligned foreign information manipulation and interference (FIMI).

At the empirical level, our study contributes to a deeper understanding of Telegram's affordances and specifically how these are evolving to remove much of the friction that once limited the discoverability of politically extreme content. Methodologically, we thereby explore how Telegram's 'similar channels' feature can be repurposed to 'snowball' Telegram datasets within a digital methods approach, providing access to the platform's 'ambient' modes of amplification.

Telegram as a site for research

Founded in 2013, Telegram started out as a relatively simple mobile chat app, similar to, for example, WhatsApp. Its founders, brothers Pavel and Nikolai Durov, had previously founded the Russian social media platform VK (initially known as VKontakte). After leaving that platform, citing increasing government interference, the brothers founded Telegram, which was initially set up as a non-profit organisation. Telegram's legal situation has been somewhat vague since its inception: Legally the company behind the platform is incorporated in two jurisdictions, the British Virgin Islands and Dubai. Although the latter seems to be the main base of operations as of 2025, it has not always been clear whether, and to what extent, development and administration of the platform is based in these locations. Berlin and Saint Petersburg have also at various times been cited as places of business, while CEO Pavel Durov also obtained French citizenship in 2021. On its website, Telegram claims that its data is stored 'across different jurisdictions' and 'in multiple data centres around the globe' (Telegram, 2025b).

This ambiguous legal situation and the lack of clarity about what jurisdiction Telegram is in the end located in reflects its positioning of itself as what one might call a 'laissez-faire'–type platform – one where content moderation is minimal, messaging is secure and private and users are in principle anonymous. This is additionally reflected in how the company describes its platform on its website: when launched, it claimed that 'At this moment, the biggest security threat to your Telegram messages is your mother reading over your shoulder. We took care of the rest' (Telegram, 2013). In any case, the image of Telegram as a secure, anonymous, open alternative to other messaging apps persists.

While Telegram remains popular with many people for everyday chat, the platform's image and affordances have also attracted actors and activities that are less welcome on many other social media platforms. Telegram has been highlighted as a platform for child sexual abuse material (CSAM), non-consensual intimate imaging (NCII) and terrorist recruitment with some regularity (Semenzin and Bainotti, 2020; Shehabat et al., 2017; Thiel et al., 2023). Additionally, its lack of 'community guidelines' or content policies has made it an attractive space for politically or ideologically extreme actors who have been banned from other platforms, such as alt-right activists, conspiracy theorists and neo-nazis (Rogers, 2020).

It additionally remains particularly popular in Eastern Europe and has served as a semi-official communications channel for both sides of the Russia–Ukraine conflict. In this context, Telegram has also been identified as a site for Russian misinformation campaigns (DFRLab, 2024). As such, Telegram has become strongly connected to the problem set of Foreign Information Manipulation and Interference (FIMI). The European External Action Service (EEAS) – the EU's diplomatic service in charge of international relations – defines the latter as:

> a pattern of behaviour that threatens or has the potential to negatively impact values, procedures and political processes. Such activity is manipulative in character, conducted in an intentional and coordinated manner. Actors of such activity can be state or non-state actors, including their proxies inside and outside of their own territory (EEAS Strategic Communications, 2024).



Figure 1. Screenshot of 'similar channels' list recommended for the official Telegram channel of Forum voor Democratie (FVDNL). Telegram has offered this feature since November 2023 for larger channels. The lists of recommendations contain up to 100 related channels. Screenshot taken in the Telegram app, desktop version.

Zooming in on the Kremlin's activities in the wake of the full-scale invasion of Ukraine (February 2022), previous research and investigations have demonstrated that these malicious, coordinated activities on Telegram can take on many forms. This includes the 'weaponisation' of digital diplomacy (Willaert and Tuters, 2025), the propagation of anti-Western messages by state-affiliated media since banned in the EU and the disruptive behaviour of pro-Russian hacker collectives organising on the platform (Kiforchuk, 2023; Kireev et al., 2024). With regard to the latter, Telegram has been shown to facilitate the Kremlin's 'hybrid warfare' efforts, for instance, through groups in which users are incentivised to perform acts of sabotage in exchange for payment (Van Bakel and Debackere, 2025).

Most academic work on Telegram has focused on its chat channels and groups, arguably the most 'social media-like' parts of the app. Groups allow anyone to send messages, channels are set up for 'broadcasting', where only the channel owner(s) can send messages, but anyone can join and read these. Both groups and channels can be joined by thousands

of people. Channels are often linked to a group in which people can discuss messages posted in the channel or interact with other channel subscribers. It is the connections between channels – for example, through messages forwarded from one channel to another – that have been of particular interest to researchers. These constellations of connected groups and channels have been described as 'Telegramspheres' (Simon et al., 2023) and can also be understood as interconnected 'issue spaces' (Rogers, 2018) in which communities form, interact with each other and afford the spread of various thematically connected types of content.

This aspect of Telegram has been the subject of research precisely because it allows one to study those issue spaces in which politically extreme or otherwise controversial actors congregate, with low risk of being banned or prosecuted. Telegram in fact also notes this on its website, proudly proclaiming that it has 'disclosed 0 bytes of user messages to third parties, including governments' and that 'Telegram won't be part of […] politically motivated censorship' (Telegram, 2025b).

This however means that it is also fertile ground for what the EU has designated as 'systemic risks', including the 'dissemination of illegal content', 'negative effects on the exercise of fundamental rights' and 'negative effects on civic discourse and electoral processes' (European Commission, 2024). FIMI is one example of a discourse that poses such a risk, which, in the absence of clear and actively enforced content policies, can easily proliferate on the platform.

At the moment of writing, there are indications that Telegram's attitude towards these issues might slowly be changing. Telegram's CEO Pavel Durov was arrested in 2024 by French authorities over the platform's lack of moderation, and there are signs that it is moderating content more proactively since (Sato, 2024). Additionally, Telegram has been very close to meeting the threshold of what the European Union considers a 'very large online platform' or VLOP, for the purposes of the EU's Digital Services Act (European Commission, 2024). Telegram claimed 40 million active EU users as of late 2023 – the threshold is set at 45 million monthly users, or roughly 10% of the EU's population, as of 2025.

VLOPs are subject to increased transparency and moderation requirements, in particular in connection with the aforementioned systemic risks, which would be counter to some of Telegram's current (lack of) policies. Whatever the future may hold, the platform is currently a relevant site for 'controversy mapping' (Venturini and Munk, 2021) or studying a controversy or issue through actors via medium affordances, with a focus on systemic risks in general and the propagation of FIMI in particular. While Telegram is not a VLOP at present, it can be positioned as a potentially central platform for such systemic risks given its history of popularity among extreme groups and use for state-sponsored misinformation campaigns. This is the issue we seek to map in this paper, zooming in on how this may be affected by FIMI and traces thereof.

Revisiting the Dutch-speaking 'Telegramsphere'

Our study focuses on the Dutch-speaking part of Telegram, revisiting a 'Telegramsphere' that prior work has found to harbour large numbers of public channels that espouse conspiratorial, anti-democratic, racist and otherwise extreme content (Simon et al., 2023; Willaert et al., 2022). During the COVID-19 pandemic, these channels formed 'disinformation networks' based on forwarded messages and embraced pro-Kremlin narratives after Russia's full-scale invasion of Ukraine in February 2022 (Willaert and Sessa, 2022).

Previous investigations have furthermore shown that the Telegram channels of two political parties from the Netherlands and Belgium, notably Forum voor Democratie (FvD) (t.me/FVDNL) and Vlaams Belang (VB) (t.me/vlbelang), have an active presence in these networks. Both parties hold seats in their respective national parliament and can be broadly characterised as far right and nationalist (de Lange, 2022; Sijstermans and Van Hauwaert, 2022). Vlaams Belang was originally founded as 'Vlaams Blok' in 1979 but was renamed to 'Vlaams Belang' after the former party was banned in 2004. VB has been characterised as a populist radical right (PPR) party (De Cleen, 2016; Mudde, 2007), with a programme promoting Flemish independence and a strict stance on multiculturalism and immigration (Vlaams Belang, 2022). Within the European Parliament, it is part of the Eurosceptic Patriots.eu opposition party (patriots.eu, 2025). VB actively uses social media as well as its own news app as an alternative to the alleged 'censorship' imposed by the 'mainstream media' (Vlaams Belang, 2025). In the wake of the deplatforming of Donald Trump from Twitter in 2021, Vlaams Belang promoted its Telegram channel as a 'censorship-free alternative' to other social media (Vlaams Belang [@vlbelang], 2021).

Founded in 2016 by Thierry Baudet, the Dutch populist radical right party Forum voor Democratie promotes an agenda similar to that of Vlaams Belang, pushing the notion of 'remigration' or the forced return of immigrants (Forum voor Democratie, 2025b; Otjes, 2021). On social media, the party has been shown to amplify conspiracy theories and other antagonistic discourses (van Raalte et al., 2021). FvD thereby actively promotes its public Telegram channel on its official website (Forum voor Democratie 2025a).

Beyond a shared political agenda, both parties are unified in their willingness to engage with fringe communities and discourses, as well as pro-Russian actors (NOS Nieuws, 2023; Struys, 2022). As Telegram readily facilitates such connections, we argue that the Telegram channels of both parties form a suitable seed from which to 'snowball' aspects of the Dutch-speaking Telegramsphere into view. We thus approach both channels as gateways that connect mainstream electoral politics with fringe channels and discourses, through both explicitly human-curated and 'dark' channel discovery features.

Research questions

Our study explores how Telegram's discovery features enable the public channels of the Dutch political party Forum voor Democratie (t.me/FVDNL) and the Flemish party Vlaams Belang (t.me/vlbelang) to function as portals connecting the political mainstream with fringe actors and discourses, including those aligned with the Kremlin. We are specifically interested in the role of Telegram's algorithmically curated lists of 'similar channels', which, through a relatively opaque recommender engine, might amplify content that the channel's owner is not explicitly engaging with. We hypothesise that these recommendations, even if they are only partly based on shared audiences, might provide access to a latent 'atmosphere' or 'ambience' surrounding a given channel, thus amplifying as well as revealing more structural antagonisms and harmful discourses on the platform (Siapera, 2019). In order to foreground this dynamic, we compare the algorithmically curated lists of channels with the sets of channels that are linked to in the form of forwarded messages by the channel owners.

Concretely, we examine these dynamics over the period from 1 July 2022 to 1 July 2024, a time marked by global events such as the end of the COVID-19 pandemic, the ongoing war in Ukraine, and elections in the USA and Europe, including federal elections in Belgium and the Netherlands. Our research questions are as follows:

1. Which channels are linked to these political Telegram channels through Telegram's channel discoverability features, and how do these channels relate to previously identified 'issue spaces' on Telegram, such as foreign information manipulation and interference (FIMI), conspiracy theories and far-right extremism?
2. What is the specific role of different channel discoverability features in this mainstreaming process? Specifically, what differences can be observed between (a) Telegram's user-curated message-forwarding feature and (b) Telegram's 'dark' similar channels feature, introduced in late 2023, which adds an algorithmically curated list of recommended channels to the profile of a given channel, based in part on what other channels members are subscribed to?

By focusing on Telegram's first algorithmic content recommendation feature, our study surfaces the platform's 'dark metrics': sets of recommendations for 'similar channels' where the underlying selection criteria and recommender engine remain largely a 'black box' to researchers. We employ computational methods to map out recommended channels and provide an overview of their semantic and network-topological relationships. Through these methods, we aim to gain access to the cultural and ideological aspects of the recommendations. Our empirical observations then inform a broader discussion of 'ambient', platformed mainstreaming on Telegram and the implications of these 'dark metrics' for digital methods research on the platform.

Through Telegram's similar channels feature, a visitor of a Telegram channel is presented with a selection of other channels that might fit their interests and to which they might subsequently wish to subscribe. Contrary to manually curated channel discoverability features such as message-forwarding, the lists of 'similar channels' are generated entirely by Telegram and thus fall outside of the control of the channel owner. According to an official Telegram blog post, the list is based on 'similarities in [the channels'] subscriber bases' (Telegram, 2023). In other words, the more people who subscribed to channel A are also subscribed to channel B, the more they are considered 'similar'. This then offers a view of channels as connected by their *audience*, as opposed to, for example, one found through forwarded messages, which is rather based on the *content* of a channel. Telegram shows 10 similar channels by default, or 100 if one has a premium Telegram subscription.

There is no further information on what makes a channel similar or what the order of the list is based on. It is not clear, for example, how many subscribers two channels share. Moreover, not all channels provide a list of similar channels. While Telegram does not offer any documentation regarding the inclusion criteria, similar channels only seem to be available for larger channels. Reports on user forums (such as Reddit's 'r/telegram' subreddit) indicate that owners of larger channels sometimes also see the feature disabled for their channel for unclear reasons. Any analysis based on this feature thus comes with the caveat that there are channels that cannot be discovered via this method, in particular smaller channels.

This underlines how Telegram is a platform where publics are by necessity 'refracted' (Abidin, 2021), and from the perspective of both a channel subscriber and owner, the platform is essentially decentralised, as there are no reliable ways to either find channels or to make your channel visible to others. Instead, like researchers, users turn to an unstable collection of features that, on the one hand, can be used to discover other channels but that are, at the same time, opaque and may disappear for unclear reasons. Arguably, this at the same time highlights the relevance of an investigation into or with these features, given their importance for users as a means of discovering new parts of the platform.

Data and method

Our research questions raise fundamental methodological questions in the field of Telegram research, such as how to identify and classify politically extreme channels.

While Telegram introduced a keyword-based global search function for premium users shortly after the data collection for the present study was conducted (Telegram, 2025a), the often idiosyncratic, vernacular nature of online discourse continues to challenge top-down, query-based approaches, warranting a further exploration of inductive data collection methods. Likewise, this study foregrounds the question of how to identify and describe the role of Telegram's affordances in 'mainstreaming' extreme content.

In order to address these questions, we propose a comparative, 'centrifugal' reading of political channels on Telegram (borrowing a concept from Bru and Willaert, 2016). In this reading, we start from our seed of two Telegram channels associated with (mainstream) electoral politics in Flanders and the Netherlands and evaluate how these channels connect to more peripheral (i.e. fringe or extreme) channels by tracing two types of 'outgoing' connections: links established by ways of messages forwarded from other channels and associations based on Telegram's lists of 'similar channels'.

The main assumption underlying our approach is that if a mainstream political channel (as part of the seed) offers a link to a fringe channel, that link contributes to the 'mainstreaming' of this fringe channel by establishing a pathway through which visitors of a political channel might be guided towards the more extreme content.

Figure 2 presents an overview of the different steps in our data analysis pipeline, which we apply to datasets collected from the same seed, but through different affordances. In the following sections, we offer a more detailed discussion of the two methods we use to empirically foreground the specific contributions of the two linkage types to the process of political 'mainstreaming' of extreme channels. Following the metaphor of a 'centrifugal reading', we aim to map the network-topological and semantic relations between mainstream political channels and the fringe channels to which they might connect. Our goal here is not to identify specific channels or actors that would spread FIMI or other problematic content, but rather to map the broader issue spaces in which the two seed channels operate, and the types of discourse that may be encountered in them. Overall, our analysis can be characterised as a 'quali–quanti' analysis (Venturini and Latour, 2010), that is, an analysis that combines quantitative techniques with qualitative interpretation.

It should be highlighted here that we strictly limit our data collection and analysis to public Telegram channels. Following previous work, we also argue that while these Telegram channels are public and can be viewed by anyone from their browser (even when one does not have a Telegram account), it cannot be assumed that these channels therefore openly available for analysis and further dissemination in a different (research) context (Willaert et al., 2022). We therefore minimise the number of channel names mentioned in the paper. As part of our (visual) network analysis, we make an exception here for a limited number of public channels that have at least 5000 subscribers and are linked to organisations rather than individual actors. Likewise, we do explicitly mention and visualise illustrative channels that are inductively surfaced in our 'distant reading' approach as relevant to the interpretation of semantic clusters in the data.

Approaches to data collection on Telegram

We collect two datasets using an established 'snowballing' method for Telegram research (Peeters and Willaert, 2022). In this method, one starts from a small set of seed channels and follows (or 'crawls') outgoing links to bring related channels into view. This process is then repeated for each set of newly identified channels until a sufficiently large dataset has been obtained.

In the literature, snowballing is typically achieved by tracing forwarded messages between channels. Forwarding was introduced along with Telegram's channels in 2015 (Telegram, 2015), and allows channel owners to 'forward' messages from other channels into their own. It can thereby be assumed that if a channel forwards a message from another channel, some meaningful connection exists between the two. Perhaps as a result of both its medium-specificity and its technical accessibility, the method of crawling forwarded messages has arguably become the most popular approach to mapping Telegram and has been used in numerous case studies (see, e.g. Peeters and Willaert, 2022; Simon et al., 2023).

Forwarded messages are visibly marked as such in the message metadata, listing the name of the channel from which the message is forwarded. Messages from a source channel might be forwarded into a target channel in order to signal agreement with a message or to boost the content of another channel. The latter is intensified in channels that operate as content aggregators and forward messages from many separate channels on a large scale (Willaert et al., 2022). Message-forwarding might in such channels be automated by bots (Peeters, 2025), but since it is still up to the user to select which channels to forward from, we consider message-forwarding an example of 'manual' content curation on the platform.

Notwithstanding the rich results that this approach produces, forward-based crawling fundamentally rests on the assumption that forwarded messages are a universal 'connector' between channels. For a channel to be discovered and included in such an analysis, it needs to either have one of its messages forwarded to another channel or to contain messages forwarded from elsewhere. However, one of the two seed channels in our case study, the channel 'vlbelang', did not in fact contain any forwarded messages at the time of data collection. This means there is no 'trail' to

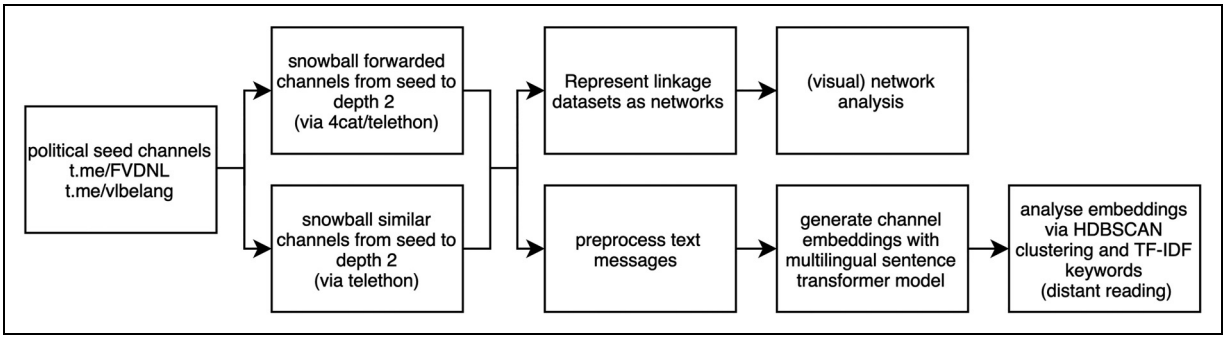


Figure 2. Overview of data processing pipeline. From our political seed channels, we 'snowball' a dataset based on forwarded messages and a dataset based on recommended similar channels. Both datasets are studied through the same methods for (visual) network analysis and an embeddings-based, 'distant reading' procedure.

follow from that channel onwards: no new channels may be discovered from it, and in an analysis of the larger space, there are no connections from 'vlbelang' to other channels. This suggests a (quantitatively) more limited role of message-forwarding for the mainstreaming of potentially extreme content. It also demonstrates the limits of the 'forward mapping' approach and highlights the need for alternative ways of discovering and mapping channels.

While forwards are one indicator of links between channels, Telegram does in fact offer other opportunities for linking. People can, for example, post a hyperlink to a channel or mention a user or channel like on many other social media, by prefixing the user or channel ID with an @ sign. Since 2023, Telegram's 'similar channels' for larger channels that contain up to 100 channels likewise provide a source of connections between channels. These features all have their own logic and can be used for discovery and mapping much like forwarded messages.

However, hyperlinks and @ mentions are essentially hand-typed and may thus become outdated or contain errors. This can be contrasted with Telegram's algorithmically curated lists of 'similar' channels introduced in 2023, which are generated entirely by Telegram, and thus fall outside of the control of the channel owner or message author. In this study, we therefore extend the snowball crawl to relations established by Telegram's recommendations for 'similar channels' as another feature through which related channels can iteratively be discovered and analysed.

Both types of channel links are examples of repurposing a 'method of the medium' (Peeters and Willaert, 2022; Rogers, 2013), appropriating Telegram's features for an analysis of the platform. It is furthermore facilitated by Telegram's API, which allows one to automate this channel discovery and mapping process. In the absence of a centralised search functionality or channel index, this is then a useful and platform-native method for identifying and analysing larger communities, issue spaces or otherwise connected constellations of channels.

In what follows, we offer a comparison of the two approaches: what one might call the 'traditional' approach, based on forwarded messages, and an alternative approach, based on similar channels. Both are then analysed via a visual network analysis and through a distant reading based on the semantic analysis of channels' messages.

Our goal is not to present one view on Telegram as superior to the other, but rather to observe the context of our two seed channels from the perspective of two separate platform affordances. This combined approach better fits what Crystal Abidin has called 'refracted publics', in which – as on Telegram – content and communities cannot be 'accessed through search' but are 'unknowable until chanced upon' (Abidin, 2021). A comprehensive mapping of such a public then logically needs to incorporate the various ways in which its constituents can be 'chanced upon' to provide a more comprehensive understanding than might be gained by choosing only one approach.

Data collection and visual network analysis

Starting from our two seed channels ('FVDNL' and 'vlbelang'), we thus collect data for all channels that can be identified after two 'snowballing' iterations. This means we first collect data from the channels that are directly linked to the seeds and then repeat the process for the new channels identified in this step. Snowballing and data collection are achieved by means of the 4CAT Capture and Analysis Toolkit (Peeters and Hagen, 2022), as well as a set of Python scripts for calling the Telegram API (see 'Data and software availability').

For the period between 1 July 2022 and 1 July 2024, this yields a dataset of 665 unique channels based on forwarded messages and a dataset of 4745 unique channels based on 'similar channels'. For both datasets, we collect the message metadata (which informs our visual network analysis) and the message texts (which are at the centre of our content analysis). In both cases, we stop our snowballing after two 'hops' from the seed channels. While more iterations would have been possible, this strikes a good balance between quantity and quality (Peeters and Willaert, 2022); in a

next iteration, channels were found to often be wholly unrelated to the seed channels or related discourse.

We first analyse our dataset as a networked collection of (loosely) related channels. It should be noted here that for the forwards-based network, while we collect messages from 665 channels, some of these contain forwarded messages from beyond our dataset; thus, a network view of this dataset contains 14,509 channels, with 13,844 of these only receiving outbound links (i.e. a message from the channel was forwarded in one of the collected channels, but the channel was not collected itself). We nevertheless include these channels as they form part of the discourse in these 665 channels and indicate thematically relevant connections.

We analyse this network, as well as the one based on channel similarity, through a 'visual network analysis', one that recognises that the structural features of such networks – like clusters of channels – are often of ambiguous significance and one that seeks to use this quality 'not as a burden, but as an asset' (Venturini et al., 2021: 3). In a space such as the one studied here, where links between channels are incidental (in the case of forwarded messages) or algorithmically derived (in the case of similar channels), this is a suitable technique because from this perspective, 'visual ambiguity mirrors some of the empirical ambiguity of the phenomena they represent' (Venturini et al., 2021: 9).

The goal is then not so much to pinpoint the exact grouping a specific channel might be considered to be part of, but rather to better observe the broader topological make-up of the space and explore suggested associations between channels. The object of analysis is not primarily the underlying network and its particular metrics and statistical make-up, but rather a rendering of this data that highlights groups of related channels (as clusters of nodes in the network) with an understanding that such groups are ambiguous, may overlap, and are subject to interpretation.

Concerning this interpretative aspect of the visual network analysis, we are aided in our identification of clusters by a calculation of the networks' modularity classes (Blondel et al., 2008) and the nodes' relative positioning (Jacomy et al., 2014) but label clusters primarily based on channel names, which in many cases give a clear indication of the channel's theme and purpose. Here the channels with more connections are considered most decisive in establishing a cluster's identity, and we provide one such representative channel as an exemplar for each cluster. In this step we are informed by earlier work on this and related Telegram spaces (Peeters and Willaert, 2022; Willaert et al., 2022), and in case of ambiguous or otherwise unclear channel names, messages in the channel are read to better understand its content.

Distant reading

We additionally analyse the message contents of the channels in each network using quantitative methods from the field of natural language processing (NLP). Specifically, we turn to vector semantics in order to inductively identify clusters of channels that are semantically similar. This approach constitutes a form of 'distant reading', in which the objective is to identify broader quantitative trends and dynamics that mark each network (dataset), rather than to engage in in-depth, 'close readings' of selected channels or messages (Moretti, 2013; Underwood, 2019). This method is particularly useful for analysing the potentially (very) large collections of Telegram channels such as those that emerge when 'snowballing' data through Telegram's 'similar channels' affordance. If larger channels list recommendations for ca. 100 additional channels, even a limited number of seed channels might in such cases already yield a dataset of thousands of associated channels after only a small number of sampling iterations.

In order to analyse the semantic dimension of these large collections of Telegram channels without conducting in-depth readings or content analyses of messages, we leverage a pretrained sentence transformer (SBERT) model to calculate the textual similarity between channels (Reimers and Gurevych, 2019, 2020). Sentence transformers are a specific type of language model that allows documents in the form of sentences or short paragraphs to be represented as a numerical vector (this is referred to as an 'embedding'). It is thereby assumed that these vectors capture (aspects of) the semantic meaning of the document and that documents with similar meanings will yield embeddings that are close to each other in the vector space. Embeddings for documents with different meanings will be spaced further apart.

The theoretical assumption underlying this numerical, embedding-based approach is that of the 'distributional hypothesis', namely, that words that occur in similar contexts tend to have similar meanings (Lenci and Sahlgren, 2023: 26–88). Likewise, the meaning of the same word form might vary depending on the contexts in which it occurs. This assumption directly underpins models for generating word-level embeddings such as word2vec (Mikolov et al., 2013). Sentence transformer models implement a similar, context-based approach to semantics in order to generate more sophisticated numerical representations of the meanings of entire sentences or paragraphs. Previous research into online antagonistic communities has demonstrated that such context-based approximations of meaning can provide insights into word-based vernacular concepts and memes (Hagen and de Zeeuw, 2023; Peeters et al., 2021). There, these methods offer the advantage that meanings of idiosyncratic concepts and words can be quantitatively inferred, making them useful for spaces marked by intensified linguistic innovation.

The objective of our current study is not to zoom in on individual words but to examine similarity between channels as a whole. Here, one of the methodological challenges presented by the Telegram channels under investigation is

that they cover a wide range of decentralised, transnational movements and communities. As such, they might contain messages in a range of different languages. To ensure that channels that are linguistically different but semantically similar still yield similar embeddings, we make use of a state-of-the-art multilingual sentence transformer model ('paraphrase-multilingual-mpnet-base-v2'), which spans over 50 languages (Hugging Face, 2025; Reimers and Gurevych, 2020). We find that this model covers 99.9% of the messages in the forwarded dataset and 99.4% of the messages in the similar channels dataset.

Because the transformer model we use is aimed at creating embeddings for short texts such as sentences and paragraphs, we cannot construct a channel vector from a concatenated document that contains all messages. Rather, constructing such a channel vector needs to happen in multiple steps. First, we clean each message (string) by removing hyperlinks, mentions and hashtags. Short messages that have less than 30 characters after cleaning are omitted from the analysis.

In this preprocessing phase, we also automatically identify the language of each message using the Python 'langdetect' library (Danilák, 2014). The resulting filtered dataset and linguistic annotations form the basis for any quantitative overviews presented in the Findings section. We refer to the Data and software availability section for further details on the availability of the processed datasets, as well as scripts used to support the 'distant reading'.

In order to create the channel embeddings, we first take a random sample of 20% of the messages of each channel in both datasets (omitting channels that result in a sample of less than 10 messages). Next, we create an embedding for each cleaned message. To this end, we encode the messaging by means of the multilingual transformer model using the Python 'sentence_transformers' library (SBERT.net, 2025). Finally, we calculate the mean of the generated message vectors. This results in a single vector that represents the 'average' meaning of all messages in the channel. As such, our aim is to uncover broader semantic patterns within the data, rather than to examine micro-level variations of meaning.

For both datasets, we then proceed to calculate the cosine distances between the normalised vectors, resulting in a cosine distance matrix that we use as the basis of an inductive clustering approach. We specifically use the Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) algorithm to identify clusters of channel vectors that are in close proximity and thus semantically similar. We then visualise the resulting clusters in a two-dimensional space using a UMAP projection, showing each channel as a point that is colour-coded for its corresponding cluster.

To facilitate the interpretation of these semantic clusters, we represent each of them as a list of defining keywords. These are obtained by identifying the 10 words with the highest term frequency–inverse document frequency (TF-IDF) scores for each cluster. The TF-IDF score increases when a word is frequent in a specific cluster but rare across all other clusters. As an illustration of the 'average' channel in each cluster, we identify its centroid, that is, the central channel that represents the mean position of all channels in that cluster. To further support the analysis of the visualisations, we highlight the vectors for the seed channels ('FVDNL' and 'vlbelang') as a point of reference.

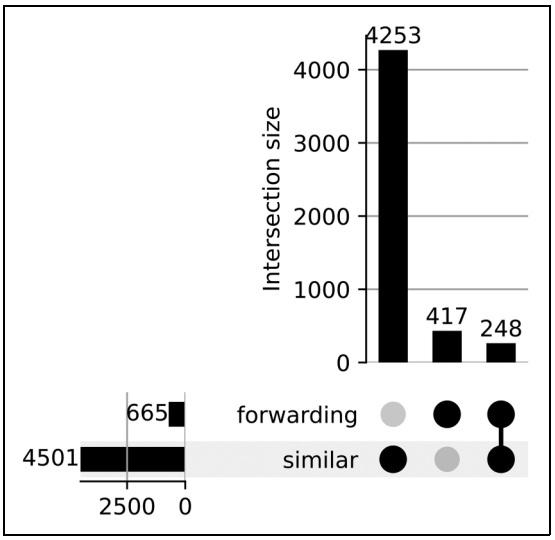


Figure 3. UpSet plot showing set overlaps between datasets snowballed from forwarded messages and through Telegram's 'similar channels' feature.

Findings

Descriptive overview of datasets

A descriptive assessment of the datasets snowballed by ways of message-forwarding and similar channels features reveals that there are significant quantitative differences between the two. The UpSet plot (Lex et al., 2014) in Figure 3 illustrates that snowballing through Telegram's similar channels feature yields a dataset that is over six times as large as the dataset obtained by following forwarded messages (respectively comprising 4501 vs 665 channels after cleaning).

As shown on the vertical bars of the plot, we furthermore find that 248 channels are shared between the two datasets. A total of 417 channels exclusively occur in the dataset snowballed form forwarded messages, whereas 4253 channels are exclusive to the similar channels dataset. A total of 169 channels in the forwarded dataset are not recommended by the similar channels feature. Conversely, 4253 channels recommended by the similar channels feature are not included in the forwarded dataset. In light of our second research question, we thus find that the similar channels feature links that the political seed channels to a large set of

channels that are otherwise not explicitly linked by the channel owners, pointing towards a dynamic of intensified (yet opaque) algorithmic amplification.

Table 1 offers a comparative overview of the linguistic composition of both datasets, zooming in on the 10 most frequent languages in each corpus. It follows that the dataset snowballed from forwarded messages is linguistically more homogeneous, with approximately 97% of the messages either in English (63.3%) or in Russian (33.6%). The dataset of similar channels is more linguistically diverse: While English is still the predominant language (accounting for 61% of messages), we also find messages in, among others, German, French, Spanish, Italian and Dutch.

This diversity can to an extent be attributed to the larger scale of the dataset, which covers a more diverse (geographic) range of channels. More fundamentally, the data here suggest that the user-curated forwarded messages allow for a more targeted engagement with channels in selected languages, specifically with those in Russian.

Table 1. Comparison of linguistic composition of both datasets (in percentages).

Language	Forwards	Similar channels
en	63.3	61.0
ru	33.6	6.9
de	0.7	9.4
fr	0.5	3.4
mk	0.5	0.0
es	0.4	2.5
it	0.3	2.2
nl	0.1	4.4
pt	0.1	3.8
bg	0.1	0.0
he	0.0	1,4
uk	0.0	0.8

Findings based on visual network analysis

In this case study, a forward-based network has one important limitation, in that it does not include the channel 'vlbelang' on account of that channel not containing any forwarded messages; it can thus only offer further insight into half of our case study, the Netherlands-oriented part around the channel 'FVDNL'. This is nevertheless instructive, as it will still help understand the immediate context of that channel. Additionally, it highlights an important difference between the two channels: whereas 'vlbelang' does not explicitly associate with any other channels through re-sharing their content, 'FVDNL' chooses to post messages from other channels, and thus actively includes itself in a wider network of Telegram channels.

A network mapping of the forward-based network around 'FVDNL' reveals a number of readily visible clusters of channels, with these clusters based on the fact that channels in a cluster post relatively more messages forwarded from the other channels in that cluster than from the rest of the network (see Figure 4). 'FVDNL' is not prominently in a cluster itself, being positioned in the periphery of what we label as the 'far-right and conspiracy theories' cluster (see also Table 2). This can be attributed to the fact that it contains forwarded messages from eight distinct channels, a relatively low amount compared to some of the more centrally positioned channels. Its positioning nevertheless fits earlier observations that 'FVDNL' is very much part of the Dutch conspiracy theory discourse as well as being positioned on the far right of the political spectrum.

Notable furthermore is that the other major channel clusters can be characterised as broadly pro-Russian, with one cluster of pro-Russian (but mostly English-language) channels relatively close to the prominent far-right and conspiracy theory cluster and a second cluster of Russian-language pro-Russian channels yet further removed. While there are no direct links between 'FVDNL' and these Russian-language channels, it does demonstrate that the channels it chooses to forward messages from can



Figure 4. Network of 1748 channels with 10 or more links to other channels (of 14,059 total), based on forwarded messages. Nodes are channels. Edges represent a message forwarded from one channel to another. Node size represents the number of connections, that is, the more messages forwarded from a channel, the larger its node is. Nodes positioned using the ForceAtlas2 layout (Jacomy et al., 2014), in LinLog mode, scaling 0.4, gravity 4.0. Colours represent modularity classes (Blondel et al., 2008) (modularity: 0.393). 163 outlying nodes are not visible in this visualisation.

Table 2. Description of observed clusters in Figure 4.

Cluster name	Clolour	Exemplar (subscribers)	Description
Far-right and conspiracy theories	Blue	dotconnectinganons (29,000)	A mixture of conspiracy theories, often with a USA focus, such as QAnon, Pizzagate and anti-vaccination
Pro-Russian geopolitics	Green	DDGeopolitics (155,000)	Predominantly English-language coverage of the Russian invasion of Ukraine, as well as related international politics; pro-Russian, anti-Ukraine narratives dominate
Russian-language political channels	Yellow	OpenUkraine (206,000)	Coverage of the Russian invasion of Ukraine and related topics, such as NATO, in the Russian language; pro-Russian, anti-Ukraine narratives dominate

be seen as a gateway to a larger, strongly pro-Russian constellation of Telegram channels, next to the more immediate association with far-right politics and conspiracy theories.

This network based on forwarded messages can be compared and contrasted with a networked view of the same dataset but based on what channels Telegram reports as being 'similar' to a given channel. As tenuous as this similarity is – being ostensibly based on shared subscribers rather than explicit or intentional association – at the time of data capture, both 'FVDNL' and 'vlbelang' did offer lists of similar channels, thus allowing for a visual network analysis of these channels and their immediate context based on what other channels they share subscribers with.

Furthermore, it allows for an assessment of how the subscriber bases of both channels differ or overlap, based on their respective positions in the network. The closer the two channels are positioned together, the more similar their subscriber bases may roughly be presumed to be. In the visualisation of this network (see Figure 5 and Table 3), the channels are somewhat close to each other but also clearly part of different channel clusters. Whereas 'FVDNL' is positioned at the edge of a cluster we characterise as broadly conspiracy theory-focused, 'vlbelang' is positioned centrally in the adjacent 'far-right and identitarian' cluster. This more or less matches the political positions of the respective parties, with both being on the far-right and (ethno-)nationalist side of the political spectrum, but with Forum voor Democratie furthermore incorporating conspiracy theories about various topics in their positioning more prominently than Vlaams Belang.

Similarly to the forward-based visual network analysis, a cluster of channels focused on discussing geopolitical current events from a pro-Russian perspective is evident. It is comparatively smaller than the one found in the other visual network analysis, and no adjacent Russian-language cluster is visible. This difference is illustrative: A hypothesis here is that while Russian-language channels may be discovered through forwards, it is less likely that a subscriber of a Dutch-language political channel – or even an English-language channel adjacent to it – would join a Russian-language channel. From the perspective of subscriber bases, then, the two seed channels are removed further from Russian-language discourse than from the perspective of their content.

One additional cluster – compared to the forward-based network – is that of Christianity-themed channels. It is somewhat surprising that this cluster is positioned closer to the 'conspiracy theories' cluster than to the 'identitarian' clusters, since identitarian movements often strongly identify with Christianity, as a way of positioning themselves in opposition to, in particular, Islam (Blum, 2024). Its positioning here as more adjacent to conspiracy theory-themed channels may be seen as a trace of what has in recent years been labelled 'conspirituality' – a confluence of conspiracy thinking and an interest in spiritual matters (Ward and Voas, 2011). Especially in the Dutch context, this has been identified as a phenomenon on the rise in the aftermath of the COVID-19 pandemic (Harambam, 2022). This would explain both the presence of such channels in the network as well as its positioning as related to conspiracy thinking rather than identitarian thought.

Overall, one might say that the Telegram presence of the parties Forum voor Democratie and Vlaams Belang can be positioned within the same broader 'Telegramsphere', owing to links formed between their respective immediate contexts through shared subscribers. Both their positioning within the same broader sphere as well as within different (sub-)clusters fits the respective political parties' political preoccupations. The comparatively reduced but still significant presence of a cluster of channels promoting pro-Russian narratives suggests that subscribers of the two seed channels have some interest in such channels, but perhaps less than suggested by the forward-based network. Alternatively, one could argue that since messages from such channels are forwarded in other, more 'local' channels, there is not so much need to join these channels directly, making them less visible in a network based on channel subscriber overlap.

In any case, the differences between the two network-based approaches discussed here demonstrate that the choice of what platform affordance to base such an analysis on matters. Depending on the chosen affordance, different nuances are highlighted, and different aspects of people's usage of the platforms are foregrounded. A forward-based network follows from how channel *owners* use the platform and establish connections. By contrast, a similarity-based

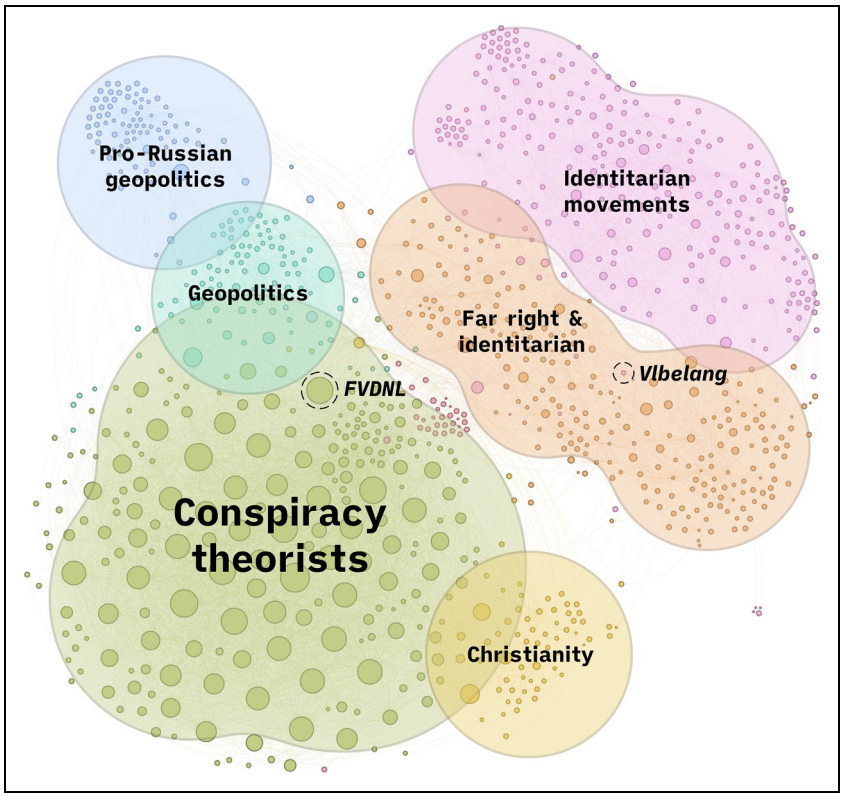


Figure 5. Network of 1004 channels with three or more similar channels (of 4745 total), based on Telegram's 'similar channels' feature. Nodes are channels. If one channel is recommended as 'similar' to another, it creates an edge between their respective nodes. Node size represents the number of connections, that is, the more often a channel is recommended as similar, the larger its node is. Nodes positioned using the ForceAtlas2 layout (Jacomy et al., 2014), in LinLog mode, scaling 0.4, gravity 25.0. Colours represent modularity classes (Blondel et al., 2008) (modularity: 0.635).

Table 3. Description of observed clusters in Figure 5.

Cluster name	Colour	Exemplar (subscribers)	Description
Pro-Russian geopolitics	Blue	DDGeopolitics (155,000)	Commentary on current events, often with a focus on the Russian invasion of Ukraine, pro-Russian narratives dominate
Geopolitics	Mint	disclosetv (380,000)	More generalised geopolitical commentary, often with a conservative/ pro-Trump/right-wing perspective
Conspiracy theorists	Green	klokkenluiders (53,000)	Conspiracy theories and 'alternative news', often in the Dutch language
Far right and identitarian	Orange	EvaVlaardingerbroek (2100)	Far-right politicians, activists and influencers, as well as right-wing 'alternative news' sources
Identitarian movements	Pink	activeclubuncensored (4600)	Nationalist, far-right and identitarian movements, often regional but with an international outlook, for example, 'Active Clubs'
Christianity	Yellow	jezuskomtspoedig (6200)	Christian channels, often quoting bible verses or interpreting current events from a religious perspective

analysis (following Telegram's documentation) shows how channel *subscribers* link one channel to another through their presence in both. It is likely that a similar analysis on the basis of hyperlinks, or @mentions, would provide yet another impression of this space.

In the discussion above, we have appropriated two separate platform affordances for the same basic method, that is, visual network analysis. This is in both cases however primarily a structural, or topological, analysis, which is based on the connections between channels rather than what goes on inside them. In addition to this, it is useful to also look at this space from a content-based perspective, which we do in the next section.

Findings based on distant reading

We use vector semantics as a 'distant reading' method for assessing the textual contents of both collections of Telegram channels. We specifically field this method with the aim of reducing the complexity of our Telegram datasets by identifying clusters of similar channels. The results of this analysis are presented in the form of scatterplots (see Figures 6 and 7), where the axes represent the two dimensions on which our data are projected, and the distances between points reflect the similarities between channels in the original higher-dimension vectors. We colour-code channels based on inductively identified HDBSCAN clusters and provide descriptions of the clusters based on TF-IDF keywords and centroid channels in Tables 4 and 5. Using the inductive 'distant reading' approach outlined earlier, we find that clearly demarcated clusters of semantically similar channels can be identified, indicating a high degree of granularity and diversity at the content level. The observed clusters and semantic fields at the content level broadly align with the dynamics revealed through visual network analysis.

As shown in Figure 6 and Table 4, we find that nine channel clusters can be identified in the Telegram dataset snowballed from forwarded messages. The largest of these is cluster 5 (comprising 179 channels), which is concerned with news or commentary related to the Russia–Ukraine war. Keywords such as 'рф' ('Российская Федерация', Russian Federation), 'всу' ('Вооружённые силы Украины', Armed Forces of Ukraine) and 'сша' ('Соединённые Штаты Америки', United States of America) indicate that the cluster is specifically preoccupied with the strategic and geopolitical aspects of the war. The centroid channel for this cluster, 'zvesdanews', is the official channel of the Russian state–owned 'Zvezda' news channel, which is run by the Russian Ministry of Defence.

This suggests that on a semantic level, through manually curated forwarded messages, the political seed channels

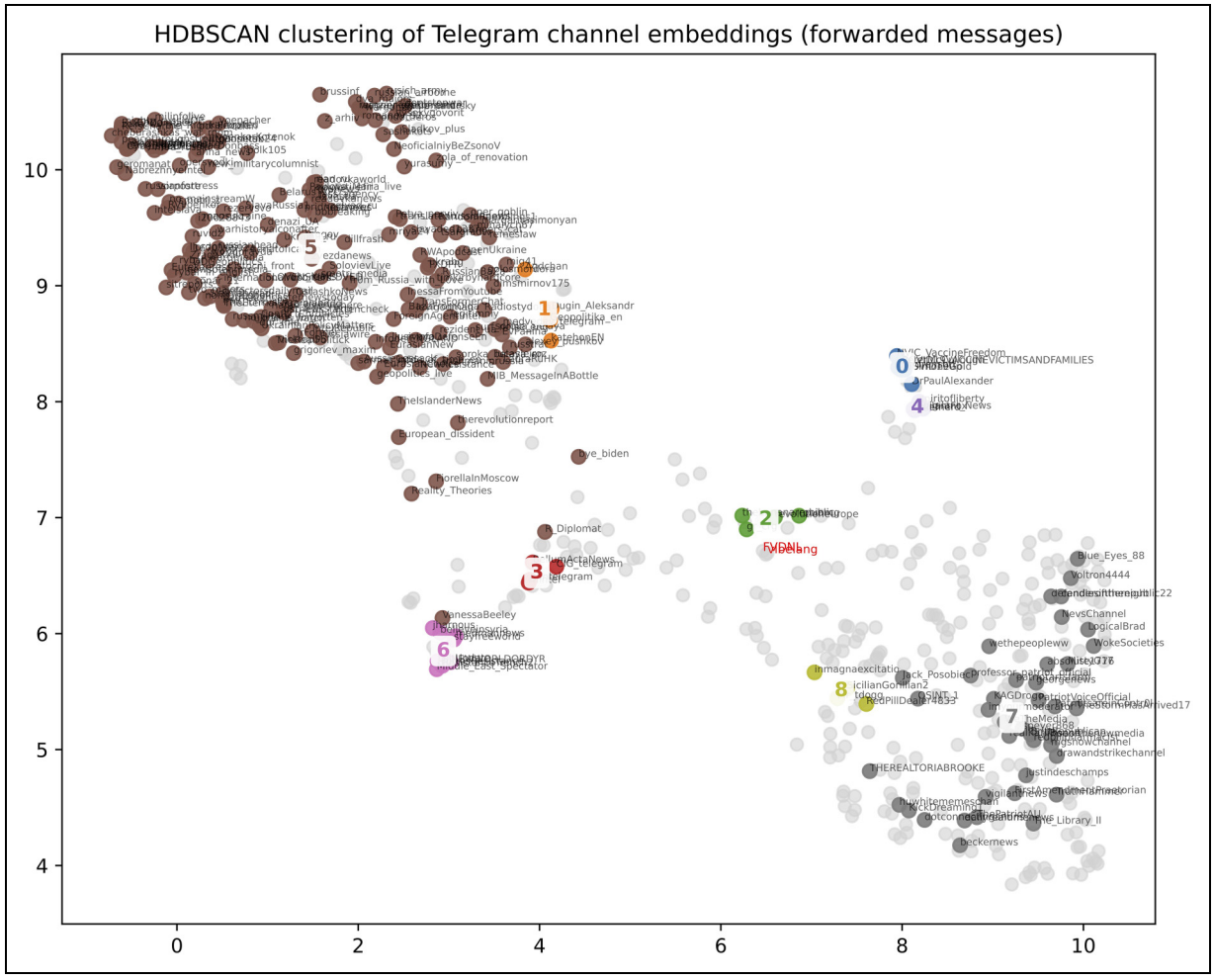


Figure 6. HDBSCAN clusters of channel vectors for the dataset snowballed on the basis of message-forwarding. HDBSCAN clustering based on cosine distance; minimum cluster size, 4; and minimum number of samples, 1. Channels (nodes) are colour-coded by cluster number. Grey nodes are part of the noise cluster (cluster number −1). Cluster numbers are positioned at the centroid channel for the corresponding cluster.

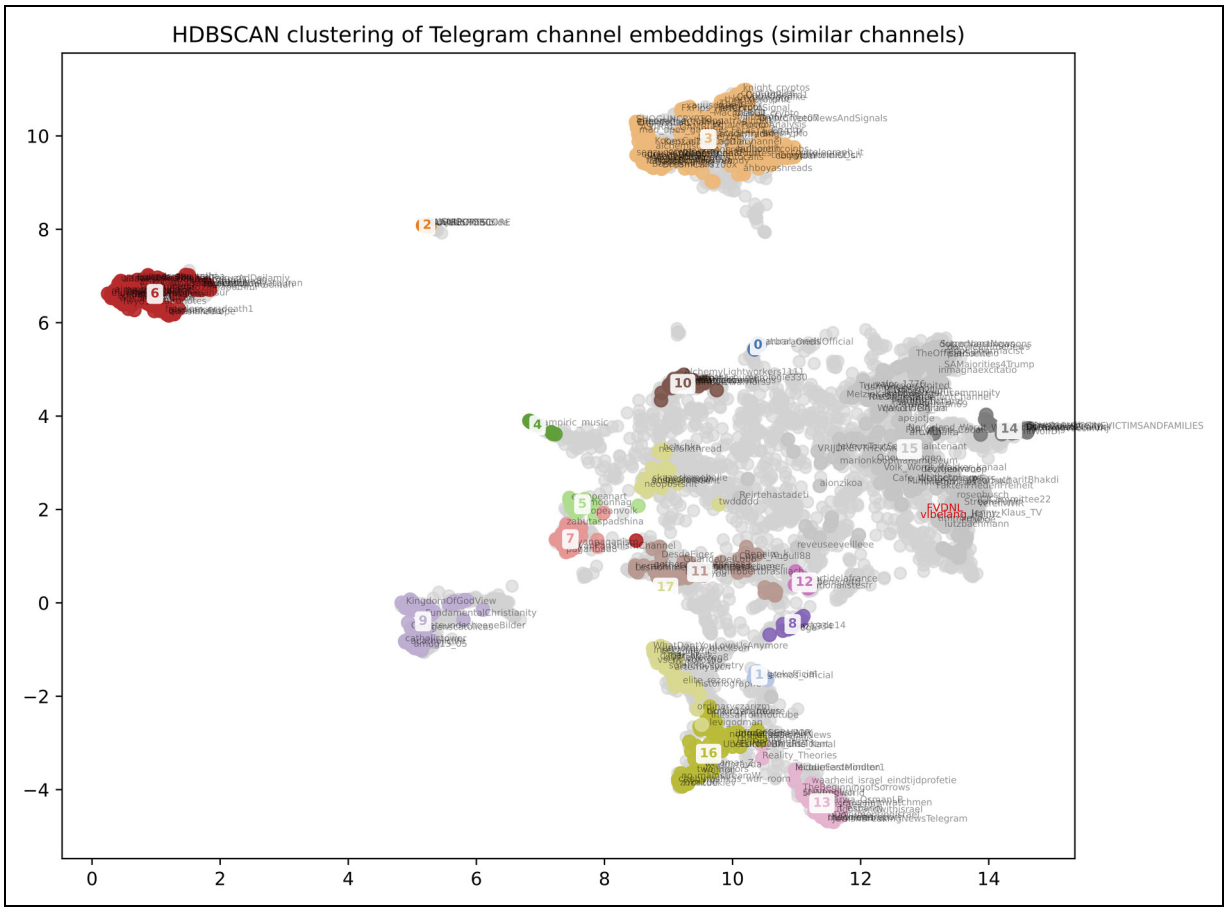


Figure 7. HDBSCAN clusters of channel vectors for the dataset snowballed on the basis of similar channels feature. HDBSCAN clustering based on cosine distance; minimum cluster size, 10; and minimum number of samples, 1. Channels (nodes) are colour-coded by cluster number. Grey nodes are part of the noise cluster (cluster number −1). Cluster numbers are positioned at the centroid channel for the corresponding cluster.

under investigation actively engage with pro-Russian perspectives on the conflict. This point is further supported by content cluster 1, the keywords of which refer to the political philosopher and ideologue Alexander Dugin and his assassinated daughter Daria Dugina. Dugin is a proponent of a 'neo-Eurasian' ideology which, geopolitically, advocates for the establishment of a Eurasian empire occupying the entire continent and which opposes the liberalism of the Anglophone world. Dugin's ideology has been shown to converge at specific points with the ideas of the European New Right (Nouvelle Droite), which explains its presence in this far-right Dutch-speaking 'Telegramsphere'. In addition to this prevalent pro-Russian messaging, other semantic clusters in the message-forwarding dataset are related to anti-vaccination activism (e.g. clusters 0 and 4), right-wing American political discourse (e.g. clusters 7 and 8), conflicts in the Middle East (e.g. cluster 3) and narrative convergences between these topics (e.g. cluster 2).

Figure 7 and Table 5 provide a quantitative perspective on the semantic clusters that can be identified in the larger dataset snowballed through Telegram's similar channels feature. We inductively identify 18 semantic clusters in this dataset. The largest of these is a cluster of channels pertaining to cryptocurrencies (cluster 3). This illustrates how channels related to extreme political positions in the Dutch 'Telegramsphere' are adjacent to channels propagating economic views hinging on libertarianism, minimal government intervention and individual (financial) sovereignty.

These positions align with the anti-government sentiment and ideas on sovereignty and nationalism that are also present in other clusters. The second largest cluster in this dataset (cluster 15), for example, contains channels concerned with alternative (geopolitical) news and conspiracy theories (marked by keywords referring to the FBI, elections, COVID and China). Correspondingly, we find clusters of channels that zoom in specifically on pro-Russian perspectives on the war in Ukraine (clusters 16 and 17), as well as clusters concerned in particular with the Israel–Hamas conflict (cluster 13).

Table 4. Characterisation of HDBSCAN clusters identified in Figure 6 based on TF-IDF keywords and cluster centroids. Keyword lists were cleaned by removing stopwords based on the Python 'stopwordsiso' library (stopwordsiso, 2020).

Cluster	TF-IDF keywords	Cluster size (no. of channels)	Centroid channel (subscribers)	Cluster description
0	chd, mccullough, myocarditis, gettr, wch, sars, cov, nvic, protein, injection	7	DrSimoneGold (96,596)	Discourse related to anti-vaccination activism
1	dugin, россии, дугиной, даши, памяти, daria, платоновой, aleksandr, войны, русского	4	Dugin_Aleksandr (23,230)	Messages related to the (Russo–Ukrainian) war, the Russian political philosopher and ideologue Alexander Dugin, and his assassinated daughter Daria Dugina
2	西行小宝, 关注西行小宝频道获取最新资讯 palestinians, oekraïne, oorlog, şi, injections, mensen, rusland	4	revolutioneurope (186, now only as group)	Alternative news and conspiracy-aligned messaging, including discussions of geopolitical conflicts
3	wagner, rafah, ria, medias, novosti, brigades, iraqi, artillery, pakistan, militants	4	gnntelegram (3793)	News on military conflicts, geopolitical tensions and militant groups
4	socials, mccullough, ivermectin, gettr, rfk, myocarditis, unvaccinated, protein, rogan, immune	4	chiefnerd (55,257)	Conspiracy theories and anti-vaccination discourse
5	подписаться, всу, россии, рф, области, украины, сша, украине, заявил, направлении	179	zvezdanews (135,431)	News or commentary related to the Russia–Ukraine war, including messages from Russian state media
6	zionist, qnAtna (translit.), bAlEArbyp (translit.), hezbullah, brigades, iof, qassam, martyrs, rafah, yemeni	9	LebUpdate (77,117)	Discourse related to conflicts in the MENA region
7	gop, flynn, kari, durham, badlands, danchenko, kash, djt, j6, lago	40	WeTheMedia (164,145)	Right-wing American political discourse
8	shooting, gop, pelosi, illegals, j6, rogan, kjv, aliens, cbp, psalm	4	SicilianGorillian2 (12,106)	Right-leaning US political discourse, covering border security and religion

In addition to these geopolitical clusters, we also find a series of clusters dealing with the coronavirus pandemic, vaccines and health more broadly. Cluster 14 thus explicitly talks about vaccines and vaccine technologies (e.g. mrna), whereas clusters 0 and 10 offer perspectives on traditional health remedies, holistic well-being and esotericism, marked by a new age discourse concerned with 'light', the 'soul' ('Seele') and 'energy' ('Energie'). We further also observe clusters of channels associated with religious discourse (cluster 6), Christianity (cluster 9) and political–cultural critique more broadly (cluster 11). The latter cluster in particular is marked by references to European philosophers such as Julius Evola, who are popular in radical right intellectual contexts. The overall right-leaning political orientation of this 'Telegramsphere' is further illustrated by clusters of channels dealing explicitly with nationalist and ethnonationalist discourse (cluster 5) and French right-wing politics (cluster 12).

Beyond thematically characterising the Dutch-speaking Telegramsphere, these observations, combined with the results of our visual network analysis, allow us to make a comparative assessment of the perspectives on Telegram afforded by snowballing datasets, message-forwarding and similar channels. In the following section, we proceed to discuss key points of similarity and divergence between the two approaches.

Discussion

Our study set out to investigate political mainstreaming of extreme content on Telegram by (a) mapping the fringe channels and issue spaces that linked to the Telegram channels of the political parties Forum voor Democratie and Vlaams Belang and (b) highlighting the specific contributions of user-curated message-forwarding and algorithmically curated lists of 'similar channels'.

We find that political channels on Telegram associated with the far right in Belgium and the Netherlands (viz. 'FVDNL' and 'vlbelang') operate as gateways towards extreme content on the platform. We have shown that Telegram's features for channel discoverability actively contribute to the mainstreaming of this extreme content.

Telegram users are thereby steered from political channels (which might be broadly publicised elsewhere, e.g. on official party websites) to the platform's more extreme content through the affordances of forwarded messages and algorithmically curated lists of 'similar' channels. By means of a 'centrifugal reading', in which we traced outgoing links from the political seed channels under investigation here, we have demonstrated that both of these affordances lead to specific, to a large extent complementary datasets. Through a quantitative, descriptive overview of the composition of both collections, we have shown that the algorithmically curated 'similar channels' feature yields a much larger, as well as linguistically more diverse set of discoverable channels.

Our subsequent examination of the data based on methods for visual network analysis and quantitative content analysis ('distant reading') has revealed both similarities as well as differences between the two datasets. At the level of similarities, we find that political channels in both cases are tied into clusters of channels associated with far-right identitarian discourse, conspiracy theories and instances of pro-Russian foreign information manipulation and interference (FIMI). When we compare these findings with previous research into the Dutch-speaking fringe on Telegram (Willaert et al., 2022), a twofold dynamic thereby demarcates itself. First, we see that 4 years after the outbreak of the global coronavirus pandemic, antivaxx conspiracy channels and channels propagating anti-establishment narratives remain persistently active on the platform. We furthermore observe a continued convergence between these conspiratorial channels and the far right, a dynamic that has previously been observed for Telegram (Willaert et al., 2022) as well as other platforms (Tuters and Willaert, 2022). Compared to previous work on the platform, we also observe a new, emerging trend in which antagonistic channels become associated with channels that propagate pro-Russian perspectives on geopolitical events, and instances of foreign information manipulation and interference (FIMI), pushed, for example, through Kremlin-backed channels such as Zvezda.

The latter point is also where both datasets most clearly diverge. We notably find that engagement with content in Russian, as well as pro-Russian perspectives more specifically, takes up a significant portion of the user-curated message-forwarding dataset. This suggests that channel owners actively, and in a focused manner, push this type of content to their followers. In the 'similar channels' dataset, Kremlin-aligned themes and perspectives are but a part of a larger, more wide-ranging landscape of channels, which also includes a diverse range of other politically extreme content amplified through this 'dark metric'. Telegram users who follow these recommendations and click through on them are thus likely to be sent in more wide-ranging directions, which are no less harmful.

The more fundamental question that follows from these observations, then, is the extent to which this mainstreaming of politically extreme content, as well as the convergences between different issue spaces (far-right extremism, conspiracy theory and FIMI), might be *facilitated* by Telegram's affordances. While we cannot make any causal claims to this end, our analysis does find traces that suggest a role for Telegram's affordances in guiding users towards specific content. One relevant signal here is the alignment of the dynamics we observe in the forwarding networks and those of the networks revealed by following 'similar channels'. According to Telegram's documentation, these similar channels are based on shared users between channels. If we see that users find their way to both conspiracy channels and far-right channels, and we see that message-forwarding likewise occurs between those channels, it might be supposed that these users found those channels *by way of* these forwarded messages.

This argument is further supported by the fact that Telegram's 'similar channels' feature is relatively new (as such limiting its role in guiding users for the datasets at hand) and the fact that Telegram, at the moment of collecting the data, lacked any other major channel discoverability features beyond message-forwarding (such as global search, which was only introduced in July 2025). At the same time, it might be argued that Telegram's 'similar channels' feature is both backward-looking in the sense that it builds on previous user behaviour and forward-looking in the sense that it might be incorporated to the extent that it is now effectively impacting the users' journey between channels on the platform.

One key element that complicates this analysis is that Telegram's recommender engine is effectively a 'black box', and we can only go by Telegram's own reporting of how the engine works. Future research is therefore required to further investigate and measure the impact of these features on processes of community formation on Telegram. Our study moreover raises questions about how the various methods of establishing links on Telegram interact with one another. Perhaps forwarded messages lead to people joining channels, which then establishes them as 'similar channels'. Or the inverse might be true, as one might join a channel after seeing it recommended as similar and then find messages to forward in their own channel. Our analysis here cannot reveal such dynamics, but we in any case note that none of these features exist in a vacuum, and a deeper analysis of how they influence users' behaviour might be an interesting direction for future research.

By way of conclusion, we highlight further methodological and conceptual implications of our study.

Conclusion

On a methodological level, we have demonstrated that affordance-based 'snowballing' methods for Telegram

Table 5. Characterisation of HDBSCAN clusters identified in Figure 7 based on TF-IDF keywords and cluster centroids. Keyword lists were cleaned by removing stopwords based on the Python 'stopwordsiso' library (stopwordsiso, 2020).

Cluster	TF-IDF keywords	Cluster size (no. of channels)	Centroid channel (subscribers)	Cluster description
0	health, wealth, oil, water, vitamin, tsp, ingredients, organic, magnesium, shilajit	12	Natural_Healing_USA (74,288)	Discourse about health, nutrition and organic or traditional remedies
1	греция, греции, ягрек, русском, греческого, греков, уведомления, подпишись, включи, вступай	10	LoveGreece (8372)	Discourse about Greece (in Russian)
2	waa, walbo, 1xbet, iyo, ka, lacag, guul, oo, aad, asxabta	19	XAAJISPORTS1 (3, channel reset in April 2025)	Discourse about betting and gambling (in Somali)
3	bitcoin, eth, btc, crypto, market, binance, usdt, chart, entry, dyor	312	real_trade_dominanta (273)	Messages about cryptocurrencies and investments
4	genre, альбом, origin, metal, блэк, drudkh, bandcamp, *iran for free*	13	Vampiric_music (no longer available)	Messages about heavy metal music
5	painting, earthporn, oc, woman, artist, museum, german, portrait, christ, figures	20	Countrymencoffee (1914)	Discourse about art and heritage
6	аллах, аллаха, аль, ибн, Allah (translit.), шейх, al- (translit.), абу, аллаху, благословит	188	munavaro (7801)	Islamic religious commentary
7	ods, pagan, germanic, folk, ancient, ancestors, paganism, pagans, christian, christianity	34	IreEtherealArt (530)	Religious discourse, with a focus on 'pagan' beliefs
8	polski, magyar, nop, polsce, égióhungária, ?ci, narodowe, odrodzenie, kattintva, nacionalista	13	radykalnemazo (no longer available)	Nationalist and ethnonationalist discourse, with a focus on Central and Eastern Europe
9	jesus, christ, thy, thee, deus, dieu, church, mary, pray, heaven	72	OrthodoxOdyssey (687)	Christian discourse
10	liebe, leben, elfenwerk, licht, *und*, energie, *Licht*, seele, *Liebe*, *natur*	24	Wholistic_Ramblings (2093)	New age, spiritual and esoteric discourse, with a focus on holistic wellness
11	mundo, vida, guerra, hombre, pueblo, evola, monde, nietzsche, De, Dios	56	memoriasdeturner (no longer available)	Political–cultural critique, with references to European philosophers popular in radical right intellectual contexts (e.g. Julius Evola, Friedrich Nietzsche)
12	français, parti, politique, partagez, faire, ans, macron, reconquête, président, zemmour	10	MarionMarechal (14,830)	Discourse on right-wing French politics
13	gaza, israel, hamas, idf, israeli, lchtzv (translit.), lhgv (translit.), lchtvh (translit.), chd (translit.), chn (translit.)	61	Marwa_OsmanLB (10,879)	Messages on the Israel–Hamas conflict
14	covid, vaccine, vaccines, health, mrna, pfizer, mccullough, rumble, subscribe, substack	24	covidtruthnet (69,531)	Messages related to COVID-19 vaccines
15	trump, biden, president, covid, mensen, china, israel, deutschland, fbi, election	260	warekracht (17,484)	Geopolitical news and conspiracy theories
16	ukrainian, armed, afu, region, kiev, всу, enemy, defense, nato, putin	94	ODNEWSS (14,482)	Pro-Russian coverage of geopolitical news
17	россии, рф, всу, сво, русских, людей, войны, сша, украины, русские	76	rus_prikoldes (6942)	Russian perspectives on the Russo–Ukrainian war

research need to be approached with some consideration. Our comparison of a dataset collected on the basis of forwarded messages with a dataset collected by ways of Telegram's more recent 'similar channels' feature has shown that, at least on a qualitative level, both datasets provide insights into similar trends and issue spaces. Specifically, we found that both datasets were marked by traces of far-right discourse, conspiracy theories and FIMI. These similarities suggest that, compared to newer affordances such as 'similar channels', datasets collected on the basis of forwarded messages might indeed yield representative samples for the wider issue spaces at hand, thus validating previous methodological work on Telegram, which has relied heavily on this particular type of snowball sampling.

At the same time, we find that for the case at hand, snowballing on the basis of 'similar channels' leads to a larger dataset due to the consistent number of connected channels that can thus be identified for each seed. Correspondingly, this leads to more granular clusters on the level of channel contents, which provides a more nuanced and detailed understanding of the 'Telegramsphere' under investigation. However, Telegram's lack of transparency regarding its 'similar channels' recommender system warrants further investigations into the actual semantics of these 'dark metrics'. In particular, more work is needed to assess the extent to which these recommendations reflect actual similarities in the user bases of channels or whether additional dimensions of channels might influence the selection and ranking process.

This methodological consideration is closely linked to broader conceptual and societal issues raised by our findings. Our research demonstrates that Telegram channels, through their discoverability features, serve as gateways between electoral politics and various extreme issue spaces. Specifically, our findings suggest that Telegram may actively amplify extreme channels (including far-right and extreme identitarian content) and instances of FIMI through its algorithmically curated 'similar channels' feature. We have referred to these recommendations as 'dark metrics'. At the level of infrastructure, this metaphor refers to the opaque nature of Telegram's recommender system, which according to the platform's documentation is based on similar audiences between channels, but for which no further details are provided. Based on our investigation, it can be added that the metaphor also captures the insidious ways in which these algorithmic recommendations amplify political fringe discourse. As we have shown, this amplification of the often extreme 'ambient' channels surrounding a given channel is beyond the control of the channel owner and tends to exceed the channels that are directly linked through manually curated forwarded messages.

This highlights the need for further systematic investigation into the relationship between this emerging algorithmic feature and the spread of potentially harmful content, especially given the opacity of Telegram's recommender system. If anything, our study raises the further question of what the objective of these recommendations actually is: Are they part of an economic strategy for retaining users on the platform by providing them with relevant content, or are there other political or ideological forces at play? As a final remark, we therefore propose to situate Telegram within the broader framework of platform and media studies that focuses on the role of nonhuman (algorithmic) actors in online spaces. As Telegram continues to grow and gain influence, the introduction of its 'similar channels' feature might indeed only be a first step towards a further algorithmic amplification of extreme content, warranting further analysis and scrutiny.

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Ethics statement

The research design of the work presented here was reviewed and approved by the Ethics Committee of the Faculty of Humanities, University of Amsterdam (reference FGW-2271).

Author contributions

Both authors contributed equally to the conception, execution and writing of this manuscript. The authors are listed in arbitrary order.

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Data and software availability

Data collection and analysis scripts accompanying the paper are available on GitHub via https://github.com/willaertt/dark-metrics-platforms-society. Datasets with the embeddings of Telegram channels on which our analyses are based are available on Zenodo via https://doi.org/10.5281/zenodo.18231759. 4CAT, the toolkit used to collect Telegram messages via crawling forwarded messages, is available from https://4cat.nl as free software.

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