Journal of Quantitative Description: Digital Media 6(2026), 1–29 10.51685/jqd.2026.008

Characterizing the Dynamics of Conspiracy-Related German Telegram Conversations during COVID-19

ELISABETH HÖLDRICH

MATHIAS ANGERMAIER

JOAO PINHEIRO NETO

JANA LASSER

University of Graz, Austria

Conspiracy theories have long drawn public attention, but their explosive growth on platforms like Telegram during the COVID-19 pandemic raises pressing questions about their impact on societal trust, democracy, and public health. We provide a temporal and network analysis of the structure of conspiracy-related German-language Telegram chats in a novel large-scale dataset, which captures a significant proportion of COVID-19-era conspiracy discourse in Germany, Austria and Switzerland. A preliminary assessment of the dataset reveals that 37% of shared links point to sources rated untrustworthy by NewsGuard, a proportion substantially exceeding those reported for other platforms and comparable discourse contexts, therefore attesting to the high prevalence of low-credibility information within this corpus. Conspiracy-related activity spikes during major COVID-19-related events, correlating with societal stressors and mirroring prior research on how crises amplify conspiratorial beliefs. We find that the top 10% of chats account for 94% of all forwarded content, portraying the large influence of a few actors in disseminating information. However, these chats operate independently, with minimal interconnection between each other, primarily forwarding messages to low-traffic groups. Lastly, we show that the dynamics of attention are much slower on Telegram than on algorithmically moderated platforms.

Elisabeth Höldrich: elisabeth.hoeldrich@uni-graz.at, Interdisciplinary Digital Lab, University of Graz, Leechgasse 34, 8010 Graz, Austria.
Corresponding author: Jana Lasser, jana.lasser@uni-graz.at
Date submitted: 2025-03-26

Keywords: conspiracy theories, social media, misinformation, telegram

Introduction

A conspiracy theory attempts to explain historical or ongoing events by a group of powerful people that conspires in secret to intervene in events for their own benefit and against the common good (Uscinski, 2017). While some scholars argue that conspiracy theories are necessary for a healthy functioning society as they play a crucial role in the marketplace of ideas where they challenge the prevailing wisdom (Uscinski, 2017), the harmful consequences of belief in them regularly become apparent: For example, the "great replacement" conspiracy theory, which is grounded in racist ideology and spread by white nationalist and far-right groups, theorises that ethnically white people are purposefully being replaced by non-white people. The theory has inspired terrorists such as Anders Breivik, who murdered 77 people in Oslo and on the island Utøya in 2011 (Ray, 2011). In the context of the COVID-19 pandemic, conspiracy theories related to vaccines saw increased popularity globally and became particularly salient in German-speaking countries (Zehring and Domahidi, 2023).

The January 6th insurrection and its close connection to belief in the QAnon conspiracy theory (Bond and Neville-Shepard, 2023) highlights the threat of conspiracy theories to democratic systems and societal cohesion. Another recent example is the COVID-19 pandemic, which has "supercharged" the discussion of conspiracy theories online, as particularly health-related conspiracy theories gained traction and widespread lockdowns contributed to increased online activity (Feldmann et al., 2020). A recent report by the Council of Canadian Academies estimates that misinformation around COVID-19, spread in large parts by conspiracy theorists, caused 2,800 additional deaths and incurred a cost of 300 million Canadian Dollars in Canada (Expert Panel on the Socioeconomic Impacts and of Science and Health Misinformation, 2023). Defining conspiracy theories remains a conceptually contested and sensitive task, as the label can be instrumentalized for epistemic silencing to marginalize non-mainstream or non-hegemonic knowledge systems (Uscinski, 2018). At the same time scholars like Vermeulen (2025) have warned against "protective conspiracy framing", which acts as a rhetorical strategy to prematurely dismiss alternative explanations and narratives as conspiratorial to safeguard institutional orthodoxy or dominant norms. Nevertheless, it is essential to establish some form of objective criteria to prevent the total relativization of truth-seeking. While misinformation typically consists of discrete, falsifiable

claims (Lazer et al., 2018), conspiracy theories function as broader epistemic frameworks (Hesse and Weidemann, 2025). They often incorporate factual information but mystify events by reframing them within a logic of hidden, malevolent intentionality orchestrated by powerful actors (Douglas et al., 2017). In this relationship between narrative and information, the conspiracy narrative provides the context of justification for individual pieces of misinformation, making them more resilient to debunking by embedding them within a cohesive, emotionally resonant storytelling framework (Lewandowsky et al., 2012).

More broadly, understanding the relationship between misinformation and conspiracy theories requires recognizing that both phenomena are connected but appear on different epistemic levels. Misinformation is the term for individual, falsifiable claims, while conspiracy theories provide a narrative structure that absorbs (mis)information (Pierre, 2020; Wimmer, 2025). The components synergize, as misinformation provides the content-level material, while the conspiratorial narratives add emotional weight and resistance to correction. It is this symbiosis that makes conspiracy theories potent narratives for the spread of misinformation (Pierre, 2020).

Conspiracy theories have existed long before the internet (Gribbin, 1974; Wood, 1982) but, at least in public perception, they seem to have become more problematic in recent years and their spread has been tied to online communication (Mahl et al., 2022; Theocharis et al., 2021). Therefore, one of the most pressing questions is the extent to which online communication contributes to the rapid spread of conspiracy theories, and which features of online communication allow conspiracy theories to thrive. Here, the messenger platform Telegram has emerged as a major factor in the dissemination of conspiracy theories. The lack of moderation attracts far-right groups and communities that share conspiratorial beliefs (Bovet and Grindrod, 2022; Curley et al., 2022; Urman and Katz, 2022; Zehring and Domahidi, 2023), and use of Telegram correlates with conspiracy belief (Hetzel et al., 2022; Schwaiger et al., 2022). While platforms such as Telegram enable large-scale, global communication, social factors such as the need for belonging (Mashuri and Zaduqisti, 2014; van Prooijen and Douglas, 2017) and separation from the outgroup of the non-believers have also been identified as drivers of belief in conspiracy theories.

The affordances of online communication, allowing for rapid dissemination of information, are implicated in driving the spread of misinformation. However, on almost all major platforms, several mechanisms that contribute to information spread are entangled and hard to separate: opaque content recommendation systems, influencers, moderation practices, and potential operations by motivated out-

side actors all contribute to the spread of content online. Here, Telegram provides the unique opportunity to study conspiracy-related information flow without the influence of content recommendation systems and moderation. In this study, we refer to the analysed Telegram communication environments as "conspiracy-related chats," as we used a fine-tuned BERT classifier to identify conspiracy content at the message level. As explained in more detail in the following section, we exclusively analysed chats where the classifier detected at least some conspiratorial messaging, ensuring the study isolates the specific discursive structures and network dynamics of these digital information ecosystems.

Problem statement This study aims to contribute to the understanding of the dynamics of conspiracy-related online discourse on Telegram during the COVID-19 pandemic, with a specific focus on German-speaking countries. To this end, we study the discourse captured in the *Schwurbelarchiv* [ANON][1] – a large corpus of predominantly German-language Telegram messages that captures a substantial part of the conspiracy-related discourse on the platform from the COVID-19 era. First, we examine how the activity in conspiracy-related Telegram chats has developed throughout the COVID-19 pandemic. Furthermore, we investigate whether conspiracy-related discourse on Telegram is better characterised as decentralized broader discourse among users versus discourse driven by a small number of influential actors. Lastly, we answer the question of how long information circulating on Telegram remains relevant to the discourse taking place there.

By Telegram's platform design, Telegram chats can have two formats. Broadcast channels, which are used primarily for one-way, broadcast-style communication, feature very few actively posting authors. Typically, only the channel owner has permission to broadcast messages, although additional administrators can be added to assist with content management [2]. In contrast, groups facilitate many-to-many communication, where a larger number of users can actively engage in discussions. In the following, we use "chats" to refer to both groups and channels together, while we will use "group" and "channel" if we aim to differentiate between the two.

Research Questions We aim to answer the following research questions:

[1] This reference leads to a data descriptor article by the same authors as the present publication. The reference has been removed to retain anonymity during peer review. All relevant information from the referenced publication that is necessary to understand the present article has been summarised in subsection "Collection, Processing, and Validation of Data" of the Methods section below.

[2] See also Telegram Channels FAQ: https://telegram.org/faq_channels?setln=uk

RQ1 How has the activity in conspiracy related Telegram chats developed over time during the COVID-19 pandemic?

RQ2 How is conspiracy discourse on Telegram better characterised: as a decentralised, collective engagement among users or as a discourse predominantly shaped by a few influential actors?

RQ3 What are the attention dynamics of Telegram, e.g. how long does a message stay relevant?

We note that we intentionally focus on structural characteristics of the discourse in the present publication and do not engage in analysis of the content of messages. Going deeper into the analysis of content would go beyond the scope of the present analysis and is something we aim to do in a future publication.

Related Works

Telegram has become a prominent platform for the dissemination of misinformation and conspiracy theories, largely due to its lack of content moderation. The absence of systematic oversight of the content being shared on the platform enables the unhindered proliferation of unverified content. As a result, Telegram serves as a hub for conspiracy theorists, far-right actors, and counterpublics, who use its features to build information networks. Understanding the dynamics of conspiracy theories on Telegram is therefore critical for addressing questions about their spread, localisation, and interconnectivity.

Quantitative studies investigating conspiracy theories on Telegram are rare (Mahl et al., 2022). The studies that do exist can be broadly divided into two categories: studies that purely focus on an analysis of the network structure between Telegram chats by inspecting forwarded messages (Bovet and Grindrod, 2022; Peeters and Willaert, 2022; Urman and Katz, 2022; Willaert et al., 2022), and studies that focus their analysis on the content of the discussions (Curley et al., 2022; Al-Rawi et al., 2022; Bodrunova and Nepiyuschikh, 2022; Hoseini et al., 2021; Gerard Gill, 2021; La Morgia et al., 2021; Zehring and Domahidi, 2023; Schlette et al., 2022; Schulze et al., 2022a; Vergani et al., 2022; Weigand et al., 2022) – predominantly via employing some form of topic modelling. Many of these studies focus on the analysis of a specific and small selection of conspiracy theories or topics such as anti-vaccination sentiment (Bodrunova and Nepiyuschikh, 2022; Curley et al., 2022; Gerard Gill, 2021; Schlette et al., 2022; Weigand et al., 2022) and QAnon (Schulze et al., 2022b; Hoseini et al., 2021). These studies analyse content from a single (Vergani et al., 2022) or very few (< 50) (Weigand et al., 2022; Schulze et al., 2022a; Schlette et al., 2022; Gerard Gill, 2021; Curley et al., 2022; Bodrunova and Nepiyuschikh, 2022;

Al-Rawi et al., 2022) Telegram chats. Interestingly, some countries such as the Netherlands (Willaert et al., 2022; Schlette et al., 2022; Peeters and Willaert, 2022) and Germany (Gunz and Schaller, 2022; Schulze et al., 2022a; Weigand et al., 2022; Zehring and Domahidi, 2023) are featured significantly more often in the existent literature than others such as Italy (Vergani et al., 2022), Russia (Bodrunova and Nepiyuschikh, 2022), Ireland (Curley et al., 2022), Australia (Gerard Gill, 2021), Canada (Al-Rawi et al., 2022), and the United Kingdom (Bovet and Grindrod, 2022). A small number of large-scale studies stand out, such as the Hoseini et al. (2021) study on the spread of the QAnon conspiracy theory in a multilingual dataset of 161 chats and the gigantic effort by La Morgia et al. (2021) to characterise "dark content" such as fakes, clones, scams, and conspiracy movements on Telegram in general in 35,382 chats.

Closest to the work presented here is the study by Zehring and Domahidi (2023) which analysed the communication networks of the German Querdenken movement, the leading mobilisers of anti-COVID protests in Germany. The study identified a total of 578 conspiracy-related public Telegram chats, resulting in a dataset of of $6,294,955$ messages spanning the time from October 28, 2015, to January 3, 2022. Their analysis revealed close ties between Querdenken and far-right actors, as well as the dissemination of content related to QAnon and COVID-19 conspiracy theories. With the use of network analysis and structural topic modelling, the study highlighted the role of Telegram as a key infrastructure for radicalising communication, fostering mistrust, and amplifying far-right narratives.

A similar, more extensive (unpublished) dataset was collected by Mohr (2023), focusing on the diffusion of COVID-19-related (mis-)information. This dataset comprises of over 433,000 chats, with complete data from 128,000 chats containing over 2 billion messages posted between January 2020 and January 2023, mainly in Russian, English and German. The content of the messages largely reflects activity from European time zones and key events such as the European COVID-19 vaccination campaign and the Russian invasion of Ukraine. The 23,000 predominantly German chats from this dataset were made available to the authors of the present study for comparative analysis to help gauge the completeness of the *Schwurbelarchiv*.

There is also research exploring related but distinct aspects of Telegram such as the economic motivations in conspiracy-related chats. Imperati et al. (2024) investigated the ecosystem of conspiracy-related Telegram chats, identifying over 17,000 such channels. Their findings highlight the monetisation strategies used by these chats, such as e-commerce, affiliate links, and crowdfunding campaigns, which

collectively generate millions of dollars. This study underscores the economic motivations behind conspiracy dissemination and the use of Telegram's environment to maintain and amplify these networks.

The above-mentioned studies show the variety of studied conspiracy theory ecosystems on Telegram, ranging from information networks and flow to their financial incentives. However, none of the studies attempt to analyse the attention dynamics on Telegram. Furthermore, while Zehring and Domahidi (2023) provides an analysis of the communities in the message forwarding network of the "Querdenken" movement in Germany in the same period of time, our work complements this by providing insight into the overall network structure and information dissemination through the network.

Methodology

We obtained IRB clearance for research with and re-publication of the data contained in the *Schwurbelarchiv* (vote of the IRB of Graz University of Technology from March 28, 2023).

Collection, Processing, and Validation of Data

The *Schwurbelarchiv* dataset, comprising approximately 24TB of data, represents one of the most extensive collections of public German-speaking Telegram chats, capturing a substantial portion of conspiracy-related discourse during the COVID-19 pandemic [ANON]. It was scraped from various public German-speaking Telegram chats, covering the time span from September 23, 2015, to August 5, 2022. The dataset was originally deposited in the Internet Archive[3] by an anonymous individual, and then further cleaned and processed by pseudonymising usernames, extracting message metadata including author, posting date, and forwarding information, removing redundant chats, and transcribing audio and video content using a Whisper speech-to-text model.

The data was gathered using a Windows Virtual Machine, with four separate Telegram Desktop sessions. Chats were then exported using Remote Desktop Protocol. Chats included in the dataset were selected following a snowball sampling approach (Jost et al., 2023) with a human-in-the-loop component to limit the number of included chats, focusing on conspiracy-related content. Importantly, the dataset exclusively contains publicly accessible Telegram channels and groups. Private chats and closed groups requiring invitation are not included.

[3] See https://archive.org/details/schwurbel-archiv

The data collection process was not under the control of the authors of this paper and no comprehensive description of the collection process is publicly available. Therefore, next to private communication with the anonymous author to clarify the sampling process, it is crucial to validate its completeness and representativeness with respect to the temporal and geographical scope studied as well as whether the content is indeed mostly related to the discussion of conspiracy theories. In [ANON] we provide a detailed assessment of the completeness of the dataset based on the coverage of chats in comparison to other similar datasets (Mohr, 2023; Zehring and Domahidi, 2023; Baumgartner et al., 2020). In addition, we use forwarded messages to estimate our coverage of the relevant full population of conspiracy-related messages sent on predominantly German-language Telegram chats in the observation period. To this end, we calculated the proportion of forwarded messages that are also present in the dataset as original messages. This is the case for close to 50% of forwarded messages contained in our dataset. We therefore estimate that our analysis captures about half of the relevant German-language conspiracy-related discourse on Telegram during the COVID-19 pandemic.

The author of the *Schwurbelarchiv* states that chats were collected in a semi-automated way, focussing on chats with conspiracy-related content[4]. We validated this assumption by measuring the amount of conspiracy-related messages in each chat. We thus classified all messages longer than 150 characters using a machine learning-based classifier to determine whether they contained conspiracy-related content. We used a fine-tuned BERT model developed by Pustet et al. (2024), which functions as a binary classifier for identifying the presence or absence of conspiracy-related content in a German-language Telegram message. According to this classification, 14 % of chats (946 chats) contained in the original *Schwurbelarchiv* do not contain conspiracy-related content. However, these chats account for only 0.1 % of all messages longer than 150 characters in the dataset. We exclude all chats that do not contain conspiracy-related content going forward. In the remaining dataset, the average proportion of messages exceeding 150 characters classified as conspiracy-related content per chat is 16 %.

To further validate that the snowball sampling approach successfully targeted the intended population of conspiracy-related discourse, we analysed the quality of shared information. One of the primary characteristics of conspiracy-related environments is their hypothesised role as a framework that validates and disseminates misinformation. We operationalise misinformation as links to untrustworthy sources using the NewsGuard database, which employs trained journalists to evaluate news domains

[4]See https://schwurbelarchiv.wordpress.com/

across nine criteria of credibility and transparency on a 0–100 scale (Lin et al., 2023; Lühring et al., 2025). Operationalising misinformation as links to untrustworthy sources has a number of limitations that influence how to interpret our findings. First and foremost, this source-based approach misses all messages that do not contain a link by design. This means that the prevalence of untrustworthy content we find can only be interpreted as a lower bound to the amount of misinformation that is potentially present in our data set. Furthermore, source-based trustworthiness ratings do not differentiate between the trustworthiness of individual articles produced by the same source. This means that a true piece of news from an untrustworthy source will be labelled as untrustworthy, and an article containing misinformation from a highly trustworthy source will be labelled as "trustworthy" – even though given the high journalistic standards of the source, the misinformation will likely be corrected in a timely manner. Lastly, journalistic practices of sources can change and therefore the trustworthiness rating from an assessment of the source in the past might not reflect the trustworthiness of the source at the time an article from it is shared.

Of the domains that links contained in our dataset point to, 42.2% are covered by the NewsGuard data base. For the German-language context, NewsGuard does not miss any major news outlets Lühring et al. (2025). Domains not present in the data base are usually associated with other social media platforms, e-commerce platforms, or websites such as Spotify Lasser et al. (2022a). We define domains with a NewsGuard score below 60 as "not trustworthy". This threshold is based on an arbitrary choice NewsGuard introduced in the past and has since removed from its documentation (NewsGuard, 2020). However, a threshold of 60 has since been established in the literature if binary classification of sources is necessary. To render our findings comparable to the literature, we use the same threshold. Binary classification of sources into "trustworthy" and "untrustworthy" has to be used carefully, especially in contexts where temporal changes are important Lühring et al. (2025) since sources can change their rating over time as described above. However, as we only want to gain a broad overview of the general prevalence of sources with a low trustworthiness, we chose to use this threshold to differentiate between sites that generally maintain basic journalistic standards and those that do not and to enable comparisons with other research that follows a similar approach. Of the links in our dataset associated with domains covered by NewsGuard, 36.7 % were classified as "not trustworthy". To contextualise this, we compared these findings to political discourse dataset on Twitter (now "X"), where the proportion of untrustworthy links shared by politicians is substantially lower: 8.3 % for members of the German AfD and 5.5 % for Republicans in the U.S. (Lasser et al., 2022b). This analysis functions as a dataset validation step rather than a quantification of misinformation prevalence on Telegram more broadly. Given that the

chats were selected on the basis of their conspiracy-related content, the proportion of links pointing to untrustworthy sources is not informative about the general information environment on the platform. It does, however, confirm that the sampled chats constitute an environment in which low-credibility information is significantly more prevalent than in mainstream political discourse, lending empirical support to the assumption that the dataset captures its intended population of conspiracy-related discourse.

Limitations of snowball sampling

While we were able to validate that the dataset predominantly contains conspiracy-related discourse and covers a substantial portion of German-language conspiracy-related discourse in the observation period, there remain some limitations of the dataset due to the sampling approach employed. As mentioned above, chats were sampled via snowball sampling. This means that, starting from a selection of "seed" chats, other chats are identified via forwarded messages originating from them. Newly discovered chats are added to the sample and used to look for new chats going forward, and all messages posted in them up to the point of their discovery are scraped and added to the dataset. This process is repeated until either saturation is reached and no chats with content relevant to the focus topic of data collection (in the present case: conspiracy-related discourse) are identified, or some other constraint like lack of time or storage capacity leads to the termination of data collection. In the case of the *Schwurbelarchiv*, data collection was terminated because the anonymous author of the archive lacked the resources to continue.

Usually, the snowball sampling process is also "guided" in the sense that chats that are not deemed relevant are removed, either via manual curation (as in the present case) or some automated approach. This is done to prune irrelevant sampling paths early as to not overwhelm the data collection capabilities with irrelevant content. As such, the process of snowball sampling introduces a high degree of uncertainty into the data collection process, as inclusion of chats is not based on pre-defined criteria alone, but rather on the discoverability through exploration in the highly uncontrolled environment that is the message forwarding network of Telegram chats. However, we note that for Telegram, snowball sampling is the *only* available sampling methodology other than manual curation of chats, as the platform lacks a searchable index of all public chats.

Given the lack of a more controlled sampling approach, we are left with noting the limitations of snowball sampling in relation to our research questions. There are three reasons that can cause a chat

to not be included in our dataset: (i) it is discovered but classified as not conspiracy-related, (ii) it is not discovered because sampling terminated before a link to the chat could be found, and (iii) it is not discovered because it is entirely disconnected from the connected network of chats in which the sampling was started. In the context of our research questions, the second and third reason are problematic, because they constitute causes of data exclusion that are not intentional. As the data collection process still relies on a computational approach requiring no direct interaction with humans, causes for systematic biases in the sample such as social desirability Parker et al. (2019) can be ruled out. However, there are structural characteristics that can render chats more likely to be included than other chats: Chats from which few messages are forwarded to other chats are more likely to be missed by the sampling. This can happen for small chats, as fewer users mean fewer chances of forwarding a message, or for chats from which fewer messages are forwarded in general, for example because users established a norm of keeping messages confidential. Chats from which few messages are forwarded are more likely missed by snowball sampling both because they are more likely to be completely disconnected, and because forwards from these chats happen less frequently, and therefore the chat is less likely to be discovered before termination of the sampling process. As discussed in more detail in Section "Discussion and Conclusions" below, this systematic bias affects predominantly our conclusions regarding the assortativity of chats.

Descriptive dataset statistics

The cleaned dataset contains 5,678 chats (2,828 channels and 2,850 groups – see also "Identification of Groups and Channels" below) with 40,501,682 original messages and 15,503,473 forwarded messages. A substantial amount of these messages are multimedia messages (e.g., images, voice messages or videos). Out of all original messages, 20% are multimedia messages, while for forwarded messages the ratio is 61%. Further descriptive statistics of the dataset are provided in Tab. 1.

Table 1: Descriptive statistics of the *Schwurbelarchiv* dataset.

	Original	Forwarded	Total
Chats			5,678
Channels			2,828
Groups			2,850
Authors	360,149	95,950	405,553
All messages	40,501,682	15,503,473	56,005,155
Text messages	36,150,296	12,615,714	48,766,010
Media messages	7,287,022	7,748,688	15,035,710
URLs in messages	9,742,105	8,546,484	18,288,589

Identification of Groups and Channels

Since the original dataset does not provide information on the type of a chat, we differentiate between the two types by assessing the number of unique actively posting users in each chat. Broadcast channel administrators include the channel name in their username when posting in the channel. Thus, by examining unique usernames, we can distinguish channels from groups. If all usernames in a chat include the chat's name, we classify it as a broadcast channel. Following this approach, we identify 49.8% (2,828) of chats as channels, while 50.2% (2,850) were classified as groups. The distribution of the number of unique authors per chat in the dataset shown in Fig. 1 reveals two distinct clusters, reflecting the underlying communication structures of groups and channels on Telegram. Groups exhibit a heavy-tailed distribution of participation, characteristic for many-to-many communication.

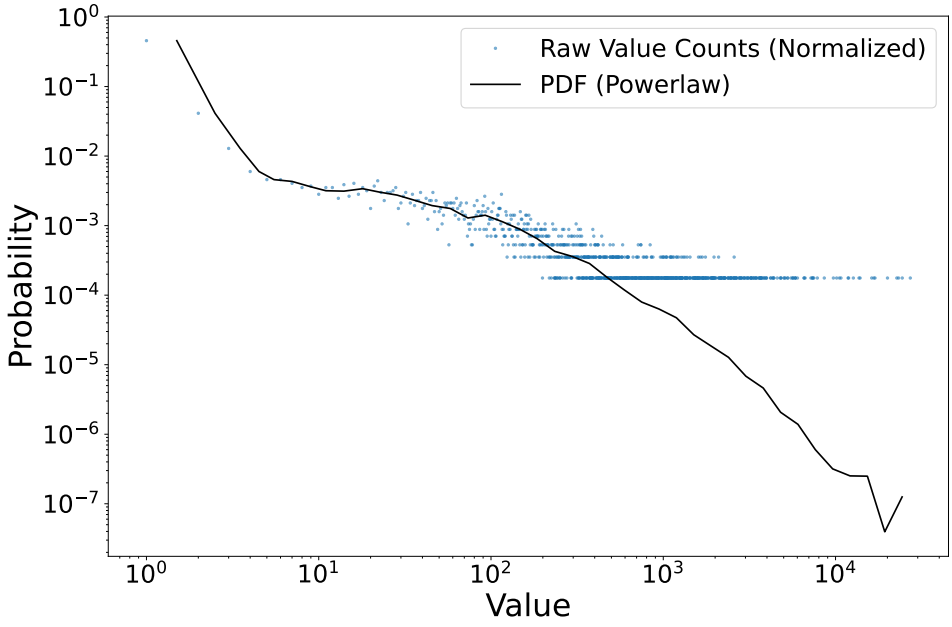

Figure 1. Log-log plot comparing the normalised raw value counts (blue) and the probability density function (PDF) of the number of authors per chat in the dataset (black).

Information Dissemination Networks

Chats within the *Schwurbelarchiv* dataset are interconnected in several ways, for example by messages forwarded between them, and the same author posting in different chats. In this study, we aim to analyse the structure of information flow through messages forwarded between chats. We therefore

create a network in which each chat is a node and a directed edge between two nodes corresponds to the number of messages forwarded from one chat to the other. To create this network, we match messages that have been forwarded with original messages. To ensure identification of the correct pair of messages without a unique ID to track forwarded messages, we match *messages* with *fwd_messages*, *author* with *fwd_author*, and *posting_date* with *fwd_posting_date_message*. The underlying assumption is that one author cannot post the same message in the same second multiple times in multiple chats. The time difference between *posting_date* of the forwarded message and *posting_date* of the earliest occurrence of the message in the dataset (e.g., the original message) further allows for analyses of information dissemination speed.

Results

The results presented in the following sections present insights into temporal and structural characteristics of the dynamics of conspiracy-related discourse and information dissemination during the COVID-19 pandemic in German language Telegram chats.

Temporal Dynamics

To address our first research question relating to the development of the activity in conspiracy-related Telegram chats over time during the COVID-19 pandemic, we analyse the temporal patterns of message activity, number of active chats, and author participation.

Figure 2 shows the number of messages and active chats per day. For a given day, active chats are defined as chats that had at least one posted message on that day. Our dataset reaches back to 2016, which allows us to contextualize the activity observed during the pandemic with the activity in the preceding years. The number of messages and active chats surged at the onset of the COVID-19 pandemic in early spring 2020, echoing prior research that links societal crises to increased activity in conspiracy-related discourse (Stein et al., 2021). The maximum was reached on January 20, 2021 – the day of the inauguration of U.S. President Joe Biden. While there is sustained high activity throughout late 2020 and early 2021, messaging activity steeply drops toward the second half of 2021, reaching pre-pandemic levels by spring 2022. The number of active chats over time closely mirrors the messaging activity in the dataset, with over 2500 active chats in early 2021 and below 100 active chats before 2019 and after 2022.

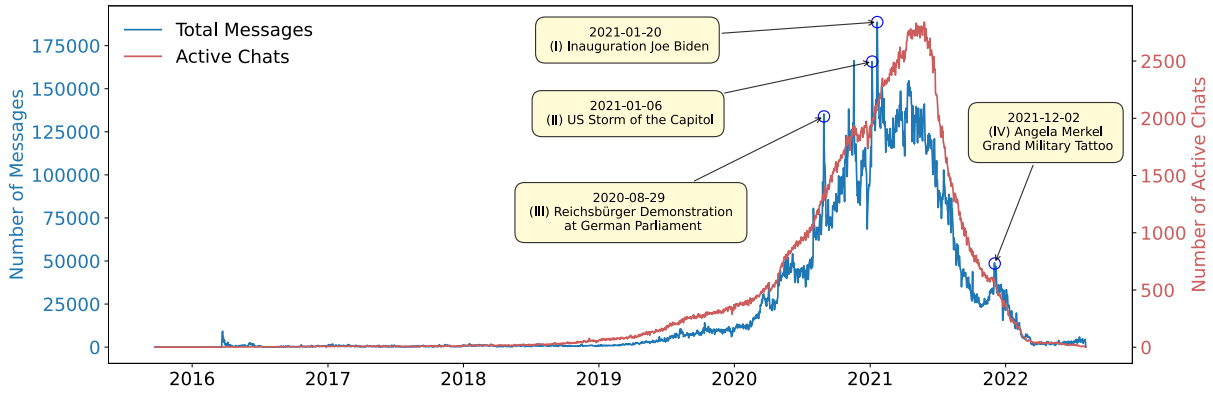

Figure 2. Number of messages (blue) and active chats (red) per day. Maxima in posting activity and related real-life events were assigned and identified manually.

The timeline shows several peaks in message activity, which we matched with real-life events occurring on the same day by searching in newspaper archives [5]. On August 29, 2020, the Reichsbürger demonstration at the German parliament took place, coinciding with a significant peak in message activity. Similarly, heightened activity is visible on January 6, 2021, coinciding with the storming of the U.S. Capitol, and on January 20, 2021, during the inauguration of Joe Biden. Another significant surge occurred on December 2, 2021, corresponding to Angela Merkel's departure as German chancellor. These peaks suggest that conspiracy-related Telegram activity is strongly influenced by broader socio-political events (Theocharis et al., 2021). However, while the co-occurrence of a major event with a spike in messaging activity is indicative of a causal relationship, to definitely assign an increase in activity to a real-life event, one would have to explore the content of the messages, possibly with the use of topic modelling. Furthermore, for some of the spikes in messaging activity (e.g. the two maxima in late 2020), we were not able to identify real-life events that coincided with the increased activity.

Next, we analyse user activity by examining the total number of messages posted per day (blue line) alongside the average number of messages posted per author and day (green line). Figure 3 reveals a gradual decline in the average number of messages per author over time. This trend suggests a change in user engagement patterns, where individual authors post less frequently over time. This decrease may reflect several underlying factors, including a growing audience of passive participants who consume content without contributing, an increasing number of active authors spreading the total message volume more evenly, or disinterest among previously active users who reduce their participation over time.

[5] https://fazarchiv.faz.net/, https://www.welt.de/schlagzeilen/, https://www.kleinezeitung.at/suche

Despite the decline in individual activity, the total message volume remains substantial, particularly during the peak periods mentioned above.

While we only capture a portion of conspiracy-related discourse, there is no reason to assume that our sample is biased towards capturing chats where activity is systematically skewed towards distinct time periods. We therefore believe that our temporal characterisation of the activity in the *Schwurbelarchiv* is a good approximation of the overall conspiracy-related activity on Telegram for the given temporal and geographical scope.

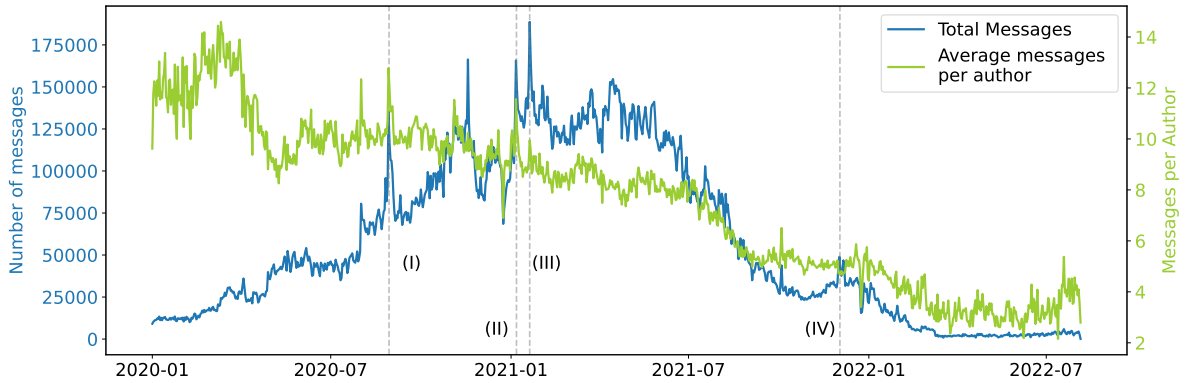

Figure 3. Number of messages in the time period between January, 2020 and August 2022 (blue) and number of messages posted per author per day (green). Vertical dashed lines indicate the events identified in Fig. 2.

Network Structure and Information Dissemination

Understanding the structure of information propagation through the network of chats can offer insights into how conspiracy-related content spreads through Telegram. Here, we aim to answer our second research question of whether discourse on Telegram is predominantly shaped by a few influential actors. In this context, one focal aspect of our analysis is the assortativity of chats, based on the in- and out-degree of forwarded messages Newman (2002). We consider a chat strongly connected to another chat when messages are frequently forwarded from one to the other, constituting a directed link between the two chats. We interpret message forwarding as an approximation of influence between chats, representing the flow of content and ideas from one chat to the next. Here, we investigate the difference between chats with a high out-degree (or *spreader* chats) and high in-degree (or *receiver* chats).

Figure 4 shows the different combinations of assortativity within our network. In network analysis, "assortativity" refers to the tendency of nodes—in this case, Telegram chats—to connect with other nodes that have similar characteristics. To understand how information flows, we examine a chat's "in-degree" (how frequently it receives forwarded messages, characterizing it as a *receiver* chat) and its "out-degree" (how frequently its messages are forwarded to other chats, characterizing it as a *spreader* chat). By comparing these metrics across connected chats, we can determine whether spreaders prefer to interact with other spreaders, receivers with receivers, or if they operate independently. The panels in Figure 4 detail these relationships:

- **a)** Receivers connecting to Receivers: We observe a positive Pearson correlation coefficient ($\rho = 0.59$) between the in-degree of a chat and its neighbour's in-degree. This indicates that *receiver* chats are assortative; chats that consume a high volume of forwarded content tend to be linked to other high-consumption chats.
- **b)** Receivers not relying on Spreaders: There is a strong negative correlation ($\rho = -0.90$) between a chat's in-degree and its neighbours' out-degree. Consequently, chats that receive a large influx of forwarded messages do not typically receive them directly from the major *spreader* groups.
- **c)** Spreaders not targeting Receivers: Complementary to panel b, a chat's out-degree is also strongly negatively correlated ($\rho = -0.79$) with the in-degree of its neighbours. This confirms that highly influential spreader groups are not primarily broadcasting their content directly into the most active receiver chats.
- **d)** Spreaders remaining independent: Finally, we observe a weak anti-correlation ($\rho = -0.11$) between out-degrees. This indicates that *spreader* groups are disassortative; they are less likely to forward content to one another.

Crucially, while these spreader chats operate independently of one another, their overall influence is massive: we found that the top 10% of *spreader* chats account for 94% of all forwarded messages in the network.

We interpret these findings as indicative of a top-down, broadcast-driven information ecosystem rather than a uniformly interconnected network. While *receiver* chats form an assortative cluster—frequently exchanging messages with one another—the overarching flow of information is driven by

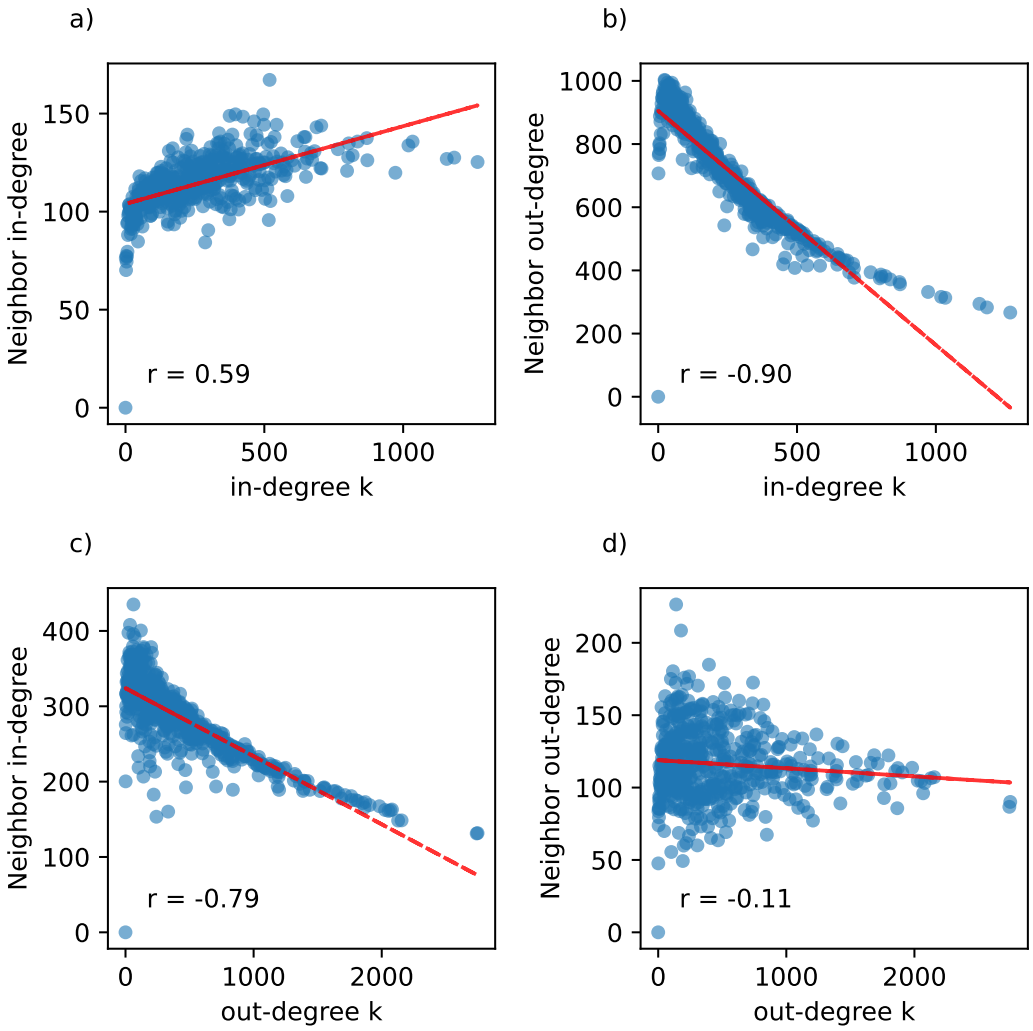

Figure 4. Four combinations between the relation of a chat's in-/out-degree to the in-/out-degree of their neighbour's.

the highly influential, disassortative *spreader* chats. Because these major spreaders rarely share content among themselves or directly with top receivers, we conclude that their messages are primarily forwarded into "ordinary" chats that lack a predominant spreader or receiver characteristic. Consequently, an average chat does not need to be deeply embedded or strongly connected within the core network to be exposed to, and influenced by, the most prominent conspiracy-related actors.

Attention dynamics

To answer our final research question, we analyse the longevity of the influence of individual messages. Here, we use the forwarding of a message as a proxy for the influence it has and investigate for how long a message is forwarded after it was posted for the first time. Figure 5 shows the cumulative probability density function of the time difference between posting of the original message and forwards of that message. We find that after approximately one day, on average 75.7% of forwards of a message will have taken place (horizontal dashed line in the figure). After one month, 95.5% of messages are not forwarded anymore. A similar analysis of the number of impressions a post receives on Twitter (now "X") shows that after 24 hours, no relevant number of impressions can be observed for 95.5% of all posts (Pfeffer et al., 2023). While forwarding behaviour is not directly comparable to the impressions analysed by Pfeffer et al. (2023), our analysis still suggests that the decay of influence of content on Telegram is much slower than on an algorithmically moderated platform such as Twitter.

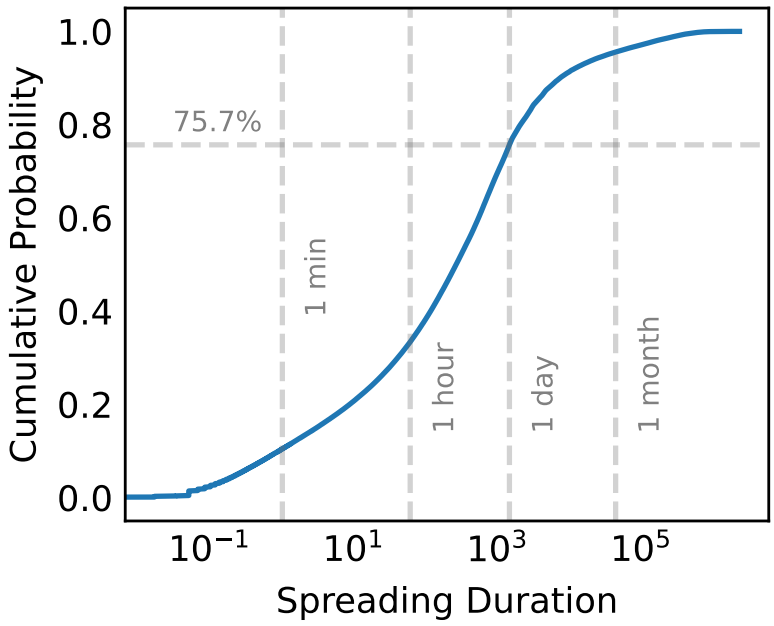

Figure 5. Cumulative probability density function of forwards of a message over time. Note that forwarding time is represented on a log-scale.

Discussion and Conclusions

Previous studies highlighted Telegram's characteristics of minimal moderation and decentralised communication which enable the spread of misinformation (Curley et al., 2022; Zehring and Domahidi, 2023). We build on these findings by analysing a new large-scale dataset, the *Schwurbelarchiv* [ANON], providing a detailed view on conspiracy-related Telegram activity during the COVID-19 pandemic with a particular focus on German-speaking countries. We examine the temporal evolution of the discourse, the structural patterns of the information flow, and the attention dynamics on the platform. As such, our study sheds light on the dynamics and characteristics of a substantial fraction of conspiracy-related discourse for a given temporal and geographical scope on Telegram.

Conspiracy-related activity within the dataset surged during the COVID-19 pandemic, with spikes in messaging activity correlating with key societal events. This temporal pattern mirrors findings from Stein et al. (2021) regarding the catalytic nature of crises. More specifically, our findings align with the theoretical framework of van Prooijen and Douglas (2017), who define a societal crisis as an impactful and rapid change that challenges existing power structures and social norms. By viewing the COVID-19 pandemic through this lens, we can interpret these messaging spikes not merely as reactions to news, but as a psychological and social response to the destabilization of established "norms of conduct". As van Prooijen and Douglas (2017) illustrate through historical precedents, such crises inherently stimulate conspiratorial belief as individuals attempt to make sense of a threatening environment – a phenomenon reflected in the heightened discourse within the Schwurbelarchiv during periods of peak societal uncertainty.

A key result emphasizes the significant influence of a few actors in disseminating information, with the top 10% of chats accounting for 94% of all forwarded content. This concentration aligns with networked gatekeeping theory (Barzilai-Nahon, 2008), suggesting that while Telegram is architecturally decentralized, its information flow is functionally hierarchical. Interestingly, these influential chats operate independently with minimal interconnection, primarily forwarding messages to low-traffic groups. This functional hierarchy carries direct implications for platform governance: targeted interventions focused on the small number of highly active spreader chats could, in principle, disrupt the majority of content dissemination across the network. However, the structural independence of these chats from one another suggests that the removal of any single actor would not automatically impede the broader dissemination infrastructure, underscoring the limitations of individually targeted moderation approaches.

An analysis of message longevity revealed that 75.6% of forwards occur within 24 hours, and 95.5% within a month. Comparatively, Twitter exhibits faster content decay, with 95.5% of impressions occurring within 24 hours (Pfeffer et al., 2023). This suggests that Telegram's design affordances (Majchrzak et al., 2013), specifically its lack of algorithmic turnover, transform the platform into a persistent archive, allowing misinformation or conspiracy theories to transition from a fleeting news item into a permanent ideological resource. We note that potential biases in our sample due to the snowball sampling approach (see below for a more detailed discussion) likely do not affect these results, as chats from which many messages are forwarded are well-represented in the sample, and there is no reason to expect that the temporal dynamics of forwarding are systematically different in undersampled chats.

Challenges, Limitations, and Directions for Future Research.

While the dataset used in this study is extensive, its representativeness is constrained by several factors. First, the dataset we study contains only public chats, excluding private discussion groups and one-to-one messaging that may play a critical role in the dissemination of conspiracy theories and misinformation. This limitation has the potential of introducing a substantial sampling bias as conversations that happen in private likely systematically differ from conversations in public chats. However, access to private conversations is neither technically nor ethically feasible (Barbosa and Milan, 2019) at scale. The few studies on private group chats rely on select groups that allow researchers to participate and collect data based on principles of informed consent (see e.g., Kligler-Vilenchik and Tenenboim (2020) for an example of such a study on WhatsApp). Therefore, it is impossible for us to assess the extent of the sampling bias. As a result, we consider our findings only valid for public channels and groups on Telegram.

Furthermore, deleted messages, which are common on Telegram Buehling (2024), pose a significant challenge to capturing the full picture of discourse dynamics. This omission could impact the robustness of findings, particularly concerning the spread of untrustworthy information, since we would expect messages including links to untrustworthy sources to be deleted at a higher rate. However, this would only further increase the share of untrustworthy links we discover, further confirming our assumptions about the data we study. In addition, the coverage of conspiracy discussions is largely centred on German-speaking countries and the COVID-19 pandemic, limiting the generalisability of the findings to other linguistic, cultural or temporal contexts.

Lastly, the dataset we study only covers part of the German-language conspiracy-related discourse on Telegram. As discussed in [ANON], we estimate that by studying the *Schwurbelarchiv*, we are able to analyse about 50% of the relevant discourse happening on Telegram at the time. While the portion of the discourse covered by our dataset is substantial, there is reason to believe that there are systematic biases in the chats that are included in our dataset. Specifically, snowball sampling likely leads to the over-representation of chats from which more messages are forwarded. Assortativity, which we measure to study the structural properties of the message forwarding network, can be affected by network sampling bias Ruggeri and De Bacco (2020). In the present case, we likely oversample chats with a higher out-degree, which leads to the exclusion of smaller chats, and chats from which fewer messages are forwarded for other reasons, such as secrecy. While our finding on the disassortativity of chats with a high out-degree (*spreader*) remains unaffected, the interpretation of the results involving chats with a high in-degree (*receiver*) warrants caution: If the undersampled chats have a high in-degree on average, this could render our conclusion that content from *spreader* chats is predominantly forwarded to chats that can neither be characterized as *spreader* nor *receiver* chats as invalid.

Our research and dataset opens up a number of avenues for future research, particularly concerning the content of messages, which we largely left untouched in the present study. For example, links related to cryptocurrency transfers contained in message texts allow for the analysis of monetisation dynamics within conspiracy-related Telegram chats, expanding the findings by (Imperati et al., 2024) regarding the economic motivations of participants in such Telegram chats. This could provide valuable insights into how financial incentives sustain and amplify conspiracy theory ecosystems.

Another opportunity for research lies in the analysis of transcribed audio content provided for the *Schwurbelarchiv* (see [ANON] for details). Audio content on platforms like Telegram is often very information-dense, yet it remains underutilised in current research on conspiracy theories and social media in general. Making use of this transcribed audio data would offer new perspectives on how conspiratorial narratives are crafted and communicated.

A comparative analysis across different platforms would also be valuable to further our understanding of how platform structure and design influence the dissemination of conspiracy-related content and misinformation. By examining differences in moderation policies, content recommendation systems, platform affordances, and user behaviours, such research could show how specific platform features contribute to the spread of these narratives.

Contributions and Final Thoughts.

The prime objective of this research was to shed light on the dynamics of conspiracy-related discourse on Telegram, focusing on temporal and structural aspects. The motivation for our work is the need to understand societal impacts of conspiracy theories during crisis, particularly on democratic processes and public health. This study contributes to the growing body of research on digital information disorders by providing a detailed analysis of conspiracy-related discourse on Telegram during the COVID-19 pandemic. By examining the temporal and structural dynamics of this discourse, we offer critical insights into the mechanisms that enable the spread of misinformation and its implications for societal trust and public policy. The study advances the understanding of information flow between super-spreaders and discussion groups that mainly receive information. As such, our findings provide important insights for public policy, particularly in designing platform governance strategies that address systemic factors, such as the lack of moderation and content recommendation systems, rather than focusing only on individual user behaviour (Chater and Loewenstein, 2022).

Funding Information

This research was funded in whole by the Austrian Science Fund (FWF), under project ORION, grant DOI 10.55776/P37280.

Data and Code Availability

Code required to reproduce Figures 1, 3 and 7 given the dataset is available at https://github.com/cs2-lab/analysis_paper. We do not publish the full dataset due to ethical concerns about the identifiability of individuals in the data. Metadata of the dataset is available under DOI 10.5281/zenodo.14704627 and the dataset is described in great detail in Angermaier et al. (2025). The full dataset is available for research purposes upon request.

Author Contributions

All authors contributed to the writing of the original draft and data curation. Elisabeth Höldrich, Mathias Angermaier and Joao Pinheiro Neto contributed to formal analysis, visualization and validation. Jana Lasser and Joao Pinheiro Neto contributed to supervision. Jana Lasser contributed to funding acquisition and project administration.

References

Al-Rawi, A., Stewart, N. K., Celestini, C., and Worku, N. (2022). Delegitimizing the Legitimate: Dark Social Movements on Telegram. *global Media Journal – Canadian Edition*, 14:28–47.

Angermaier, M., Hoeldrich, E., Lasser, J., and Neto, J. P. (2025). The schwurbelarchiv: a german language telegram dataset for the study of conspiracy theories.

Barbosa, S. and Milan, S. (2019). Do not harm in private chat apps: Ethical issues for research on and with whatsapp. *Westminster Papers in Communication and Culture*, 14(1).

Barzilai-Nahon, K. (2008). Toward a theory of network gatekeeping: A framework for exploring information control. *Journal of the American Society for Information Science and Technology*, 59(9):1493–1512.

Baumgartner, J., Zannettou, S., Squire, M., and Blackburn, J. (2020). The Pushshift Telegram Dataset. *Proceedings of the International AAAI Conference on Web and Social Media*, 14:840–847.

Bodrunova, S. S. and Nepiyuschikh, D. (2022). Dynamics of Distrust, Aggression, and Conspiracy Thinking in the Anti-vaccination Discourse on Russian Telegram. In Meiselwitz, G., editor, *Social Computing and Social Media: Design, User Experience and Impact*, volume 13315, pages 468–484. Springer International Publishing, Cham.

Bond, B. E. and Neville-Shepard, R. (2023). The rise of presidential eschatology: Conspiracy theories, religion, and the january 6th insurrection. *American Behavioral Scientist*, 67(5):681–696.

Bovet, A. and Grindrod, P. (2022). Organization and evolution of the uk far-right network on telegram. *Appl. Network Sci.*, 7(1):76.

Buehling, K. (2024). Message deletion on telegram: Affected data types and implications for computational analysis. *Communication Methods and Measures*, 18(1):92–114.

Chater, N. and Loewenstein, G. (2022). The i-Frame and the s-Frame. *Behaviour and Brain Sciences*.

Curley, C., Siapera, E., and Carthy, J. (2022). Covid-19 protesters and the far right on telegram: Co-conspirators or accidental bedfellows? *SM+S*, 8(4):20563051221129187.

Douglas, K. M., Sutton, R. M., and Cichocka, A. (2017). The Psychology of Conspiracy Theories. *Current Directions in Psychological Science*, 26:538–542. Publisher: SAGE Publications Inc.

Expert Panel on the Socioeconomic Impacts and of Science and Health Misinformation (2023). Fault Lines. Technical report, The Council of Canadian Academies.

Feldmann, A., Gasser, O., Lichtblau, F., Pujol, E., Poese, I., Dietzel, C., Wagner, D., Wichtlhuber, M., Tapiador, J., Vallina-Rodriguez, N., Hohlfeld, O., and Smaragdakis, G. (2020). The lockdown effect: Implications of the covid-19 pandemic on internet traffic. In *Proceedings of the ACM Internet Measurement Conference*, IMC '20, page 1–18. ACM.

Gerard Gill (2021). Fascist cross-pollination of Australian conspiracist Telegram channels. *FM*.

Gribbin, W. (1974). Antimasonry, Religious Radicalism, and the Paranoid Style of the 1820's. *The History Teacher*, 7(2):239–254. Publisher: Society for History Education.

Gunz, H. and Schaller, I. (2022). Antisemitic Narratives on YouTube and Telegram as Part of Conspiracy Beliefs about COVID-19. In *Antisemitism on Social Media*. Routledge, first edition.

Hesse, J. and Weidemann, C. (2025). Conspiracy theories and religious worldviews: Unraveling a complex relationship. *Episteme*, 22(4):1035–1054.

Hetzel, N., Klawier, T., Prochazka, F., and Schweiger, W. (2022). How do COVID-19 conspiracy beliefs, exposure to alternative sources and social media correlate in Germany? *SCM*, 11:508–535.

Hoseini, M., Melo, P., Benevenuto, F., Feldmann, A., and Zannettou, S. (2021). On the Globalization of the QAnon Conspiracy Theory Through Telegram. arXiv:2105.13020 [cs].

Imperati, V., Morgia, M. L., Mei, A., Mongardini, A. M., and Sassi, F. (2024). The conspiracy money machine: Uncovering telegram's conspiracy channels and their profit model.

Jost, P., Heft, A., Buehling, K., Zehring, M., Schulze, H., Bitzmann, H., and Domahidi, E. (2023). Mapping a dark space: Challenges in sampling and classifying non-institutionalized actors on telegram. *M&K Medien & Kommunikationswissenschaft*, 71(3-4):212–229.

Kligler-Vilenchik, N. and Tenenboim, O. (2020). Sustained journalist–audience reciprocity in a meso news-space: The case of a journalistic whatsapp group. *New Media & Society*, 22(2):264–282.

La Morgia, M., Mei, A., Mongardini, A. M., and Wu, J. (2021). Uncovering the Dark Side of Telegram: Fakes, Clones, Scams, and Conspiracy Movements. *arXiv*.

Lasser, J., Aroyehun, S. T., Simchon, A., Carrella, F., Garcia, D., and Lewandowsky, S. (2022a). Social media sharing of low-quality news sources by political elites. *PNAS Nexus*, 1(4):pgac186.

Lasser, J., Aroyehun, S. T., Simchon, A., Carrella, F., Garcia, D., and Lewandowsky, S. (2022b). Social media sharing of low-quality news sources by political elites. *PNAS Nexus*, 1(4):pgac186.

Lazer, D. M. J., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., Metzger, M. J., Nyhan, B., Pennycook, G., Rothschild, D., Schudson, M., Sloman, S. A., Sunstein, C. R., Thorson, E. A., Watts, D. J., and Zittrain, J. L. (2018). The science of fake news. *Science*, 359(6380):1094–1096.

Lewandowsky, S., Ecker, U. K. H., Seifert, C. M., Schwarz, N., and Cook, J. (2012). Misinformation and Its Correction: Continued Influence and Successful Debiasing. *Psychological Science in the Public Interest*, 13(3):106–131. Publisher: SAGE Publications Inc.

Lin, H., Lasser, J., Lewandowsky, S., Cole, R., Gully, A., Rand, D. G., and Pennycook, G. (2023). High level of correspondence across different news domain quality rating sets. *PNAS nexus*, 2(9):pgad286.

Lühring, J., Metzler, H., Lazzaroni, R. M., Shetty, A., and Lasser, J. (2025). Best practices for source-based research on misinformation and news trustworthiness. *Journal of Quantitative Description: Digital Media*, 5.

Mahl, D., Schäfer, M. S., and Zeng, J. (2022). Conspiracy theories in online environments: An interdisciplinary literature review and agenda for future research. *New Media & Society*, page 14614448221075759. Publisher: SAGE Publications.

Majchrzak, A., Faraj, S., Kane, G. C., and Azad, B. (2013). The contradictory influence of social media affordances on online communal knowledge sharing. *Journal of Computer-Mediated Communication*, 19(1):38–55.

Mashuri, A. and Zaduqisti, E. (2014). We believe in your conspiracy if we distrust you: the role of intergroup distrust in structuring the effect of islamic identification, competitive victimhood,

and group incompatibility on belief in a conspiracy theory. *Journal of Tropical Psychology*, 4:e11.

Mohr, S. (2023). Inference of modular structures in dynamical systems and the application to telegram data. Master's thesis, University of Göttingen, Göttingen, Germany.

Newman, M. E. (2002). Assortative mixing in networks. *Physical review letters*, 89(20):208701.

NewsGuard (2020). Newsguard rating process and criteria (internet archive). Online; accessed 2020-06-30.

Parker, C., Scott, S., and Geddes, A. (2019). Snowball sampling. *SAGE research methods foundations*.

Peeters, S. and Willaert, T. (2022). Telegram and Digital Methods: Mapping Networked Conspiracy Theories through Platform Affordances. *M/C J*, 25.

Pfeffer, J., Matter, D., and Sargsyan, A. (2023). The half-life of a tweet. *Proceedings of the International AAAI Conference on Web and Social Media*, 17:1163–1167.

Pierre, J. M. (2020). Mistrust and misinformation: A two-component, socio-epistemic model of belief in conspiracy theories. *Journal of Social and Political Psychology*, 8(2):617–641.

Pustet, M., Steffen, E., and Mihaljevic, H. (2024). Detection of conspiracy theories beyond keyword bias in german-language telegram using large language models. In *Proceedings of the 8th Workshop on Online Abuse and Harms (WOAH 2024)*, page 13–27. Association for Computational Linguistics.

Ray, M. (2011). Oslo and Utøya attacks of 2011. *Encyclopedia Britannica*.

Ruggeri, N. and De Bacco, C. (2020). Sampling on networks: estimating spectral centrality measures and their impact in evaluating other relevant network measures. *Applied Network Science*, 5(1):81.

Schlette, A., van Prooijen, J.-W., Blokland, A., and Thijs, F. (2022). The online structure and development of posting behaviour in Dutch anti-vaccination groups on Telegram. *New Media & Society*, page 146144482211284.

Schulze, H., Hohner, J., Greipl, S., Girgnhuber, M., Desta, I., and Rieger, D. (2022a). Far-right conspiracy groups on fringe platforms: A longitudinal analysis of radicalization dynamics on Telegram. *Convergence: The International Journal of Research into New Media Technologies*, 28:1103–1126.

Schulze, H., Hohner, J., Greipl, S., Girgnhuber, M., Desta, I., and Rieger, D. (2022b). Far-right conspiracy groups on fringe platforms: a longitudinal analysis of radicalization dynamics on Telegram. *Convergence*, 28(4):1103–1126.

Schwaiger, L., Schneider, J., Rauchfleisch, A., and Eisenegger, M. (2022). Mindsets of conspiracy: A typology of affinities towards conspiracy myths in digital environments. *Convergence: The International Journal of Research into New Media Technologies*, 28:1007–1029.

Stein, R., Ometa, O., Shetty, S., Katz, A., Popitiu, M., and Brotherton, R. (2021). Conspiracy theories in the era of covid□19: A tale of two pandemics. *International Journal of Clinical Practice*, 75.

Theocharis, Y., Cardenal, A., Jin, S., Aalberg, T., Hopmann, D. N., Strömbäck, J., Castro, L., Esser, F., Van Aelst, P., de Vreese, C., Corbu, N., Koc-Michalska, K., Matthes, J., Schemer, C., Sheafer, T., Splendore, S., Stanyer, J., Stepinska, A., and Stetka, V. (2021). Does the platform matter? Social media and COVID-19 conspiracy theory beliefs in 17 countries. *New Media & Society*, page 14614448211045666. Publisher: SAGE Publications.

Urman, A. and Katz, S. (2022). What they do in the shadows: examining the far-right networks on Telegram. *Inf., Commun. Soc.*, 25(7):904–923.

Uscinski, J. E. (2017). The Study of Conspiracy Theories. *Argumenta*, 3(2):1–13.

Uscinski, J. E. (2018). The study of conspiracy theories. *Argumenta*, 3(2):233–245. Special Issue.

van Prooijen, J.-W. and Douglas, K. M. (2017). Conspiracy theories as part of history: The role of societal crisis situations. *Memory Studies*, 10(3):323–333. PMID: 29081831.

Vergani, M., Martinez Arranz, A., Scrivens, R., and Orellana, L. (2022). Hate Speech in a Telegram Conspiracy Channel During the First Year of the COVID-19 Pandemic. *Social Media + Society*, 8:205630512211387.

Vermeulen, N. (2025). Seeing conspiracy theorists everywhere as a conspiracy paradox. *Communications Psychology*, 3(1):115.

Weigand, M., Weber, M., and Gruber, J. (2022). Conspiracy Narratives in the Protest Movement Against COVID-19 Restrictions in Germany. A Long-term Content Analysis of Telegram Chat Groups. In *Proceedings of the Fifth Workshop on Natural Language Processing and Computational Social Science (NLP+CSS)*, pages 52–58, Abu Dhabi, UAE. Association for Computational Linguistics.

Willaert, T., Peeters, S., Seijbel, J., and Van Raemdonck, N. (2022). Disinformation networks: A quali-quantitative investigation of antagonistic Dutch-speaking Telegram channels. *FM*.

Wimmer, L. (2025). Why disinformation, fake news, and conspiracy theories are not fiction: A view from philosophical aesthetics and literary studies. *Review of Philosophy and Psychology*, pages 1–17.

Wood, G. S. (1982). Conspiracy and the Paranoid Style: Causality and Deceit in the Eighteenth Century. *The William and Mary Quarterly*, 39(3):402–441. Publisher: Omohundro Institute of Early American History and Culture.

Zehring, M. and Domahidi, E. (2023). German corona protest mobilizers on telegram and their relations to the far right: A network and topic analysis. *Social Media + Society*, 9(1):20563051231155106.