Conspiracy Narratives in the Protest Movement Against COVID-19 Restrictions in Germany. A Long-term Content Analysis of Telegram Chat Groups.

Manuel Weigand
Goethe University Frankfurt
weigand.mnl@gmail.com

Maximilian Weber
Goethe University Frankfurt
m.weber@soz.uni-frankfurt.de

Johannes Gruber
Vrije Universiteit Amsterdam
j.b.gruber@vu.nl

Abstract

From the start of the COVID-19 pandemic in Germany, different groups have been protesting measures implemented by different government bodies in Germany to control the pandemic. It was widely claimed that many of the offline and online protests were driven by conspiracy narratives disseminated through groups and channels on the messenger app Telegram. We investigate this claim by measuring the frequency of conspiracy narratives in messages from open Telegram chat groups of the *Querdenken* movement, set up to organize protests against COVID-19 restrictions in Germany. We furthermore explore the content of these messages using topic modelling. To this end, we collected 822k text messages sent between April 2020 and May 2022 in 34 chat groups. By fine-tuning a Distilbert model, using self-annotated data, we find that 8.24% of the sent messages contain signs of conspiracy narratives. This number is not static, however, as the share of conspiracy messages grew while the overall number of messages shows a downward trend since its peak at the end of 2020. We further find a mix of known conspiracy narratives make up the topics in our topic model. Our findings suggest that the *Querdenken* movement is getting smaller over time, but its remaining members focus even more on conspiracy narratives.

1 Introduction

Conspiracy narratives already existed way before the rise of social networks or messenger services (see Goertzel, 1994), but their spread was generally modest. In the last decade, however, there have been recurrent debates about the rise of conspiracy narratives in public and media discourse. Two factors in particular are made responsible for this: first, social networks have allowed so-called alternative news media to emerge, exposing the visibility of the widespread existence of conspiracy narratives in society; and second, the COVID-19 pandemic was a catalyst for misinformation, conspiracy narratives, and populist protest (Boberg et al., 2020) over the last two years. Research in the past has shown that conspiracy narratives emerge more likely when people feel loss of control and uncertainty (Goertzel, 1994; Lamberty, 2020). It was, therefore, not surprising that conspiracy narratives began to circulate relatively quickly at the onset of the COVID-19 pandemic.

In Germany, several demonstrations against measures of the government to control the COVID-19 pandemic began to take place in the middle of 2020. In the context of this movement, criticism of government measures often merged with the belief that conspiratorial secret organizations ultimately determine the actions of governments during the pandemic. Over time, the so-called *Querdenken* (transl. to "lateral thinking") movement emerged as the main collective that organised many of the protests and connected groups scattered throughout Germany. In particular, the Stuttgart initiative *Querdenken 711* was a role model for many smaller initiatives in numerous regions of Germany. At the movement's demonstrations, the prevalence of common conspiracy narratives could not be missed. As Lamberty et al. (2022) have suggested, the messenger service Telegram played a major role in the mobilization and organization of the protests in Germany. Furthermore, Simon et al. (2022) suggest that the affordances of Telegram as a platform with lenient content guidelines led to networks forming around more radical content and the spread of conspiracy narratives in Dutch-language public Telegram channels discussing developments in the COVID-19 pandemic.

In this short contribution, we analyze conspiracy narratives in Telegram groups in the specific context of the *Querdenken* movement using supervised and unsupervised machine learning approaches for a systematic automated content analysis. We attempt to focus on conspiracy narratives, following

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a relatively basic operationalization: conspiracy narratives are beliefs and convictions that attempt to interpret historical and contemporary events and general societal changes as a conspiracy and/or secret plan by a group of powerful actors (Pigden, 1995; Keeley, 1999). Scholars have pointed out that the prevalence of conspiracy narratives could be one key indicator of radicalization (Schulze et al., 2022), as it could act as "radicalization catalysts" (Lamberty, 2020). We, therefore, address important concerns for social cohesion with our two research questions:

RQ1: How prevalent are conspiracy narratives in Telegram groups that set out to organize protest against COVID-19 measures in Germany over time?

RQ2: What kind of conspiracy narratives make up the discussion in these groups?

Additionally, we want to know how to automatically detect conspiracy narratives from a technical standpoint in order to pave the way for broader scope research on the topic.

2 Data

We use data from *Querdenken* Telegram chat groups that are publicly viewable without joining the groups (see Appendix A for selection process and list of groups). There are also info channels where only selected people can post, while in the open chat groups anyone who joins can post. To protect the privacy of message senders, we only use the time and text of a sent message. We use all public chat groups that are advertised on a page of the main initiative.

2.1 Dataset

We crawled over one million messages sent between 29.04.2020 and 29.05.2022. Since we focus on text messages, messages that contain only a video, an image or a link have been removed with regular expressions. Resulting in a corpus of 821,903 messages that were exchanged in 34 groups. In the beginning, the *Querdenken* initiative was primarily active in Southern Germany. In Eastern Germany, the *Querdenken* movement never established a foothold as other groups already occupied the same ideological space. However, we decided to focus on the *Querdenken* groups because of their supposed appeal on a wider part of society.

2.2 Annotation

We use expert annotations to manually code a sample of the messages. Four experts labeled 4,863 messages. In addition, to compare intercoder reliability, each expert also labeled the same 100 randomly selected messages. The κ agreement is 0.82. The guidelines for annotating differentiates between two classes. A message is annotated as showing signs of conspiracy (annotated as 1) if it clearly indicates signs of conspiracy narratives (see Appendix B for details). A message is annotated as not showing signs of conspiracy (annotated as 0), if no terminology related to know conspiracy is used or the coder cannot determine if the message contains signs of conspiracy narratives.

3 Methods

The manually labeled data is used to train different supervised machine learning models. The best performing model is a fine-tuned distilbert model (Sanh et al., 2019). To evaluate the performance of the models, we use 5-fold cross-validation. We fine-tune an already fine-tuned model for German toxic comment classification – “distilbert-base-german-cased-toxic-comments” (ML6 Team, 2022). Our model classifies the messages in a 2-way classification (message shows signs of conspiracy / does not show signs of conspiracy). The average macro F1-Score for this model is 0.851 and therefore outperforms other experiments (e.g. SVM, Naive Bayes). However, the SVM had an F1-Score of 0.69 for the class "signs of conspiracy" (compared to 0.76 for the best performing model) while being less computationally expensive. The best performing method, the fine-tuned distilbert model is trained on all annotated data to get the final model, which we use to automatically label the remaining 822k messages.

To analyze trends in the data, we perform a frequency analysis. In addition, we analyze the topics of messages showing signs of conspiracy by using a Structural Topic Model (STM).

	F1	SD	Recall	Precision
no signs of conspiracy	0.946	0.006	0.966	0.927
signs of conspiracy	0.757	0.017	0.692	0.837
macro avg	0.851	0.012	0.829	0.882

Table 1: F1-Scores for the different labels and Macro F1-Score. Mean and standard deviation over 5 runs with different test and dev sets

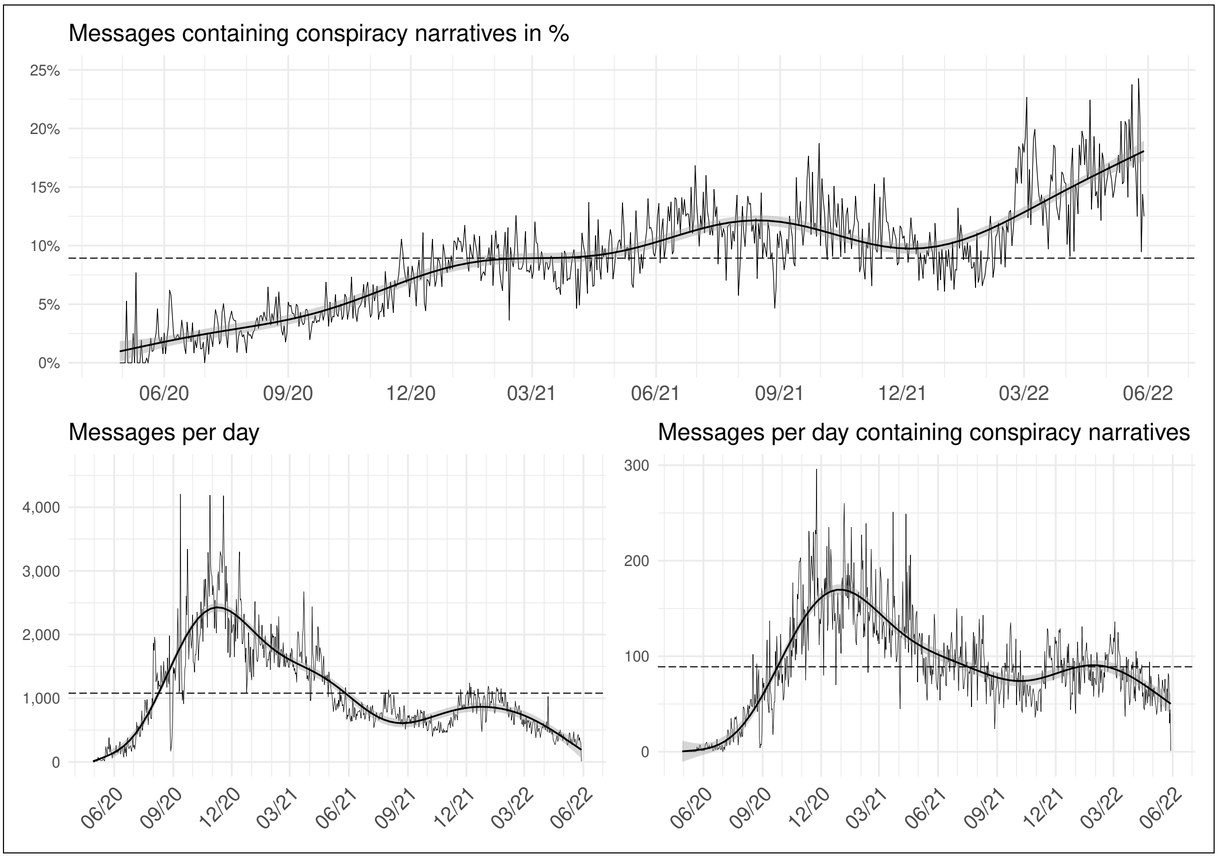

Figure 1: Trend curves. Ratio of messages that include signs of conspiracy over time (top graph). Frequency of messages sent in the chat groups (bottom left) and frequency of messages containing signs of conspiracy over time (bottom right)

4 Temporal analysis

Over a period of more than two years, users in the groups we analyzed sent an average of 1080 messages per day. The number of messages, and thus the activity of the groups, had its peak towards the end of 2020. Since then and especially the mid of 2021, the participation has been on a downward trend and the groups of the *Querdenken* movement were no longer active by the same degree. In April 2022, the monitored groups averaged around 457 messages per day.

Concerning the prevalence of conspiracy narratives (**RQ1**), our trained model identified 67,698 messages containing characteristics of conspiracy narratives, representing 8.24% of the total corpus. Over the two years, the average was 89 messages per day. With regard to the distribution of all messages in the corpus, the identified messages containing conspiracy narratives follow a similar trend. The prevalence of classified messages is highly correlated with the total message volume, and peaked at the end of 2020 and has been on a downward trend since then, although not quite as steep as the total message volume. However, we found an increasing uptrend in the proportion of messages containing conspiracy narratives to the whole corpus. A look at these numbers confirms this impression: The share of messages containing signs of conspiracy narratives is increasing over time and is still ongoing. In particular, a further increase has been noticeable since February 2022 peaking at values around 20%.

5 Topic Model

We chose an STM model with 10 topics after following the approach outlined by Roberts et al. (2019) to decide on an optimal number of k (see Appendix C for details). Table 2 shows the five words with the highest β-probability and the highest FREX value (Airoldi and Bischof, 2016) respectively.

What we find is that most of the topics describe different categories of common conspiracy narratives (**RQ2**). The most prevalent topics describe how the "Altparteien" (old parties) would control the media to stay in power (T5), how the govern-

Table 2: STM Topics

Topic (prevalence)		Terms
T5 (21.8%)	prob	germany, government, politics, state, land
	FREX	afd, antifa, querdenker, vote, the left
T3 (12.8%)	prob	vaccination, virus, dr, pandemic, vaccine
	FREX	study, pcr-test, infection, tested, rki
T9 (12.8%)	prob	people, children, life, fear, world
	FREX	humanity, nature, old, suffering, earth
T7 (10.1%)	prob	__, t.me, channel, video, media
	FREX	t.me, subscribe, stuttgart basic law protests, kenjebsen, wearemore
T1 (9.1%)	prob	reset, great, money, world, million
	FREX	reset, ikb, great, partner, donate
T6 (9.1%)	prob	usa, the, gates, ukraine, russia
	FREX	ukraine, russia, putin, biden, nato
T4 (9.1%)	prob	freedom, people, police, resistance, berlin
	FREX	stage, restoration, streets, rally, peaceful
T10 (6.9%)	prob	merkel, measures, lockdown, germany, federal government
	FREX	chancellor, bundestag, chancellor, angela, autumn
T8 (5.4%)	prob	telegram, o'clock, compulsory vaccination, flag:German, think
	FREX	1k, news, flag:Austrian, @faktenfriedenfreiheit, web
T2 (2.8%)	prob	health, masks, mask, work, phone
	FREX	phone, ministry, social, integration, nothing

[a] Some Unicode characters were replaced (e.g., flag:German used to be a flag emoji)
[b] German words were translated, see original version of the table in Appendic C)
[c] German compound words have been separated in the translation

ment and other elites would conceal how damaging the corona vaccine is and use allegedly fake PCR-tests to convince people they are sick (T3), and that the vaccination campaign and mandatory vaccination laws are illegal and constitute crimes against humanity that are supposedly already fought in several court cases (T9). Two topics tie in with a collection of larger global-scale conspiracies narratives like the *"Great Reset"* (T1) and narratives in which Bill Gates, Barack Obama, Joe Biden or the *"Deep State"* secretly control the pandemic, the vaccine as well as other crises in the world (T6). Interestingly, Russia's war on Ukraine is lumped in here and the US or the aforementioned actors are made responsible for it — essentially repeating some of the claims spread by Russian news. Consequently, T6's prevalence increases massively, after the start of the invasion on 24 February 2022 — which is the only noteworthy shift in prevalence for a topic over time (see details in Appendix C). In the less prevalent topics we see narratives talking about the obligation of "awake" citizens to resist against the elites who try to use Corona to control the "sleeping" mainstream public of Germany (T4); how the measures against the pandemic would secretly constitute a power grab similar to the "Ermächtigungsgesetz von 1933" (Enabling Act of 1933) (T10); and narratives surrounding the alleged negative and harmful impact of masks (T2).

Overall, we are able to directly link most of the topics to known conspiracy narratives. The two exceptions are T8 and T7 which inform about future protest events and advertise alternative news content, often with a reference to censorship and how the content was already removed from YouTube or archives of TV-stations, allegedly because it contains the truth.

6 Conclusion

In this paper, we explored conspiracy narratives in German Telegram chat groups in which people organize protest against restrictions introduced due to the COVID-19 pandemic (i.e. the *Querdenken* movement). Using an automated machine learning approach, we were able to analyze 822k text messages sent in open chat groups. Despite the decrease in overall activity in the Telegram groups since late 2020, we found an upward trend in the relative share of messages containing conspiracy narratives. The topic model maps the different types of conspiracy narratives that we encountered in the dataset and that play a role in the group discussions. Moreover, the fact that almost all themes can be clearly linked to a conspiracy narrative shows the robustness of our approach to automatically detect conspiracy narratives despite remaining uncertainty in the Distilbert model.

Our analysis suggests that the remaining core of people in the *Querdenken* Telegram groups is increasingly immersed in conspiracy narratives, which appear to become the ideological reference point of the movement after many of the measures implemented to control the pandemic in Germany have been lifted. This might be a meaningful issue considering that beliefs in conspiracy narratives are a key element of radicalization dynamics (Schulze et al., 2022). Moreover, because the affinity for conspiracy narratives, or the individual "conspiracy mentality", as social psychologists (Imhoff and Bruder, 2014; Lamberty et al., 2022) refer to it, could lead the remaining core of the movement to shift to other topics, which are suitable for conspiracy ideological mobilization. We observe, for example, that much news regarding the Russian invasion in Ukraine are made sense of in the groups by falling back on previously common narratives of international cabals, predominantly from the US, who allegedly control crises in the world for their own gains. In the future, this increasing detachment from reality could bring with it the potential for further disintegration of social cohesion in Germany.

We acknowledge the limitation that our study excluded most protest groups from East Germany, as some of these do not operate under the label of the *Querdenken* movement, even if they share some of the same goals and ideologies.

7 Ethical Considerations

All data we use in the analysis is publicly available through the official Telegram API, or in the Telegram App itself, and joining the public groups we queried is not necessary to gain access (see Appendix A for details on the groups). We did not collect or store any user data, such as telephone numbers, names or user handles of group members. The metadata for each message consists only of the group URL and timestamp. When we show individual messages as examples, we do not disclose the time of posting or the group name, to minimize any remaining impact on the anonymous authors of the message. Therefore, we do not expect any negative impact on the authors of the messages we examine. We follow the Terms of Service of the Telegram API: https://core.telegram.org/api/terms.

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Appendix

A Data

We use all public chat groups of the local *Querdenken* initiatives linked on the initiative's directory on May 1, 2022 at https://app.querdenken-711.de/initiatives-directory. The groups add parts of the local area telephone code to their name. The telegram groups are named accordingly: "https://t.me/querdenken[number]". List of the groups: 201, 215, 234, 235, 238, 242, 284, 30, 351, 381, 441, 511, 53, 6051, 615, 6201, 621, 69, 713, 7141, 7171, 718, 7192, 721, 751, 762, 763, 775, 791, 793, 8331, 8341, 89m, 911. All publicly available Telegram posts were collected via Python and the Telethon library, which is built on top of the official Telegram API.

B Coding Guidelines

Read the guidelines for annotating conspiracy narratives carefully

Definition of conspiracy narratives

- The belief and conviction in narratives which try to interpret historical and present events and general social change as a conspiracy and secret plan of a group of powerful actors.

Guiding Questions

- There are secret organizations that have great influence on political decisions

- Politicians and other leaders are just puppets of the powerful actors behind them

- The government uses COVID-19 to monitor and control the people

- The government conceals the truth from the population

- COVID-19 is orchestrated by (evil) actors

General Rules

- Do not take links (urls) into account when annotating

- Emojis, if easily interpretable, can be taken into account

- When annotating use the scheme: contains no signs of conspiracy narratives: 0, contains signs of conspiracy narratives: 1

- A message is annotated as **not showing signs of conspiracy (annotated as 0)**, when at least one of the following is true:

  1. The message contains no signs of conspiracy narratives
  2. The message contains terminology related to known topics of conspiracy narratives
  3. It cannot be determined, whether the message contains signs of conspiracy narratives (e.g., since referenced information is missing or unknown)

- A message is annotated as **showing signs of conspiracy (annotated as 1)**, when:

  1. The message clearly indicates signs of conspiracy narratives
  2. One of the guiding questions applies

Examples

Example messages that should be considered as showing signs of conspiracy:

- "Ist auch nichts anderes als in Deutschland. Das ist ein vom Deep State finanzierte Radiosender." [*"It's no different than in Germany. It's a Deep State-funded radio station."*]

- "[...] wie der Krieg jetzt mit der Plandemie zusammenhängt [...]" [*[...] how the war is now connected with the plandemy [...]*]

- "Die Verbrecher sind erst zufrieden, wenn sie ihre Agenda vom Great Reset durchgeknüppelt haben. Dazu muss der Bürger mit aller Macht gezwungen werden. Da spielen menschliche Opfer keine Rolle." [*"The criminals will not be satisfied until they have bludgeoned through their agenda of the Great Reset. The citizen must be forced to do this with all his might. Human sacrifice doesn't matter."*]

- "[...] das gelingt bei vielen die masse schaut auf den virus und der wef kann im hintergrund mit hilfe der regierungsmarionetten das system umwandeln wie auch immer das dann aussehen soll" [*"[...] this succeeds with many the masses look at the virus and the wmf can transform the system in the background with the help of the government puppets however that should look then"*]

- "[...] ihr ziel durch zwangsimpfungen die zahl der toten zu maximieren wird in seiner ganzen skrupellosigkeit erkennbar [...]" [*"[...] their goal of maximizing the number of deaths through compulsory vaccination becomes apparent in all its unscrupulousness [...]"*]

- "Das interessiert Merkel nicht, auch nicht die pharmaindustrie(Bill gates). Die Diktatur hat gestern begonnen, als Merkel sagte, nicht geimpfte werden vom Leben ausgeschlossen. Sie hat damit einen Buerger Krieg angezettelt." [*"Merkel doesn't care, neither does the pharma industry(Bill gates). The dictatorship started yesterday when Merkel said unvaccinated will be excluded from life. She started a civil war with that."*]

C Details on the topic modelling with STM

As suggested by Roberts et al. (2019), we ran STM models with the same parameters ($\alpha = 50/k$, $\eta = 0.01$) but varying k from 5 to 15 topics. We then calculate semantic coherence (Mimno et al., 2011) and exclusivity for each topic in each model. As (Roberts et al., 2014) note, high semantic coherence can be obtained by choosing a low number for k. However, exclusivity usually increases with k, meaning that one can evaluate an optimal number of topics by considering the trade-off between the two. In Figure 2, we see that 10 appears to be a good choice for a k as there is a local peak for the mean semantic coherence while exclusivity still grows from 9 to 10 topics.

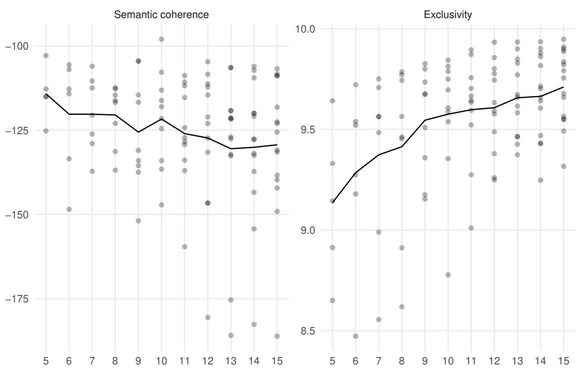

Figure 2: Model diagnostics by number of topics

Table 3: STM Topics, German original

Topic (prevalence)		Terms
T5 (21.8%)	prob	deutschland, regierung, politik, staat, land
	FREX	afd, antifa, querdenker, wählen, linken
T3 (12.8%)	prob	impfung, virus, dr, pandemie, impfstoff
	FREX	studie, pcr-test, infektion, getestet, rki
T9 (12.8%)	prob	menschen, kinder, leben, angst, welt
	FREX	menschlichkeit, natur, alten, leiden, erde
T7 (10.1%)	prob	__, t.me, kanal, video, medien
	FREX	t.me, abonnieren, stuttgartgrundgesetzdemos, kenjebsen, wirsindvielmehr
T1 (9.1%)	prob	reset, great, geld, welt, millionen
	FREX	reset, ikb, great, partner, spenden
T6 (9.1%)	prob	usa, the, gates, ukraine, russia
	FREX	ukraine, russia, putin, biden, nato
T4 (9.1%)	prob	freiheit, menschen, polizei, widerstand, berlin
	FREX	bühne, wiederherstellung, straßen, kundgebung, friedlich
T10 (6.9%)	prob	merkel, maßnahmen, lockdown, deutschland, bundesregierung
	FREX	kanzlerin, bundestag, bundeskanzlerin, angela, herbst
T8 (5.4%)	prob	telegram, uhr, impfpflicht, flag:German, denkt
	FREX	1k, news, flag:Austrian, @faktenfriedenfreiheit, web
T2 (2.8%)	prob	gesundheit, masken, maske, arbeit, telefon
	FREX	telefon, ministerium, soziales, integration, nix

[a] Some Unicode characters were replaced (e.g., flag:German used to be a flag emoji)

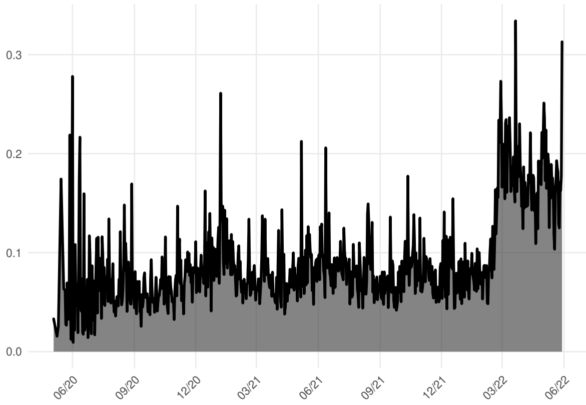

Figure 3: Topic prevalence (mean γ) over time for T6

Table 3 shows the original German version of Table 2. Figure 3 displays the change in prevalence over time for Topic 6.