Appendices

Appendix A. Dutch access words used to identify Telegram chats and channels

Politics related:

politiek, verkiezingen, forum voor democratie, JFVD, JA21, partij voor de vrijheid, groenlinks, bij1, thierry baudet, geert wilders, mark rutte, wybren van haga, lilian marijnissen

Internet celebrities mentioned by the media with respect to conspiracy thinking:

jensen, lange frans, don maarten

(Alternative) news related:

nieuws, de dagelijkse standaard, geenstijl, cafe weltschmerz, onafhankelijke pers nederland, blck bx tv, de redacteur

Protests and activism related:

actie, avondklok, demonstratie, koffie, nederland, ouders, opstand, recht, rellen, samen, tegen, verzet, vrijheid, wakker, viruswaarheid, viruswaanzin, vizier op links, moders voor vrijheid, vrouwen voor vrijheid, gewoonvrij

Conspiracy related:

waarheid, qanon nederland, nederland, q patriots, platte aarde, complot, wrwy, red pill, covfefe, WWG1WGA

(Con)spirituality related:

bewust, verstand, spiritueel, natuur, jezus, vrouwenkracht, partij de nieuwe mens, liefde

Health and COVID-19 related:

zorg, vaccinatie, artsen, mondkapje, coronavaccin, gezondheid, informatie

Access words that did not yield chats and channels:

fvd, pvv, juiste antwoord, Joost Eerdmans, boerburgerbeweging, caroline van der plas, vvd, Volkspartij voor Vrijheid en Democratie, Mark Rutte, d66, Democraten 66, Sigrid Kaag,groenlinks, Jesse Klaver, Sylvana Simons, pvdd, partij voor de dieren, Esther

Ouwehand, sp, socialistische partij, pvda, partij van de arbeid, Lilianne Ploumen, cda, Christen-Democratisch Appel, Wopke Hoekstra, christenunie, Gert Jan Segers, sgp, Staatkundig Gereformeerde Partij, Kees van der Staaij, beweging denk, Farid Azarkan, 50plus, Liane den Haan, Volt Nederland, Laurens Dassen, politicus, tweede kamer, Willem Engel

Appendix B. Screenshot of tweet

Figure 7. The leader of the Dutch far-right party encourages his Twitter followers to follow his party on Telegram.

Appendix C. URL-s in data set

From the total of 217,428 unique URL-s that were shared in our data set, the most shared domain was YouTube with 37883 entries, which made up over 10,4% of all URL-s shared in our data set. Two unique URL-s were shared by the most channels or chats (*n* = 45) on a given day. The content of both URL-s was accessed via the "Wayback Machine"(*Wayback Machine*, n.d.) – a digital archive of websites and web content– given that both were removed since their publishing date. One of the top shared URL-s was a link to a since-deleted YouTube video (i.e., due to violating platform guidelines) of the leader of the far-right party (FvD), Thierry Baudet, where he "exposed" the Rockefeller foundation during a speech in the Dutch Parliament. The other URL linked to an official PDF file published by the Council of Europe debating ethical and legal considerations of combating the coronavirus pandemic.

We resolved all the shortened URLs and removed meaningless URLs using the steps outlined below.

According to our analyses, there were a total of 7957 shortened URLs based on a list of known shorteners (N = 85). This constituted 2.2 percent of the analyzed URLs. After resolving these shortened URLs we obtained the domain of each URL (i.e., the resolved list containing all the long URLs and those that used to be shortened) and used this list to filter out all instances where a given URL was only pointing to a domain (e.g., https://web.telegram.org) or it was incomplete/broken (https://www.bpoc2020).

Following these steps we filtered out a total of 60 URLs that pointed to domains or were broken/incomplete URLs (i.e., not fully typed or incomplete or containing extra characters that broke the URL). Arguably even if these incomplete or incomplete/wrongly typed URLs were forwarded in their broken state, the fact that users did not have access to what was behind those URLs should exclude them from further analyses. We repeated the network analyses using the final list of resolved URLs.

Appendix D: Temporal development of chat and channel activity

The bottom graph of Figure 4 illustrates that during the first time period there were very few active chats and channels that had users who sent messages. Specifically, we don't see many chats and channels that were active for the most part of T1 (until 2020-03-19). However there appears to be a slight increase in the amount of active chats and channels starting from the end of 2018, and especially from the second half of 2019 which is partly in line with the findings of Urman and Katz (2020) who observed a huge spike of new far-right channels starting from mid 2019.

Although this time period roughly coincides with major bans of far-right users on mainstream social media such as Facebook and Instagram (Hern, 2019; Lorenz, 2019), we only see a small increase in activity. Hence, the reason behind the slight uptick may be better explained by the increase of Telegram usage in general, which escalated dramatically between 2018 and 2019 (i.e., from 200 million to 300 million), and has been increasing in the same rate (i.e., 100 million additional users each year) to date (**?**). A more substantive, and gradual increase in the number of chats ans channels over time can be more clearly observed starting T2. It appears that more chats and channels were active since COVID-19 was declared a pandemic in March 2020. Furthermore, T3 represents a shorter but very active period with regards to chat and channel activity over time. The figure illustrates that as the Dutch government introduced stricter lockdown measures, which included a curfew, the amount of active chats and channels over time has increased and remained high in general until the end of T3.

Appendix E: Codebook

Our aim was to categorize chats and channels based on what they promised to stand for. Specifically, given that the chat and channel names may be the first aspect that users rely on when upon deciding whether they wish to join a chat or channel, we also decided to categorize chats and channels based on what they claim to stand for rather what they actually deliver (which we learned can be very different things). Channels and chats were categorized by the following criteria:

Categories:

- politics (in general, such as elections)
- pol_right (right-wing politics)
- pol_left (left-wing politics)
- act_freedom (activism for freedom of speech)
- act_farmers (farmers protest groups)
- act_covid (activism against COVID-19 measures)
- act_riot (riots in response to COVID-19 measures)
- alt_news (alternative news)
- mainstream_news (mainstream news)
- alt_news_celeb (alternative news catered by internet celebrities)
- anti_establishment (explicitly anti-establishment groups)
- covid (groups dedicated to discussing corona in general)
- covid_conspiracy (groups dedicated to discussing corona as a conspiracy)
- conspiracy (groups where spirituality and conspiracy thinking fuses together)
- spirituality (groups dedicated to religious or spiritual activities)
- health_wellness (health and wellness group)
- doxxing (public revealing of personal information and attack on individuals)

If channel/chat available follow the steps below: Always start with the name of the channel (what does it promise)

- If chat channel name refers to any of the categories above select the most applicable category.
- If chat channel name ambiguous check whether the description refers to any of the categories above select the most applicable category.
- If description not available or unclear scroll to the first post of the chat/channel and find the most appropriate category
- If the first messages are not clearly indicating the topic of the chat/channel scroll further until it become clear.
- If all messages are deleted pick category based on title
- If title unclear categorize as uncategorized

If channel/chat taken offline:

- Judge by the name of the chat or channel the category as close as possible.
- If not possible then categorize it as uncategorized.

Appendix F: Chat and channel types

Table 1.: Chats and channels.

Chat/Channel ID	Type	Size	Category
fvd_nl	chat	363.0	pol_right
Forumvoordemocratiefvd	chat	48.0	pol_right
fvdfans	chat	11.0	pol_right
jfvdnl	chat	27.0	pol_right
wilderspvv	chat	271.0	pol_right
partijvoordevrijheid	chat	63.0	pol_right
geertwildersss	chat	40.0	pol_right
vriendenvangeertwilders	chat	82.0	pol_right
FvDgroup	chat	19.0	pol_right
NLPolitiek	chat	96.0	politics
verkiezingen2021	chat	6.0	politics
DeBataafseRepubliek	chat	7989.0	conspiracy
deredacteur	chat	692.0	alt_news
sameninactie	chat	644.0	act_freedom
beeldmateriaal	chat	448.0	act_farmers
InfoAvondklok	chat	1120.0	act_covid
boete_avondklok	chat	809.0	act_covid
avondkloknl	chat	6.0	act_covid
worldwidenetherlands	chat	8920.0	act_freedom
vervoervoordemonstranten	chat	2095.0	act_freedom

NederlandWorldWideDemonstration	chat	1896.0	act freedom
vervoervoordemonstrantenchat	chat	NAN	act freedom

Table 1 – *Continued from previous page*

Chat/Channel	Type	Size	Category
defendrotterdam	chat	136.0	act_freedom
DeKoffieClub	chat	585.0	act_covid
dvo_open_koffiecorner	chat	357.0	act_covid
deparallellemaatschappij	chat	922.0	act_freedom
Nederland_in_het_verzet	chat	700.0	act_freedom
vrijewinkel_nederland	chat	1493.0	act_freedom
oudersmetzorgen	chat	491.0	act_covid
ouders0497	chat	34.0	act_covid
wakkereouders	chat	14.0	act_covid
bezorgdeoudersschijndelchat	chat	59.0	act_covid
oudersvoorvrijheid	chat	378.0	act_freedom
jongereninopstand	chat	565.0	act_freedom
burgerwachtNio	chat	258.0	act_freedom
boereninopstand	chat	352.0	act_farmers
denhaaginopstand	chat	127.0	act_covid
boereninopstand2_0	chat	55.0	act_farmers
opstand19	chat	7.0	act_covid
VechtVoorRechtt	chat	393.0	pol_right
rellennl2	chat	3388.0	act_riot
rellen1	chat	7265.0	act_riot
eindhovenrwinachat	chat	683.0	act_riot
rellen023	chat	268.0	act_riot
rellen3	chat	NAN	act_riot
samen1voornl	chat	1001.0	act_freedom

Table 1 – *Continued from previous page*

Chat/Channel	Type	Size	Category
neetegen15meter	chat	489.0	act_covid
Kletschat burgers tegen onrecht	chat	181.0	act_freedom
SpoedWet	chat	172.0	act_covid
vrijheid	chat	59.0	act_freedom
WijZijnDeVrijheid	chat	1651.0	act_freedom
klokkenchat	chat	3017.0	act_freedom
GeweldTegenWakkeren	chat	80.0	act_freedom
wakkerenchat	chat	1192.0	conspiracy
wwncommunity	chat	871.0	conspiracy
wakkerAmsterdam	chat	503.0	conspiracy
wakkergroningen	chat	505.0	conspiracy
wakeyupp	chat	736.0	conspiracy
wakkere	chat	NAN	conspiracy
gewoonvrij	chat	NAN	act_freedom
waarheidbovenalles	chat	786.0	conspiracy
deelwatjeweet	chat	111.0	covid
zoektocht	chat	37.0	conspiracy
covidwaarheid	chat	22.0	covid
nederlandsverzet21	chat	10395.0	conspiracy
ikknaagaandepotenvanRutteenKaag	chat	4801.0	act_freedom
QPatriotsEindhoven	chat	342.0	conspiracy
complotgekkies	chat	8.0	conspiracy
whereWeGo1WeGoAlll	chat	909.0	conspiracy
SpiritualiteitOpHollandseBodem	chat	10.0	spirituality

Table 1 – *Continued from previous page*

Chat/Channel	Type	Size	Category
vaccinatiewaarheid	chat	484.0	covid
natuurlijf_chat	channel	40.0	health_wellness
NatuurlijkVrijOnderwijsGO	chat	26.0	act_freedom
JEZUSLEEFTOFFICIAL	chat	NAN	spirituality
PartijDeNieuweMens_chat	chat	15.0	spirituality
bronvanonvoorwaardelijkeliefde	chat	319.0	spirituality
geloofhoopliefde	chat	23.0	spirituality
mondkapjesverzetgroep	chat	1023.0	covid
zondermondkapje	chat	211.0	covid
boetemondkapje	chat	268.0	covid
coronavaccinschatgroep	channel	664.0	covid_conspiracy
coronavaccinsbijwerkingen	channel	2371.0	covid_conspiracy
gezondheidineigenhand	channel	137.0	health_wellness
natuurlijkegezondheid	channel	174.0	health_wellness
gezondegeest	channel	44.0	spirituality
kritischezorgverleners	channel	121.0	act_covid
virussenbestaanniet2	channel	68.0	conspiracy
artsenvoorvrijheid	channel	4766.0	act_covid
mondkapjesverzet	channel	258.0	act_covid
mondkapjesontheffing	channel	36.0	covid
vaccinatie	channel	20.0	covid_conspiracy
zorgmedewerkersverenigd	channel	949.0	act_covid
ikzorgenbenwakker	channel	204.0	conspiracy
liefde_en_verbinding	channel	6.0	spirituality

Table 1 – *Continued from previous page*

Chat/Channel	Type	Size	Category
optochtliefdeenlichtRotterdam	channel	12.0	act_covid
fakkeltochtemmen2021	channel	23.0	spirituality
Liefdespioniers	channel.	21.0	spirituality
Waarheid_Eindtijd Profetie	channel	221.0	conspiracy
vrouwenkracht_academie	channel.	358.0	spirituality
PartijDeNieuweMens	chat	26.0	spirituality
degeboden	channel	61.0	spirituality
natuurlijf	channel	389.0	health_wellness
joumij	channel	78.0	spirituality
gezelligspiritueel	channel	18.0	spirituality
eefbewustnederland	channel	25101.0	health _wellness
bewustzijncentrumapofyliet	channel	151.0	spirituality
bewustrein	channel	17.0	conspiracy
BewustmakendNEWSNOW	chat	110.0	alt_news
c0r0naboelsjit	channel	711.0	covid_conspiracy
wrwynl	channel	407.0	conspiracy
RedPillJournal	channel	NAN	conspiracy
covfefereport	channel	787.0	conspiracy
platteaarde	channel	314.0	conspiracy
complotmemes	channel	NAN	conspiracy
complotwappies	channel	67.0	conspiracy
onderzoekenvancomplotten	channel.	19.0	conspiracy
qanon_GLF AstharCommanders	channel	103.0	conspiracy
Qnld_2020	channel	24.0	conspiracy

Table 1 – *Continued from previous page*

Chat/Channel	Type	Size	Category
QanonNederland	channel	14.0	conspiracy
Waarheid	channel	27.0	conspiracy
GeleHesjesCentraal	channel	8.0	act_freedom
viruswaanzin	channel	13548.0	covid_conspiracy
viruswaarheidvideos	channel	144.0	covid_conspiracy
viruswaarheid_zooms	channel	66.0	covid_conspiracy
viuswaarheid	channel	10.0	covid_conspiracy
viruswaanzinbelgie	channel	369.0	covid_conspiracy
viruswaanzinbe	channel	36.0	covid_conspiracy
vizieroplinks	channel	4766.0	doxxing
XRNLbroadcast	channel	1347.0	act_climate
moedersvoorvrijheid	channel	392.0	act_freedom
vrouwenvoorvrijheid	channel	5796.0	act_freedom
WakkerWezen	channel	7572.0	alt_news
Wakker2020	channel	524.0	alt_news
verzetsblaadje	channel	200.0	anti_establishment
verzetwestland	channel	261.0	anti _establishment
demonstratietegendeoverheid	channel	21.0	anti _establishment
klokkenluiders	channel	31998.0	act_freedom
klokkenvideos	channel	1501.0	act_freedom
finaciele	channel	460.0	act_freedom
vrijheids	channel.	36.0	act_freedom
neetegenanderhalvemeter	channel	1727.0	act_covid
demo_vervoer	channel	427.0	act_freedom

Table 1 – *Continued from previous page*

Chat/Channel	Type	Size	Category
burgerstegenonrecht	channel	26.0	act_freedom
rellen2	channel	1622.0	act_riot
eindhovenrwina	channel	927.0	act_riot
RechtsVerbonden	channel	59.0	pol_right
nederlandinopstand	channel	646.0	anti_establishment
wijdeouders	channel	2607.0	act_covid
devrijeomroep_koffiecorner	channel.	85.0	alt_news
avondklok	channel	329.0	act_covid
avondklokn	channel	51.0	act_covid
FuckAvondKlok	channel	33.0	act_covid
avondklokzeeland	channel	35.0	act_covid
avondklokamsterdam	channel	28.0	act_covid
DeDagelijkseStandaard	channel	3048.0	alt_news
dagelijksestandaard	channel	79.0	alt_news
thepostonline	channel	33.0	alt_news
geenstijll	channel.	242.0	alt_news
cafeweltschmerz	chat.	5984.0	alt_news
onafhankelijkepers	channel	3976.0	alt_news
blckbxtv	channel	13509.0	alt_news
bataafsenieuws	channel	5490.0	alt_news
leefbewust	channel	1669.0	health_wellness
robertjensenshow	channel	2149.0	alt_news_celeb
langefranspodcast	channel	9172.0	alt_news_celeb
donmaartenofficial	channel	891.0	alt_news_celeb

Table 1 – *Continued from previous page*

Chat/Channel	Type	Size	Category
onkorrekt	channel	58.0	conspiracy
PolitiekBIJ1	channel	34.0	pol_left
thierrybaudet	channel	858.0	pol_right
Juiste	channel	429.0	pol_right
JongerenFVD	channel	548.0	pol_right
FvDMedia	channel	37.0	pol_right
FVDNL	channel	26346.0	pol_right
fvdgeluid	channel	5169.0	pol_right

Note: All chats and channels categorized

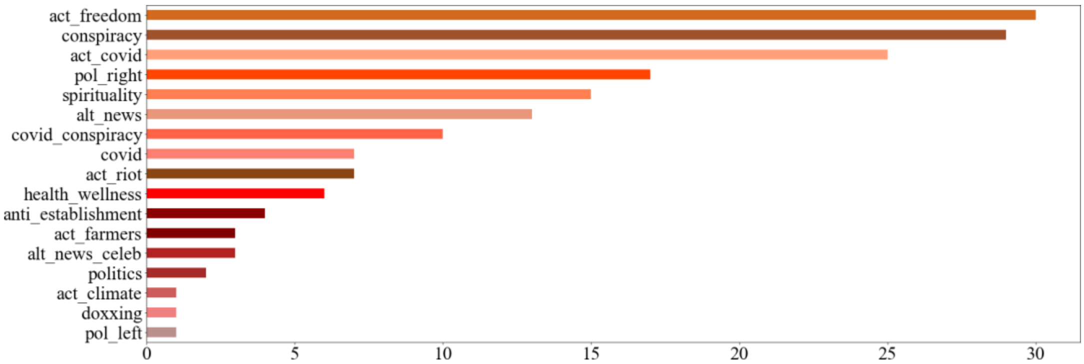

Figure 8. Frequency of chats and channel types.

Appendix G: Alternative data collection approaches

We also considered two alternative data collection approaches hoping to gather a more comprehensive collection of Dutch-language Telegram chats/channels. The first method was searching through two existing large databases: Tgstat.com, and the Pushshift Telegram data set. (Baumgartner, Zannettou, Keegan, Squire, & Blackburn, 2020). Both of these databases proved to be unsuitable either due to the availability of very few, or no Dutch-language chats/channels (corresponding to our search queries).

Appendix H: Network metrics

.1. Network Measures

1.1. Density

Network density is one of the most common measures of describing social network and it assesses the connectedness of nodes in the network. Density scores are calculated by dividing all connections by all possible edges in the network. Density scores can fall between 0 and 1 and, where the higher the score the denser (i.e., connected) a network is.

1.2. Transitivity

Transitivity describes the likelihood of two nodes being connected if they have a neighboring node in common. Scores can fall between 0 and 1. High transitivity indicates that the network contains densely connected clusters of nodes.

1.3. Degree Assortativity

Degree assortativity can be understood as a Pearson correlation coefficient and it indicates the similarity of connections in the graph with regards to the node degrees. Degree assortativity scores can fall between -1 and 1, where positive scores indicate that similar nodes tend to connect to one another, while negative scores indicate that dissimilar nodes have a tendency to connect to one another.

1.4. Network centralization

Network centralization indicates the extent to which connections within a graph are clustering around central nodes. The measure is calculated by the the combined node degree centrality scores within a given cluster (Himelboim, Smith, Rainie, Shneiderman, & Espina, 2017), where nodes with high centrality levels are more influential. Centralization scores range between 0 to 1, where 0 indicates no centralization while 1 indicates high centralization.

1.5. Modularity

Modularity evaluates how good the partition of communities is. *'This method tries to maximise the difference between the actual number of edges in a community and the expected number of such edges.'* (Traag, Waltman, van Eck, Waltman, & van Eck, 2019, p. 1). Modularity scores can fall between 0 and 1, where lower scores suggest a weaker and more centralized community structure, and scores closer to 1 a strong decentralized community structure with dense connections within communities and sparse connections between clusters (M. E. J. Newman & Girvan, 2004).

Network properties over time

Table 3 summarizes the properties of each network graph regarding the number of nodes and edges per network after the application of a disparity filter.

Table 3. Graph properties over time.

Network	Nodes	Edges
Discussion network graphs		
T1 (2017-03-18 - 2020-03-10)	6 (16)	3
T2 (2020-03-11 - 2021-01-19)	48 (51)	75
T3 (2021-01-20 - 2021-06-18)	88 (76)	205
Content overlap network graphs (URL overlap)		
T1 (2017-03-18 - 2020-03-10)	2 (18)	1
T2 (2020-03-11 - 2021-01-19)	52 (35)	44
T3 (2021-01-20 - 2021-06-18)	104 (44)	139
Content overlap network graphs (Topic similarity)		
T1 (2017-03-18 - 2020-03-10)	122 (46)	461
T2 (2020-03-11 - 2021-01-19)	112 (56)	281
T3 (2021-01-20 - 2021-06-18)	99 (69)	182

Note: Properties calculated after backbone extraction.
Number of isolates in parentheses.

Appendix I: Neural topic modelling with BERTopic

In order to run BERTopic we had to transform our data into short texts given that BERTopic operates on so called sentence transformers that have been trained on a large collection of sentences and short paragraphs. When removing missing values on Telegram messages (i.e., texts) we got 1,452,917 rows of text. The length of these texts varied to a great extent. While some only had a few tokens, others a few thousand, in some cases over 9,000 tokens.

Given that our dataset contained mostly Dutch-language texts but also some messages that were written is other languages, we decided to use the ”paraphrase-multilingual-MiniLM-L12-v2” sentence transformer model that can be used to obtain text embedding of over 100 languages (Reimers & Gurevych, 2019).

We used sentence tokenizers to split long texts into sentences via punctuation marks. However, we encountered a small number of outlier documents (i.e., 13,376) that were extremely long and did not have any punctuation marks (e.g., long list of emojis, extremely long (senseless) texts), which made it impossible to split them using sentence tokenizers. Therefore, we were forced to use a cutoff point after the 1000th character token (i.e., approximate length of an average sentence) to obtain shorter texts that were suitable for BERTopic.

Please note that whenever we encountered these long texts we only retained the text before the cutoff point and dropped everything else for two main reasons: The first one relates to the fact that running BERTopic is a highly computationally expensive process. Retaining all the sentences of the outlier texts increased the size of our data-frame tenfold compared to the original data-frame. Although we had access to GPUs and quite some gigabytes of RAM to run our BERTopic models, we quickly ran into memory errors whenever attempting to fit BERTopic to such a large data set with over 10 million rows of text.

Thus, we needed to evaluate the value added of these outliers and come up with an approach that at least partly included them. This leads us to the second, more substantive reason. We argue that the outlier documents would have been much too long for any user to read thoroughly on smart phones and even on desktop. Most users would at best skim these texts or read the first few lines and scroll further. Although we cannot assume that every users who encountered these long messages followed this logic, we are fairly confident that only retaining the first few sentences of the outliers represent en ecologically valid compromise that partly integrated these into exploring the narrative space surrounding chats/channels. Then excluded all texts that had less than 3 character tokens, which were often just single punctuation marks or special characters. Following these steps we obtained 125 topics.

We conducted topic modelling over time as well as topic modelling per chat/channel. We merged these two data frames to provide input for network analyses based on topic similarity.

Table 2.: Topics.

Topic number	Topic
0	kinderen_wakkeren_belicht_perspectief
1	vaccinatie_vaccineren_vaccins_coronavirus
2	nederland_amsterdam_nederlandse_nederl
3	mp4_tg user_user id_forecast432hz
4	geld_euro_banken_cash
5	video_uitzending_filmpjes_videos
6	politie_politiegeweld_politieagenten_p
7	verkiezingen_audit_arizona_ballots
8	bijbel_christenen_pope_jezus christus
9	huisarts_ziekenhuis_patiënten_patiënt
10	bus_trein_vervoer_steden
11	donald trump_president trump_presiden
12	000_miljoen_miljard_1000
13	demonstranten_demonstreren_protest_pr
14	fake news_mainstream media_fake nieuw
15	leugens_leugenaar_waarheid komt_leuge
16	oorlog_militairen_wereld oorlog_solda
17	europa_belgië_europese_france
18	corona maatregelen_coronacrisis_coron
19	sterven_zelfmoord_dood gaan_mensen do
20	rechter_rechters_tribunaal_rechtbank
21	nazi_zionisten_jews_holocaust
22	satanische_satanisten_satanic_satanis

Table 2 – *Continued from previous page*

Topic number	Topic
23	testsamenleving_testen testen_negatie
24	foto_plaatje_fotos_screenshots
25	thierrybaudet __just_tweeted____just
26	rusland_russia_russische_russian
27	android_iphone_apps_smartphone
28	racisme_racist_racistisch_black lives
29	paniek_mensen bang_angst angst_scare
30	co2_windmolens_klimaatverandering_bio
31	criminelen_gevangenis_arrestaties_cri
32	telegram groep_telegram kanaal_telegr
33	lezen_goed lezen_ga lezen_begrijpend
34	winkels_supermarkten_winkelen_klanten
35	humor_grappig_sarcastisch_blijven lac
36	berlijn_berlin_germany_deutschland
37	vrijheid_vrijheden_vrijheid terug_vri
38	israël_israel_israëlische_netanyahu
39	masker_maskers_masks_face masks
40	schapen_schapen wakker_sheep_koeien
41	water_watch water_waterkanon_drinkwat
42	2021_2020_maart 2021_mei 2021
43	vliegtuigen_drones_helicopters_heliko
44	groepen_groep groep_groepen groep_gro
45	honden_hesjes_gele hesjes_dogs
46	china_chinese_taiwan_beijing

Table 2 – *Continued from previous page*

Topic number	Topic
47	gene_genetische_gene decode_genetisch
48	pcr_pcr test_pcr tests_tests
49	facebook_account_censuur_verwijderd
50	eten_voedsel_gegeten_honger
51	nieuwe wereld_new world_world order_w
52	koningshuis_prins_koninklijke_royal
53	donker licht_lichtwerkers_licht duist
54	april_maart_februari_datum
55	gates_bill gates_melinda gates_gates
56	moslims_islam_moslim_mohammed
57	koffie_koffie drinken_koffiedrinken_m
58	fvd fvd_zoeken_ga kijken_checken
59	drinken_alcohol_cola_coca cola
60	kanker_cancer_chemo_tumor
61	5g_4g_radiation_elektromagnetische
62	muziek_song_music_zingen
63	law_grondwet_rechtsstaat_wettelijk
64	avond_vannacht_ga vanavond_gaan vanav
65	boeren_voedsel_farmers_boerderij
66	baan_werkgever_werknemer_boss
67	ship_schepen_ships_containerschip
68	tweet_tweets_twitter account_twitter
69	bitcoin_crypto_blockchain_cryptocurre
70	msm media_fake_nieuws brengen_komt ms

Table 2 – *Continued from previous page*

Topic number	Topic
71	bewustzijn_hersenen_3d_mind control
72	energie_energy_energieën_energetische
73	weekend_zondag_zaterdag_vrijdag
74	wetenschappers_experimenten_lab_weten
75	liefde_liefde overwint_kracht liefde_
76	complottheorieën_complottheorie_compl
77	trollen_trol_troll_trolls
78	amerika_america_united_amerika amerik
79	hoop hoop_laten hopen_hoop echt_hoop
80	geluid_horen_hear_geluiden
81	reptielen_zoo_reptiel_zooo
82	bloemen_flowers_bloemen leggen_flower
83	tg user_user id_user_id
84	echte naam_nieuwe naam_naam verandere
85	youtube_verwijderd youtube_youtube ka
86	museumplein_museum_museum plein_zonda
87	herhaalt_geschiedenis herhaalt_duizen
88	vuurwerk_vuur_fire_flame
89	patriots_patriot_patriot talk_patriot
90	sneeuw_winter_ijs_sneeuwt
91	geweld_geweld gebruiken_agressie_gewe
92	toppers_topper_geweldig_toppunt
93	reden_warum_reden reden_redenen
94	lockdown_lockdowns_lockdown lockdown_

Table 2 – *Continued from previous page*

Topic number	Topic
95	pharma_big pharma_farmaceutische_farm
96	nicholasveniamin_bastiaansen_russian_
97	fb_gedeeld fb_fb pagina_delen fb
98	spijt_sorry hoor_sorry zeggen_nee sor
99	feestje_feest_festival_feesten
100	goed idee_idee goed_idee idee_leuk i
101	pandemie_pandemic_pandemieën_2025
102	kabinet_demissionair kabinet_lockdow
103	demo_demo gaan_demo vandaag_volgende
104	channel_nieuw kanaal_groepen_goed ka
105	respect elkaar_respect mensen_diep r
106	romeo_romeos_poging doodslag_politie
107	censuur_censureren_censorship_gecens
108	slaven_slavernij_slave_slavery
109	pill_red pill_pill journal_pil
110	vlag_flag_false flag_false
111	weken_maanden_paar weken_weken maand
112	voetbalsupporters_olympische spelen_
113	afrika_ghana_president_africa
114	goud_zilver_silver_gold
115	shaking_eff_caution_pfffff
116	britse_uk_britse variant_england
117	callingaspadeaspade_wearethecure1_wh
118	ufo_aliens_alien_buitenaardse

Table 2 – *Continued from previous page*

Topic number	Topic
119	anderhalve meter afstand meter afsta
120	vertrouwen vertrouw trust vertrouw n
121	game spelletjes spelfouten games
122	bankier illuminati dood gevonden int
123	gay transgender lgbt transgenders
124	derde oog ogen open oogjes blinde

Note: All topics identified by BERTopic

Python and R scripts are publicly available at https://github.com/psyronika/Linked_in_the_dark.

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