What happens on the fringes, stays on the fringes?

Information flows in the contemporary media system

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Appendices

Chapter 2

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

Appendix C: 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 D: Chat and channel types

Table 11: 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
defendrotterdam	chat	136.0	act_freedom

Table 11 – *Continued from previous page*

Chat/Channel	Type	Size	Category
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
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

Table 11 – *Continued from previous page*

Chat/Channel	Type	Size	Category
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
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

Table 11 – *Continued from previous page*

Chat/Channel	Type	Size	Category
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
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
QanonNederland	channel	14.0	conspiracy

Table 11 – *Continued from previous page*

Chat/Channel	Type	Size	Category
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
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

Table 11 – *Continued from previous page*

Chat/Channel	Type	Size	Category
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
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

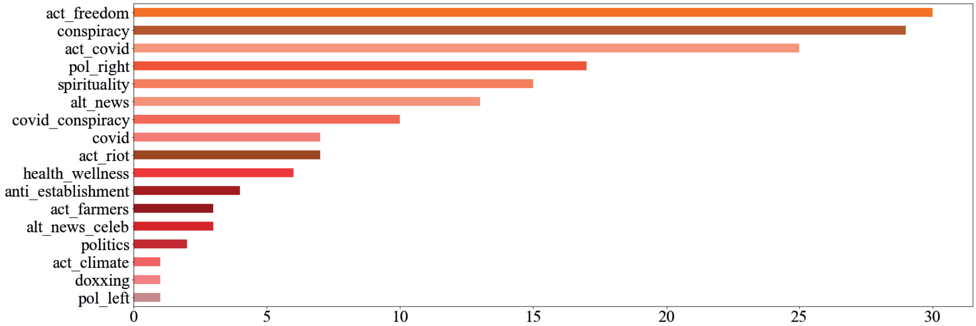

Figure 27: Frequency of chats and channel types.

Appendix E: Network Measures

Density

Network density is one of the most common measures of describing social networks 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.

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.

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.

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 et al., 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.

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 et al., 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).

Appendix F: Network properties over time

Table 12 summarizes the properties of each network graph regarding the number of nodes and edges per network after the application of a disparity filter.

Table 12: 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 G: Neural topic modelling with BERTopic

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 13: 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
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

Table 13 – *Continued from previous page*

Topic number	Topic
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
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

Table 13 – *Continued from previous page*

Topic number	Topic
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
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 13 – *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
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

Chapter 3

Appendix H: Rationale behind keyword choice to query 4chan

The reason why we opted for this particular search query is threefold. First, we were only interested in content related to the Russian invasion of Ukraine that was posted on 4chan/pol to assess how the dark platform agenda influenced other agendas regarding the war. Therefore, we opted for a search query that was as relevant to the investigated context as possible and, at the same time, did not yield too many irrelevant and duplicate results. Second, given the limited computational resources we had access to for computationally expensive analyses (e.g., involving neural topic modeling), we had to ensure that our dataset would not surpass the limits of our available resources. Third, 4CAT (Peeters & Hagen, 2021), the tool we used for data collection, also had limitations concerning how much data a user can download using their infrastructure [70] While these two keywords are certainly not the only ones that may indicate discussions regarding the Russian invasion of Ukraine, given the download limitations of 4CAT, and our computational resources for subsequent analyses, we had to limit the number of posts obtained from 4chan/pol (i.e., the more keywords used the high the number of posts). Therefore, we opted for keywords that were as relevant to the investigated context as possible and at the same time did not yield too many irrelevant and duplicate results. We argue that posts mentioning either Russia or Ukraine should reflect the main discussion points related to (both sides of) the Russian invasion of Ukraine. Taking all of the above into account, we argue that under the current circumstances using the search query 'Russia OR Ukraine' to match as many relevant posts to the Russian invasion of Ukraine as possible represents a reasonable decision.

[70] The more keywords in a search query, the more data gets pulled.

Appendix I: Data preparation choices for BERTopic modeling

We excluded all documents which had less than 20 characters and more than 2000 characters, given that the optimal document length for BERTopic is sentences and short paragraphs. If a word does not have any neighbors, then it is virtually impossible for BERTopic to place this word in a 384 dimensional vector space in a precise way. We also excluded all documents that were longer than 2000 characters given that BERTopic uses sentence transformers and any document that is longer than 2000 words would be considered an outlier. We considered taking the first paragraph of extremely long documents or summarizing them. However, we excluded these options after due consideration for the reasons outlined below.

First, as the majority of these very long documents mostly originated from Reddit, they didn't follow a clear inverted pyramid structure like news articles do (Pöttker, 2003). As such, we could not be sure whether the essence of Reddit posts was also situated at the very beginning of the posts, which excludes the first approach. Second, although text summarising via transformer models is becoming a popular approach, the outliers we attempted to summarize into were too long to summarize via this method. Third, extremely long posts are arguably unlike the average Reddit post. As such, they might well be dismissed by users when scrolling through their feeds, especially if they seek news. Finally, similar to news articles, breaking up these extremely long documents into sentences and then considering every sentence as a separate document would have increased the computational requirements of the BERTopic model to a level we did not have enough resources to comply with.

We used the lead paragraph of each news article (i.e., article description) instead of the full text. We argue that only using the lead paragraph of articles instead of their full text body represents a reasonable choice given that journalist follow an inverted pyramid structure when writing news articles (Pöttker, 2003). Generally speaking the first paragraph of news articles contains the essence of each article followed by more tangential (i.e., less crucial) information in the following sections. If the articles did not have an easily distinguishable lead paragraph (e.g., they were very short or only featured a video URL) than we used their title for analyses. We believed it reasonable to assume that the article title could be a good summary of the content in most of cases[71].

We decided to only use submissions (i.e., opening posts) from Reddit. Our rationale was that an opening post is arguably a stronger agenda setter then a comment under a post. Following Reddit's premise of being the front page of the internet, the average user would first encounter submissions and would only dive into the comment section if they considered the opening posts

[71] Only a handful of them did not have such a lead paragraph.

Table 14: Number of documents on each platform.

Platform	n documents
4chan/pol	588951
r/ukraine	66476
r/news	55812
r/worldnews	55547
r/politics	21572
The New York Times	9399
The Kyiv Independent	2610
Justin Trudeau	546
President Biden	404
Ursula von der Leyen	261
Boris Johnson	247
Volodymyr Zelensky	245
Charles Michel	208
Fumio Kishida	18
Emmanuel Macron	15
Olaf Scholz	2

Note: Number documents per platform/information source after filtering.

worthy of their sustained attention. We argue that if a comment would contain information that and agenda-setting capacity outside of its domain then it would become a post of its own eventually on Reddit. The comments under these opening posts or headlines if you will are comparable to reactions to a piece of news. We deliberately did not include such reactionary content with respect to documents from any other investigated agenda.

Appendix J: Most frequent topics per agenda

Figure 28: Top 10 most frequent topics per studied agendas.
Note: Bars have the same color when the same topic is present across studied agendas.

Appendix K: Initial Word intrusion task

The first validation task that the coder has to perform was a word intrusion task, which involved presenting coders with 5 words where we replaced one of the top topic words (i.e., words with the highest probability of representing the topics) with a so called 'intruder term' (i.e., a word from a different topic) which does not reflect initially extracted topic. The coders' task was to successfully identify the intruder term in each of the 589 annotation tasks. For this task we made use of Qualtrics. Similar to Chang et al. (2009) we performed a word intrusion task using six untrained annotators to check the validity of the topics. Five of the six annotators were second year Bachelor students who were especially interested in communication science, the media, and politics. The sixth coder was the lead author of the current study. All six coders were proficient in English but none of them were native speakers. All six annotators were asked to find the 'intruder word' from a list of 5 top topic words, where four of them were words with the highest probability of belonging to the same topic while one was a top word from a different topic. We set up this task in Qualtrics. We employed majority voting to determine whether humans were able to grasp topics similarly to BERTopic. Results showed that the majority of human annotators were able to pick the correct intruder for 460 topics, whereas 129 of the topics appeared to result in disagreement between human annotators and BERTopic. Specifically, the majority vote for 65 topics was the fourth top word, for 62 topics the third top word, and for topic the second, and for one topic the first word. This result is also in line with how BERTopic extracts and ranks the top topic words. Namely, while the first word is the most representative of the topic, the last one (in this case the fourth word) is the least representative. Therefore, it makes sense that the second most chosen term was the fourth word by annotators, and so forth. The mean self-reported difficulty level of annotation tasks was 1.97 on a five-point scale. The main reasons the annotators found the task difficult was a lack of knowledge of specific terms, jargon, and slang especially coming from 4chan/pol, ambiguous interpretation of certain topics, abbreviations, specialized vocabulary, and references to actors' names who annotators were unfamiliar with. See Figure 29 for an example task below where the main topic is about abortions and roe vs wade while the intruder word is ISS:

Word intrusion task –annotators' experiences

The overall experiences of annotators with the word intrusion task are listed below. The average self-reported difficulty level of the annotations task was 1.97 on a 5-point scale[72]. These experiences were raised during a deliberation session as well as part of the annotation process

[72]Due to a survey error with a slider question, Qualtrics did not record difficulty level at times. In these cases the authors imputed 3 given that the slider was in the middle of the scale by default and when left unclicked it failed to record the response

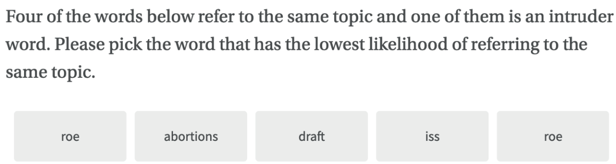

Figure 29: Example word intrusion task. The intruder term is 'iss'.

where participants could flag and describe cases where they were not confident about their choices.

- Repeated words in a topic were confusing – the top words from certain topics were sometimes the same terms with various spellings
- sometimes words did not seem to be part of the same topic without their context
- a lot of specialized vocabulary, abbreviations, and slang/jargon coming from 4chan which necessitated the use of Google – such tasks would ideally have required domain experts
- coding derogatory topics may be an ethical and moral concern for annotators – they may know the correct intruder but still be reluctant to choose it so that the resulting topic does not add up to a derogatory topic
- certain topics were more specific than others. It seems that the model output sometimes managed to extract extremely specific topics which were closer to events. However, other time the resulting topic was on a much higher level of abstraction.

Appendix M: Topic matching task

The second validation task presented coders with a document (i.e., a piece of text we used to train BERTopic on) alongside two topic options, where each option reflected the top words of the topic derived by BERTopic on the one hand, and the top words of another random topic that reflected a different topic. The coders' task was be to select the topic that contained the word group that best reflected the topic of the text above.

We employed stratified random sampling on the full dataset in order to obtain our validation set ($N_{validation} = 589$). Specifically, in this sample each topic was represented only once while

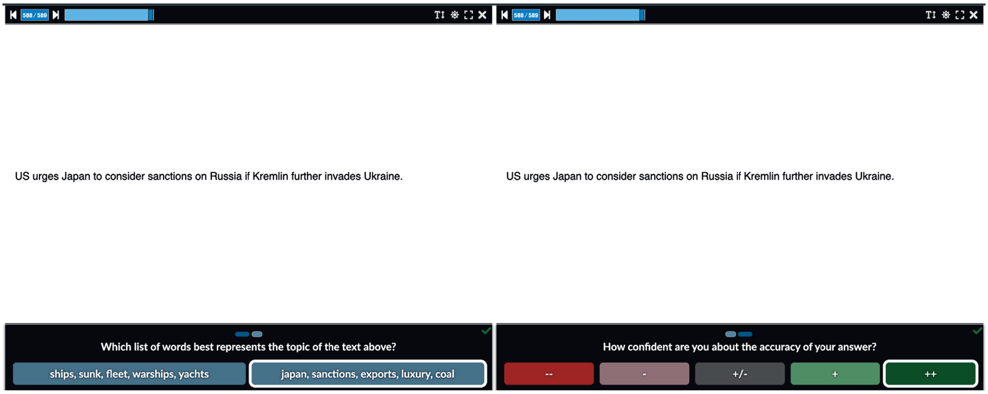

Figure 30: Example topic intrusion task and confidence question. The correct topic is selected.

the platforms of origin of each document in the corpus were proportionally represented following their original proportions in the dataset we sampled from ($N_{dataset} = 801,016$). Each task was set up in a way that coders saw a text on the top of the page and two topic options in the bottom. Figure 30 illustrates the task.

Appendix N: Topic Matching task - annotators' experiences

As opposed to the word intrusion task, the annotators did not have as many complaints about issues with respect to confusion and specialized vocabulary. The task was overall much more clear and intuitive to all annotators. Even if coders were not familiar with certain terms, and jargon having the document that provided context to the topic helped them to a great extent. These are also reflected int he results of the topic intrusion task where all 589 topics passed this test. Topics that were marked with low confidence were, however excluded as these often reflected ambiguity and or incoherent topics.

Appendix O: Raw influence scores across and within agendas

Figure 31 shows raw influence scores on the agenda level and Figure 32 illustrates the raw scores on the individual level. These scores can be interpreted as the expected percentage of topics emerging on a destination agenda/entity due to topics that previously emerged on a source agenda/entity. For instance, we found that the topics that first appeared on the social media agenda of the public were expected to cause 15.69% of topics on the social media agenda of politicians and 19.28% of topics on the traditional media agenda. Topics first emerging on the dark platform agenda expected to cause 11.11% of topics on the social media agenda of the public, 8.15% of topics on the social media agenda of politicians and 6.63% of topics on the traditional

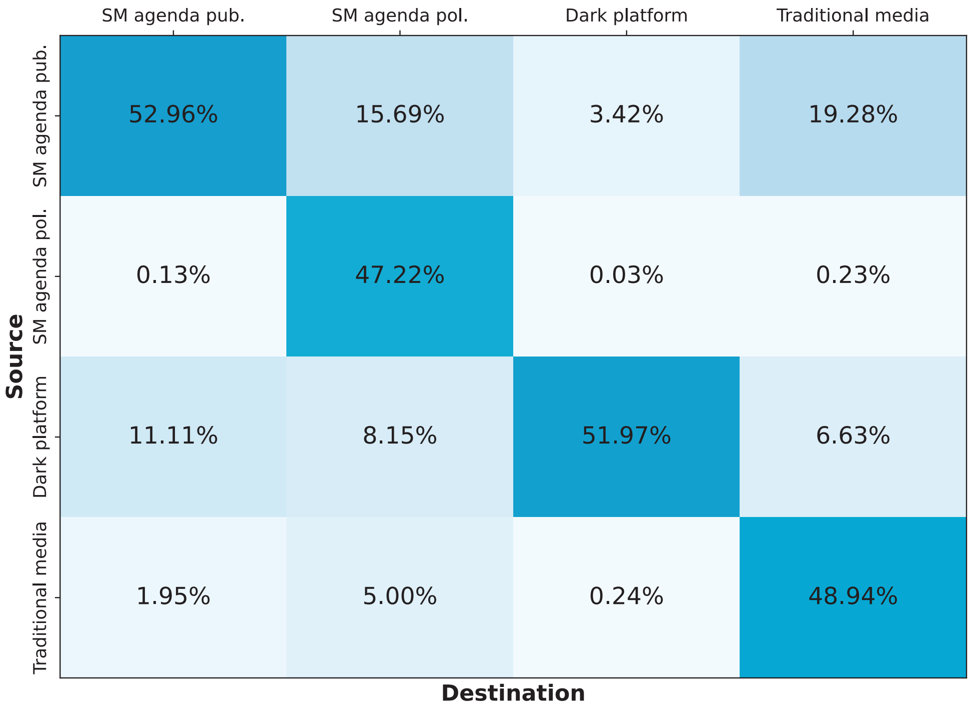

Figure 31: Raw influence scores of each agenda on other agendas.

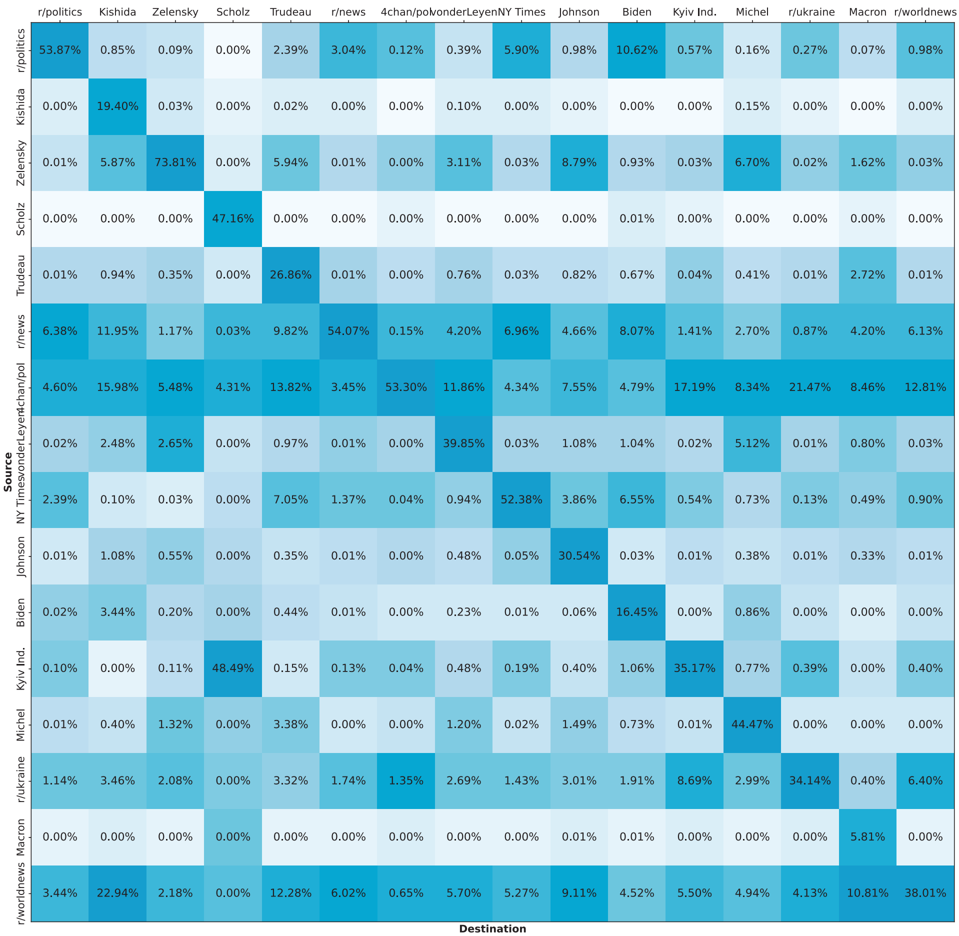

Figure 32: Raw influence (i.e.,efficiency) of each individual entity within agendas

Table 15: Descriptive statistics for toxicity-related measures in the Dark Platform agenda.

Measure	Mean	SD	Min	Max
Toxicity	0.29	0.25	0.00	0.99
Severe toxicity	0.06	0.12	0.00	0.96
Identity attack	0.17	0.19	0.00	0.96
Insult	0.20	0.23	0.01	0.93
Profanity	0.17	0.24	0.01	0.96

Note: Scores were obtained for the top 10 most influential topics ($N = 14,341$).

media agenda.

Appendix P: Toxicity-related measures on agenda and topic-level

The scores obtained for each of these indicators reflect probabilities with values falling between 0 and 1. Higher scores indicate a greater likelihood of a text being perceived to contain one of the aforementioned indicators of harmful language. For instance, if a post scores 0.8 on insult, 8 out of 10 would consider the post insulting. For an in-depth discussion about how the scores are calculated, we refer to the Docs of Perspective API.[73]

Using toxicity rates rather than mean scores

For instance, let's consider the following example: Set A with scores [0.4, 0.4, 0.4] has a mean score of 0.4. Using the threshold-based approach with 0.7, all three scores would be labeled as non-toxic (0), leading to a 0% toxicity rate. On the other hand, Set B with scores [0.8, 0.2, 0.2] also has a mean score of 0.4. However, with the threshold-based approach, the first score is labeled as toxic (1), and the other two as non-toxic (0), resulting in a 33% toxicity rate, effectively highlighting the presence of harmful language in this set. Thus, the threshold-based approach offers a more nuanced and accurate representation of the dataset, making it a better choice for assessing the prevalence of harmful language compared to the potential limitations of mean scores.

[73] https://developers.perspectiveapi.com/s/docs?language=en_US

Table 16: Descriptive statistics for toxicity-related measures in the SM agenda of the public.

Measure	Mean	SD	Min	Max
Toxicity	0.1	0.1	0.00	0.94
Severe toxicity	0.00	0.00	0.00	0.00
Identity attack	0.00	0.00	0.0	0.00
Insult	0.03	0.07	0.01	0.80
Profanity	0.04	0.07	0.01	0.90

Note: Scores were obtained for the top 10 most influential topics ($N = 10,769$).

Table 17: Descriptive statistics for toxicity-related measures in the SM agenda of (G7+) politicians.

Measure	Mean	SD	Min	Max
Toxicity	0.03	0.04	0.00	0.56
Severe toxicity	0.00	0.00	0.00	0.02
Identity attack	0.01	0.02	0.0	0.28
Insult	0.01	0.02	0.01	0.47
Profanity	0.02	0.0	0.01	0.53

Note: Scores were obtained for the top 10 most influential topics ($N = 989$).

Table 18: Descriptive statistics for toxicity-related measures in the Traditional media agenda.

Measure	Mean	SD	Min	Max
Toxicity	0.06	0.07	0.00	0.66
Severe toxicity	0.00	0.00	0.00	0.00
Identity attack	0.03	0.05	0.0	0.49
Insult	0.02	0.04	0.01	0.70
Profanity	0.02	0.03	0.01	0.65

Note: Scores were obtained for the top 10 most influential topics ($N = 2218$).

Table 19: Topic level toxicity-related measures in the Dark Platform agenda (mean scores).

Toxicity	Severe toxicity	Identity attack	Insult	Profanity	Topic
0.267488	0.050753	0.212799	0.170304	0.145692	refugees, refugee, polish, asylum, shelter
0.235572	0.049215	0.133673	0.158566	0.147120	donate, donations, donation, donating, charity
0.245253	0.043300	0.122184	0.164138	0.144404	ships, sunk, fleet, warships, yachts
0.365269	0.092910	0.218630	0.284322	0.235990	trudeau, canadians, truckers, leafs, quebec
0.434174	0.119626	0.298035	0.338563	0.239053	cats, dogs, pets, rescued, vet
0.219739	0.037398	0.101003	0.153243	0.134538	aid, package, congress, funding
0.287641	0.045456	0.179275	0.170364	0.132944	crimes, icc, prosecutor, investigation, warcrimes
0.242126	0.042394	0.115840	0.169380	0.151484	council, veto, abstained, unsc, condemning
0.319565	0.067929	0.179895	0.211082	0.181037	kiev, ghosts, reaper, fighter, mig
0.272540	0.047007	0.136222	0.169198	0.140209	generals, lieutenant, colonel, regiment, office

Table 20: Topic level toxicity-related measures in the SM agenda of the public (mean scores).

Toxicity	Severe toxicity	Identity attack	Insult	Profanity	Topic
0.100099	0.004786	0.036936	0.036206	0.031098	biden, sanctions, obama, putin, economy, china
0.072597	0.003747	0.028802	0.027028	0.028042	rubles, currency, euros, usd, buy
0.126000	0.006552	0.056757	0.037092	0.044512	ships, sunk, fleet, warships, yachts
0.040131	0.001475	0.010926	0.018327	0.016755	debt, lease, loan, debts, loans
0.113836	0.014148	0.065032	0.042870	0.057599	anthem, lyrics, concert, songs, sing
0.145231	0.011374	0.086581	0.040146	0.048083	belarus, belarusian, belarusians, lukashenko
0.135742	0.006203	0.083132	0.043825	0.034149	crimes, icc, prosecutor, investigation, warcrimes
0.079529	0.003183	0.045267	0.023593	0.023777	council, veto, abstained, unsc, condemning
0.098574	0.005768	0.060412	0.027806	0.032241	kharkiv, kharkov, izium, severodonetsk, troops
0.096084	0.005465	0.040335	0.026356	0.033810	migs, poland, planes, airfields, fly

Table 21: Topic level toxicity-related measures in the SM agenda of the (G7+) politicians (mean scores).

Toxicity	Severe toxicity	Identity attack	Insult	Profanity	Topic
0.019978	0.001112	0.005817	0.009458	0.014964	facebook, twitter, youtube, instagram
0.032024	0.001377	0.008817	0.011736	0.019446	crypto, bitcoin, cryptocurrency, binance, blockchain
0.023395	0.001710	0.012779	0.009598	0.016158	serbia, serbs, kosovo, serb, bosnia
0.036228	0.001424	0.017057	0.017466	0.011515	trudeau, canadians, truckers, leafs, quebec
0.175015	0.007450	0.051530	0.079116	0.110589	cyber, anonymous, hackers, ddos, cyberattacks
0.036053	0.001966	0.014177	0.012961	0.019409	johnson, boris, lockdown, minister, zelenskyyua
0.025851	0.001676	0.010898	0.009779	0.016235	eu, candidate, union, granting, joining
0.022143	0.001282	0.006025	0.009271	0.016054	climate, solar, drilling, fuels, offshore
0.038284	0.001678	0.014853	0.013593	0.010929	corridors, evacuation, humanitarian, evacuate, evacuated
0.021310	0.001264	0.005915	0.010521	0.014573	queen, prince, elizabeth, william, royal

Table 22: Topic level toxicity-related measures in the Traditional media agenda (mean scores).

Toxicity	Severe toxicity	Identity attack	Insult	Profanity	Topic
0.082423	0.003867	0.035165	0.031445	0.026456	zelensky, zelenskyy, zelenskiy, zelenski, zelinsky
0.032949	0.001202	0.005868	0.017587	0.016286	crypto, bitcoin, cryptocurrency, binance, blockchain
0.066081	0.001800	0.021555	0.034641	0.021499	jan, gop, court, pennsylvania, congressional
0.065661	0.002592	0.024544	0.019775	0.021921	abortion, roe, abortions, draft, rights
0.037515	0.001509	0.014109	0.014727	0.016303	olympics, olympic, beijing, athletes, fifa
0.069705	0.003114	0.035611	0.015239	0.020339	kharkiv, kharkov, izium, severodonetsk, troops
0.028392	0.001190	0.005660	0.012330	0.013260	climate, solar, drilling, fuels, offshore
0.147626	0.007056	0.075855	0.024106	0.034564	kharkiv, oblast, shelling, chernihiv, kramatorsk
0.050847	0.002298	0.021036	0.013363	0.016382	fly, enforce, airspace, nato, impose
0.084583	0.002470	0.052156	0.042539	0.023748	jackson, brown, judge, nominee, senate

Table 23: The rate of harmful language indicators for each topic in the SM agenda of public.

Toxicity	Severe toxicity	Identity attack	Insult	Profanity	Topic
10.0%	0.5%	3.7%	3.6%	3.1%	biden, sanctions, obama, putin, economy
7.3%	0.4%	2.9%	2.7%	2.8%	rubles, currency, euros, usd, buy
12.6%	0.7%	5.7%	3.7%	4.5%	ships, sunk, fleet, warships, yachts
4.0%	0.1%	1.1%	1.8%	1.7%	debt, lease, loan, debts, loans
11.4%	1.4%	6.5%	4.3%	5.8%	anthem, lyrics, concert, songs, sing
14.5%	1.1%	8.7%	4.0%	4.8%	belarus, belarusian, belarusians, lukashenko, b...
13.6%	0.6%	8.3%	4.4%	3.4%	crimes, icc, prosecutor, investigation, warcrimes
8.0%	0.3%	4.5%	2.4%	2.4%	council, veto, abstained, unsc, condemning
9.9%	0.6%	6.0%	2.8%	3.2%	kharkiv, kharkov, izium, severodonetsk, troops
9.6%	0.5%	4.0%	2.6%	3.4%	migs, poland, planes, airfields, fly

Table 24: The rate of harmful language indicators for each topic in the SM agenda of (G7+) politicians.

Toxicity	Severe toxicity	Identity attack	Insult	Profanity	Topic
2.0%	0.1%	0.6%	0.9%	1.5%	facebook, twitter, youtube, instagram, blocked
3.2%	0.1%	0.9%	1.2%	1.9%	crypto, bitcoin, cryptocurrency, binance, block...
2.3%	0.2%	1.3%	1.0%	1.6%	serbia, serbs, kosovo, serb, bosnia
3.6%	0.1%	1.7%	1.7%	1.2%	trudeau, canadians, truckers, leafs, quebec
17.5%	0.7%	5.2%	7.9%	11.1%	cyber, anonymous, hackers, ddos, cyberattacks
3.6%	0.2%	1.4%	1.3%	1.9%	johnson, boris, lockdown, minister, zelenskyyua
2.6%	0.2%	1.1%	1.0%	1.6%	eu, candidate, union, granting, joining
2.2%	0.1%	0.6%	0.9%	1.6%	climate, solar, drilling, fuels, offshore
3.8%	0.2%	1.5%	1.4%	1.1%	corridors, evacuation, humanitarian, evacuate, ...
2.1%	0.1%	0.6%	1.1%	1.5%	queen, prince, elizabeth, william, royal

Table 25: The rate of harmful language indicators for each topic in the Traditional media agenda.

Toxicity	Severe toxicity	Identity attack	Insult	Profanity	Topic
8.2%	0.4%	3.5%	3.1%	2.6%	zelensky, zelenskyy, zelenskiy, zelenski, zelinsky
3.3%	0.1%	0.6%	1.8%	1.6%	crypto, bitcoin, cryptocurrency, binance, block...
6.6%	0.2%	2.2%	3.5%	2.1%	jan, gop, court, pennsylvania, congressional
6.6%	0.3%	2.5%	2.0%	2.2%	abortion, roe, abortions, draft, rights
3.8%	0.2%	1.4%	1.5%	1.6%	olympics, olympic, beijing, athletes, fifa
7.0%	0.3%	3.6%	1.5%	2.0%	kharkiv, kharkov, izium, severodonetsk, troops
2.8%	0.1%	0.6%	1.2%	1.3%	climate, solar, drilling, fuels, offshore
14.8%	0.7%	7.6%	2.4%	3.5%	kharkiv, oblast, shelling, chernihiv, kramatorsk
5.1%	0.2%	2.1%	1.3%	1.6%	fly, enforce, airspace, nato, impose
8.5%	0.2%	5.2%	4.3%	2.4%	jackson, brown, judge, nominee, senate

Chapter 4

Appendix Q: System specifications

Our system consisted of two NVIDIA A10 GPUs running with driver version 515.43.04 and CUDA version 11.7. We had 48 GB RAM at our disposal with an additional 500 GB storage mounted.

Appendix R: Prompts

This section highlights all prompts used to instruct our models to perform the validation task. The prompts used by LlaMA 7B-chat and LlaMA 13B-chat were identical as such we only display each prompt for one model. Each step of the prompting procedure results in a so called 'chain' that consists of a custom system prompt to focus the LLM on the task at hand and give it clear rules, an example prompt to show a good example of the output expected, and a main prompt that determined the exact format the output should be delivered. At each step of the chaining process specific input variables and output variables were generated. In the final step of the prompting procedure we generate an 'overall chain', which is a sequential chains from all previous chains to run our models.

Chain 1: Extract topics

input variables: text1, text2, keywords1, keywords2, proper nouns1, proper nouns2 **output variables:** topics

system prompt:
You are a helpful, respectful and honest assistant for labeling topics. A "topic" is a fundamental subject or theme that encompasses all aspects related to a particular area of interest or discussion. A topic serves as the overarching framework for exploring and discussing various facets within that subject. A topic comprises of a main topic and a subtopic. A main topic is an overarching theme, a subtopic is a more specific thematic or content-based divisions within a broader main topic. All main topics are labeled Politics if the documents' keywords and proper nouns relate to politics. For instance if the text discusses the economy but a politician, party, or government is mentioned either in the text or in the keywords then it should be categorized as Politics and not Economy.
Main topic: Politics; Subtopic: Elections and campaigns Main topic: Economy; Subtopic: Interest rates Main topic: Health; Subtopic: Mental health Main topic: Entertainment; Subtopic: Film and Television
If a text mentions politics, politicians names functions, parties, policy, or any other

politics-related term, the main topic should always be Politics.

You must always return a main topic and a subtopic and nothing else in the following format: Main topic1 : Subtopic1:;, Main topic2: Subtopic2:
Only return the label and nothing more for each text.

example prompt:

I have a document pair of the following texts:
- Contact met de kiezer; Deze keer zie je geen lijsttrekkers in windjacks rondlopen op markten. Kandidaat-Kamerleden moeten noodgedwongen online contact zoeken met de kiezers. Zoals de lijsttrekker van de ChristenUnie, Gert-Jan Segers, te zien is op de bovenstaande afbeelding terwijl hij vragen beantwoordt die kiezers hem stellen op het online platform Instagram. In plaats van direct met de burgers te praten, spreken politici nu voor de camera's. Livestreams op Facebook zijn ook populair. Zo had Mark Rutte dit weekend een gesprek met horeca-ondernemers en zond de VVD dat uit op Facebook. Naast de online campagne werd er dit weekend ook op de ouderwetse manier geflyerd. Maar de meeste campagnevoerende partijleden gingen niet aanbellen uit angst voor verdere verspreiding van het coronavirus. Forum voor Democratie was de enige partij die de straat op ging om campagne te voeren. Met een vrijheidskaravaan bezocht de partij Nijmegen en Venlo voor een manifestatie. Toen er meer dan tweehonderd mensen kwamen opdagen, moest burgemeester Hubert Bruls de bijeenkomst voortijdig beëindigen, hoewel deze wel was aangekondigd en aangevraagd. Een bezoeker in Venlo twitterde dat het centrale plein voor het eerst sinds carnaval vorig jaar weer vol stond met de komst van Baudet.
- Forum voor Democratie op zoek naar extra stemmen; Terwijl andere partijen zich nauwelijks op straat vertonen, reist Forum voor Democratie stad en land af. Deze optredens trekken niet alleen de aandacht van kiezers; het Openbaar Ministerie onderzoekt nu ook of het campagneteam van Baudet de coronaregels op grote schaal heeft overtreden. Volgens getuigen werden bij een bezoek aan Urk honderden handen geschud. En dan was er nog de volmachtrel. In een live-uitzending riep Baudet zijn kijkers op om zoveel mogelijk volmachtstemmen te regelen, aangezien kiezers dit jaar niet twee, maar drie volmachtstemmen mogen uitbrengen om de kans op besmetting te verkleinen. "Een persoon kan eigenlijk vier keer stemmen, als je maar die volmachten kunt regelen," zei Baudet, en dat was een enorme kans. Maar het ministerie van Binnenlandse Zaken zei: "Ho, dat is niet de bedoeling en is niet toegestaan." Het campagneteam van Forum leek daar toen al achter te komen, want de suggestie om stemmen te regelen werd snel uit de video van Baudet geknipt. Baudet houdt echter wel openlijk vast aan

zijn standpunt dat er een grote kans is op verkiezingsfraude, maar dan door anderen, uiteraard.

The topic of each text is described by the following keywords: 'livesessies', 'vrijheidskaravaan', 'flyerende', 'facebook', 'windjacks'; besmettingskansen', 'volmachtsstemmen', 'schielijk', 'volmachten', 'baudets'
The following proper nouns appear in each text: Gert-Jan Segers, Mark Rutte, Forum voor Democratie, Hubert Bruls, Baudet; Forum voor Democratie, Forum voor Democratie, Ministerie kijkt, Urk, Baudet, Baudet, Baudet, Baudet

Based on the information about the topic above, please create a short label of the topic for each text. Only return the label and nothing more for each text in the following format:

Main topic 1: Politics; Subtopic1: Elections and campaigns; Main topic 2: Politics; Subtopic2: Elections, campaigns and fraud

main prompt:
[INST] I have a document pair of the following texts: {text1} and {text2}

The topic of each text is described by the following keywords: {keywords1} and {keywords2}
The following proper nouns appear in each text: {proper_nouns1}, {proper_nouns2}

Based on the information about the topic above, please create a short label of this topic for each text. Only return the label and nothing more for each text in the following format: Main topic 1 : Subtopic1: ; Main topic 2: Subtopic2: [/INST]

Chain 1.1: Extract main topic from topics for matching

input variables: topics

output variables: main topics

system prompt:

You are a helpful, respectful and honest assistant for extracting the main topic from a topic. A topic comprises of a main topic and a subtopic. A main topic is an overarching theme, a subtopic is a more specific thematic or content-based divisions within a broader main topic. Main topic: Business; Subtopic: Interest rates Main topic: Health; Subtopic: Mental health Main topic: Entertainment; Subtopic: Film and Television Main topic: Politics; Subtopic: Elections

A main topic is everything before the word 'Subtopic'. Given a topic, you must always return the main topic nothing else in the following format: Main topic1:, Main topic2: Only return the main topic label and nothing more for each text.

example prompt:

Based on the information about the topic above, please extract the main topic from each topic. A main topic is everything before the word 'Subtopic'. In this case this word is Politics. Only return the label of the main topic and nothing more in the following format:

Main topic 1: Politics; Main topic 2: Politics

main prompt:

[INST] I have a pair of topics: {topics}

Based on the information about the topic above, please extract the main topic from each topic. Only return the label of the main topic and nothing more in the following format:

Main topic 1: ; Main topic 2: [/INST]

Chain 2: Evaluate main topic level match

input variables: main topics
output variables: topic evaluations

system prompt:

You are a helpful, respectful, and honest assistant for comparing the main topics of two texts. In this comparison, a match is solely based on the main topic and nothing else.

example prompt:

The main topic of each text is described by the following labels:

Main topic 1: Politics; Main topic 2: Politics;

Based on the information about the main topics above, please write a short evaluation about whether the two texts match on a main topic level. Make sure to only return the evaluation and nothing more in the following format:

Topic Evaluation: Yes, the two texts match on a main topic level because both texts touch upon the broader context of Politics as seen by their main Topic.

main prompt:

[INST] The main topic of each text is the following: {main_topic}

Based on the information about the topics above, please write a short evaluation about whether the two texts match on a main topic level. Make sure to only return the evaluation and nothing more in the following format: Topic Evaluation: [/INST]

Chain 2.1: Extract words used to make main topic-level evaluation decision

input variables: text1, text2, main_topic, topic_evaluation
output variables: topic_words

system prompt: You are a helpful, respectful, and honest assistant for comparing the main topics of two texts. In this comparison, a match is solely based on the main topic and nothing else. Your task is to provide a list of comma separated keywords for each text that you used to make your evaluation. Only provide a list and nothing more. Avoid notes, thank yous and any other filler information.

example prompt:

I have a document pair of the following texts:
– Contact met de kiezer; Deze keer zie je geen lijsttrekkers in windjacks rondlopen op markten. Kandidaat-Kamerleden moeten noodgedwongen online contact zoeken met de kiezers. Zoals de lijsttrekker van de ChristenUnie, Gert-Jan Segers, te zien is op de bovenstaande afbeelding terwijl hij vragen beantwoordt die kiezers hem stellen op het online platform Instagram. In plaats van direct met de burgers te praten, spreken politici nu voor de camera's. Livestreams op Facebook zijn ook populair. Zo had Mark Rutte dit weekend een gesprek met horeca-ondernemers en zond de VVD dat uit op Facebook. Naast de online campagne werd er dit weekend ook op de ouderwetse manier geflyerd. Maar de meeste campagnevoerende partijleden gingen niet aanbellen uit angst voor verdere verspreiding van het coronavirus. Forum voor Democratie was de enige partij die de straat op ging om campagne te voeren. Met een vrijheidskaravaan bezocht de partij Nijmegen en Venlo voor een manifestatie. Toen er meer dan tweehonderd mensen kwamen opdagen, moest burgemeester Hubert Bruls de bijeenkomst voortijdig beëindigen, hoewel deze wel was aangekondigd en aangevraagd. Een bezoeker in Venlo twitterde dat het centrale plein voor het eerst sinds carnaval vorig jaar weer vol stond met de komst van Baudet.
– Forum voor Democratie op zoek naar extra stemmen; Terwijl andere partijen zich nauwelijks op straat vertonen, reist Forum voor Democratie stad en land af. Deze optredens trekken niet alleen de aandacht van kiezers; het Openbaar Ministerie onderzoekt nu ook of het campagneteam van Baudet de coronaregels op grote schaal heeft overtreden. Volgens getuigen

werden bij een bezoek aan Urk honderden handen geschud. En dan was er nog de volmachtrel. In een live-uitzending riep Baudet zijn kijkers op om zoveel mogelijk volmachtstemmen te regelen, aangezien kiezers dit jaar niet twee, maar drie volmachtstemmen mogen uitbrengen om de kans op besmetting te verkleinen. ”Een persoon kan eigenlijk vier keer stemmen, als je maar die volmachten kunt regelen,” zei Baudet, en dat was een enorme kans. Maar het ministerie van Binnenlandse Zaken zei: ”Ho, dat is niet de bedoeling en is niet toegestaan.” Het campagneteam van Forum leek daar toen al achter te komen, want de suggestie om stemmen te regelen werd snel uit de video van Baudet geknipt. Baudet houdt echter wel openlijk vast aan zijn standpunt dat er een grote kans is op verkiezingsfraude, maar dan door anderen, uiteraard.

The main topic of each text is described by the following labels:

- Main topic 1: Politics; - Main topic 2: Politics;

The following evaluation describes whether the two texts match on a main topic level:
- Topic Evaluation: Yes, the two texts match on a main topic level because both texts touch upon the broader context of Politics as seen by their main Topic.

Based on the information above please provide a list of comma separated words that indicate the words that best describe the topic of each text. Make sure to only return the comma separated list of words and nothing else in the following format:
Contact met de kiezer, Kandidaat-Kamerleden, Online contact, Instagram, Politici voor de camera's, Livestreams op Facebook, Flyeren, Angst voor verspreiding van het coronavirus, Forum voor Democratie, Vrijheidskaravaan, Burgemeester Hubert Bruls, Bezoeker in Venlo, Centrale plein, Baudet; Forum voor Democratie, Optredens, Openbaar Ministerie, Coronaregels overtreden, Bezoek aan Urk, Handen schudden, Volmachtrel, Volmachtstemmen regelen, Ministerie van Binnenlandse Zaken, Verkiezingsfraude

main prompt:

[INST]I have a document pair of the following texts: {text1} and {text2}

The main topic of each text is the following: {main_topic}

The following evaluation describes whether the two texts match on a main topic level: {topic_evaluation}

Based on the information above please provide a list of comma separated words that you used to make this evaluation. Make sure to only return the comma separated list of words and nothing else in the following format: [/INST]

Chain 3: Create match label based on evaluation

input variables: topic_evaluation
output variables: match_topic

system prompt:

You are a helpful, respectful and honest assistant for classifying whether two texts match on a main topic level based on an evaluation provided.

At each request explicitly assign one of the two labels below. 0 - no match 1 - topic match

Make sure you to only return the label and nothing else.

example prompt:

The following evaluation describes the topic match level: Yes, the two texts match on a main topic level. Both texts touch upon the broader context of Politics. Based on this information, please assign either '0 - no match' or '1 - topic match'. Make sure to only return the label and nothing more in the following format: 1

main prompt:

[INST] The following evaluation describes the topic match level: {topic_evaluation}

Based on this information, please assign either '0 - no match' or '1 - topic match'. Make sure to only return the label and nothing more in the following format: [/INST] """

Chain 4: Identify news events

input variables: text1, text2, proper_nouns1, proper_nouns2, 'keywords1', 'keywords2', topics
output variables: news events

system prompt: You are a helpful, respectful and honest assistant for identifying the news event described in a pair of documents. News events are specific events that lead to news coverage, such as a specific debate on a specific day in a specific parliament, a specific accident, or a specific football match. They can be covered by one or more articles in one or more outlets, but relate to one specific and identifiable event and are thus much more fine-grained than news topics, issues, or news categories. News events can span over multiple days but not more than 10 days. Therefore articles that cover the same news event are published within the same few hours and in the course of a few days.

Provide your answer as an explanation in maximum 100 tokens. Make sure you to only return the news event identified and nothing else. Be very specific, name actors and places where possible.

example prompt:

I have a document pair of the following texts: - Contact met de kiezer; Deze keer zie je geen lijsttrekkers in windjacks rondlopen op markten. Kandidaat-Kamerleden moeten noodgedwongen online contact zoeken met de kiezers. Zoals de lijsttrekker van de ChristenUnie, Gert-Jan Segers, te zien is op de bovenstaande afbeelding terwijl hij vragen beantwoordt die kiezers hem stellen op het online platform Instagram. In plaats van direct met de burgers te praten, spreken politici nu voor de camera's. Livestreams op Facebook zijn ook populair. Zo had Mark Rutte dit weekend een gesprek met horeca-ondernemers en zond de VVD dat uit op Facebook. Naast de online campagne werd er dit weekend ook op de ouderwetse manier geflyerd. Maar de meeste campagnevoerende partijleden gingen niet aanbellen uit angst voor verdere verspreiding van het coronavirus. Forum voor Democratie was de enige partij die de straat op ging om campagne te voeren. Met een vrijheidskaravaan bezocht de partij Nijmegen en Venlo voor een manifestatie. Toen er meer dan tweehonderd mensen kwamen opdagen, moest burgemeester Hubert Bruls de bijeenkomst voortijdig beëindigen, hoewel deze wel was aangekondigd en aangevraagd. Een bezoeker in Venlo twitterde dat het centrale plein voor het eerst sinds carnaval vorig jaar weer vol stond met de komst van Baudet.
- Forum voor Democratie op zoek naar extra stemmen; Terwijl andere partijen zich nauwelijks op straat vertonen, reist Forum voor Democratie stad en land af. Deze optredens trekken niet alleen de aandacht van kiezers; het Openbaar Ministerie onderzoekt nu ook of het campagneteam van Baudet de coronaregels op grote schaal heeft overtreden. Volgens getuigen werden bij een bezoek aan Urk honderden handen geschud. En dan was er nog de volmachtrel. In een live-uitzending riep Baudet zijn kijkers op om zoveel mogelijk volmachtstemmen te regelen, aangezien kiezers dit jaar niet twee, maar drie volmachtstemmen mogen uitbrengen om de kans op besmetting te verkleinen. "Een persoon kan eigenlijk vier keer stemmen, als je maar die volmachten kunt regelen," zei Baudet, en dat was een enorme kans. Maar het ministerie van Binnenlandse Zaken zei: "Ho, dat is niet de bedoeling en is niet toegestaan." Het campagneteam van Forum leek daar toen al achter te komen, want de suggestie om stemmen te regelen werd snel uit de video van Baudet geknipt. Baudet houdt echter wel openlijk vast aan zijn standpunt dat er een grote kans is op verkiezingsfraude, maar dan door anderen, uiteraard.

The following keywords appear in each text: 'livesessies', 'vrijheidskaravaan', 'flyerende', 'facebook', 'windjacks'; besmettingskansen', 'volmachtsstemmen', 'schielijk', 'volmachten', 'baudets'

The following proper nouns appear in each text: Gert-Jan Segers, Mark Rutte, Forum voor Democratie, Hubert Bruls, Baudet; Forum voor Democratie, Forum voor Democratie, Ministerie kijkt, Urk, Baudet, Baudet, Baudet, Baudet

The topic of each text is the following: Main topic 1: Politics; Subtopic: Elections and campaigns;
Main topic 2: Politics; Subtopic: Elections, campaigns and fraud

Based on the information above, please identify the news events that describe the texts. Be as specific as possible. Make sure to only return the events and nothing more for each text in the following format:

Event 1: Most political parties are shifting their campaign activity strategies due to the COVID-19 pandemic; Event 2: Forum voor Democratie party's campaign activities violate COVID-19 regulations while other parties have more pandemic-proof strategies.

main prompt: [INST] I have a document pair of the following texts: {text1} and {text2}

The following keywords appear in each text: keywords1 and keywords2 The following proper nouns appear in each text: {proper_nouns1}, {proper_nouns2}

The topic of each text is the following: {topics}

Based on the information above, please identify the news events that describe the texts. Make sure to only return the news events and nothing more in the following format: [/INST]

Chain 5: Evaluate news event level match

input variables: news_events, date1, date2
output variables: event_evaluation

system prompt: You are a helpful, respectful and honest assistant for evaluating whether two texts pertain to the same news event. News events are comprised of specific events that lead to news coverage around a news story, such as a specific debate on a specific day in a specific parliament, a specific accident, or a specific football match.
They can be covered by one or more articles in one or more outlets, but relate to one specific and identifiable event and are thus much more fine-grained than news topics, issues, or news categories.
News events can span over multiple days but not more than 10 days. Therefore articles that

cover the same news event are published very close in time, a matter of hours or maximum a few days. Different news events can also be published on the same date or on a very close date.
The most important criteria for determining whether the two texts pertain to the same news event are the events mentioned in the text. The date overlap is a secondary objective.

An event within a news event must refer to a specific event or related developments around the event. A news event can include various articles, reports, and updates from news outlets, all contributing to the coverage of that specific event or issue and its surrounding aspects.
For example, the news event might revolve around the presidential election of a specific year, detailing campaign events, candidate profiles, polling data, and key issues. Provide your answer as an explanation in maximum 100 tokens. Make sure to only return the evaluation and nothing else.

example prompt:

The news events of each text is the following: -Event 1: Most political parties are shifting their campaign activity strategies due to the COVID-19 pandemic;
-Event 2: Forum voor Democratie party's campaign activities violate COVID-19 regulations while other parties have more pandemic-proof strategies.

The publishing dates of the texts is the following:
date1: 01/03/2021; date2: 01/03/2021

Based on the information above, please write a short evaluation about whether the two texts match on a news event level. Make sure to only return the evaluation and nothing more in the following format:

Event Evaluation: Both texts focus on one particular news event, the election campaign and party campaign activities amid the COVID-19 pandemic which is distinctive event. Both texts discuss aspects of the same election campaign, political parties and campaign strategies during the pandemic indicating that they pertain to the same news event. The texts were also published at a similar time and date which further indicates that they belong to the same news event.

main prompt: [INST] The news events of each text is the following: {news_events}

The publishing dates of the texts is the following: {date1} and {date2}

Based on the information above, please write a short evaluation about whether the two texts match on a news event level. Make sure to only return the evaluation and nothing more in the following format: [/INST]

Chain 6: Provide single label for news event level match

input variables: event_evaluation
output variables: match_event

system prompt: You are a helpful, respectful and honest assistant for classifying whether two texts match on news event level based on an evaluation provided.

At each request explicitly assign one of the two labels below. 0 - no match 1 - event match

Make sure you to only return the label and nothing else.

example prompt:

The following evaluation describes the news event match level: Both texts focus on one particular news event, the election campaign and party campaign activities amid the COVID-19 pandemic which is distinctive event. Both texts discuss aspects of the same election campaign, political parties and campaign strategies during the pandemic indicating that they pertain to the same news event. The texts were also published at a similar time and date which further indicates that they belong to the same news event. Based on this information, please assign either '0 - no match' or '1 - topic match'. Make sure to only return the label and nothing more in the following format:

main prompt: [INST] The following evaluation describes the news event match level: {event_evaluation}

Based on this information, please assign either '0 - no match' or '1 -event match'. Make sure to only return the label and nothing more in the following format: [/INST]

Chain 7: Create and run sequential chain

Based on all the previous

input variables: text1, text2, proper_nouns1, proper_nouns2, keywords1, keywords2, date1, date2
output variables: topics, main_topic, topic_evaluation, topic_words,match_topic,news_events,event_evaluation, match_event

Appendix S: Inter-coder reliability

Three annotators and the expert annotator performed the coding of an overlap sample ($n = 89$). The initial inter-coder reliability measured by Krippendorff's α between the 3 annotators and the expert annotator was 0.65 with respect to main topic level-matches and 0.38 with respect to the news events level matches. During this process we identified a text that was not a snippet of a news article, but rather the solution to a crossword. After removing text pairs when one of the text was this particular item ($n = 8$) Krippendorff's α slightly increased to 0.66 for topic match level and 0.41 for news events match level. As such, after reconvening and more coder training, another round of overlap coding was performed on another overlap sample ($n = 89$) drawn from the same corpus of document pairs ($N = 9897$). The results of the second overlap annotation round were much improved for both the topic-level matches (Krippendorff's $\alpha = 0.78$) and for news event-level-match (Krippendorff's $\alpha = 0.75$). Hence were confident that the annotators would perform well and highly similarly on the main corpus.

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Author contributions

Author contributions

The section below outlines author contributions to the empirical chapters. **Chapter 1** and **Chapter 5** were written solely by Mónika Simon.

Chapter 2 • Inside Dark Platforms

Researchers involved: Mónika Simon (MS), Kasper Welbers (KW), Anne C. Kroon (AK), and Damian Trilling (DT)

Conceptualization: MS, KW, AK, DT
Methodology: MS, DT, KW
Data collection: MS
Data analysis: MS
Writing (original): MS
Writing (review and editing): MS, KW, AK, DT
Visualization: MS, KW

Chapter 3 • From Darkness to Light

Researchers involved: Mónika Simon (MS), Savvas Zannettou (SZ), Kasper Welbers (KW), Anne C. Kroon (AK,) and Damian Trilling (DT)

Conceptualization: MS, KW, AK, DT
Methodology: MS, SZ
Data collection: MS
Data analysis: MS, SZ
Writing (original): MS
Writing (review and editing): MS, SZ, KW, AK, DT
Visualization: MS

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Chapter 4 • **Validating methods tracing information flows**

Researchers involved: Mónika Simon (MS), Kasper Welbers (KW), Anne C. Kroon (AK), and Damian Trilling (DT)

Conceptualization: MS, KW, AK, DT
Methodology: MS
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Data analysis: MS
Writing (original): MS
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Visualization: MS

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What happens on the fringes, stays on the fringes?

Information flows in the contemporary media system

The increasingly fragmented but at the same time interwoven nature of the contemporary information landscape poses new challenges to existing theory and methodology in understanding the information flows that shape public debate.

Through three empirical chapters, this dissertation seeks to unravel the intricate role of dark platforms in the contemporary media system. It not only sheds light on their multifaceted impact but also provides methodological and theoretical insights that can advance our understanding of information flows within the ever-evolving, multilayered information ecosystem.