Mapping user discourses about blocking, unfollowing and muting on Twitter

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Abstract

The article maps tweets by German-speaking Twitter users about disconnective platform practices such as blocking, unfollowing and muting. It identifies network clusters of topic-specific affiliation and interaction based on retweet and reply relationships as well as semi-automatic content analysis, and it investigates potential exchanges between the clusters. The article corroborates findings from earlier qualitative studies that tweets about disconnective action concentrate in political discourse networks, while also hinting at topic clusters beyond political expression that demand further investigation. Finally, it suggests that reciprocal communicative exchanges about disconnective action are rather limited to discussions among affiliates, while single replies and mentions by members from other and potentially opposing political groups still occur relatively often.

Keywords

Disconnection, Disengagement, Selective Avoidance, Cross-cutting Communication, Political Discourse, Social Media, Twitter, Network Analysis

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1. Introduction

Studies on disconnectivity and disconnective action in the use of social media platforms have become an independent field of research in media and communication studies in recent years (Kuntsman & Miyake 2019; Treré et al. 2020; Jansson & Adams 2021). The term *disconnective action* does not refer to a categorically sharp concept, but for the present context it is primarily intended as a distinction from "connective action" (Bennett and Segerberg, 2012), which shaped the early theorization of social media and its new forms of networking and communitization. Disconnective action accordingly covers a broad spectrum of actions from total withdrawal from social media platforms (cf. Dremljuga 2018; see also Syvertsen 2017) to acts of content "curation" (Merten 2020) or "selective avoidance" within a platform (Skoric et al. 2022). Most succinct for the second pole is certainly the practice of *unfollowing* as a counterpart to following, which was considered the epitome of connective action. In the sense used here, however, the term disconnective action is also used as a common denominator for other forms of action that aim to minimize exposure or the possibility to be contacted by certain users: this entails, for example, the actions of *blocking* or *muting* in addition to unfollowing. Most research on the topic of platform-internal disconnection has been conducted through surveys and interviews (John & Dvir-Gvirsman 2015; Dremljuga 2018; Merten 2020; Bozdag 2020), with some exceptions (Wheatley & Vatnoey 2019, 2022). In contrast, the research presented here was based on an interest in user discourses about these actions on the platform Twitter (now "X") and, in particular, about the practice of blocking. In a former qualitative study, we found that some disconnective behaviors are more controversial than others among Twitter users. For example, blocking was sometimes viewed positively as a necessary means of protection against verbal attacks and sometimes negatively as an encroachment on communicative freedom. Details on the controversies surrounding blocking are documented in Krämer & Otto (2023). In these investigations it also became clear that disconnective actions such as blocking are regularly given a special political meaning by users, and that political boundary markers are expressed when talking about such actions. By documenting, calling for or criticizing disconnective events and actions, users position themselves vis-à-vis their audience in terms of their own political stance and identity.

The present article aims to revisit this trace of the symbolic-political significance of the discourse on disconnective action on Twitter. It presents two previously unpublished network analyses that were conducted in parallel with the qualitative study mentioned above. For a long time, Twitter has been perceived as a particularly political platform in Germany, or political communities within Twitter were considered to be more vocal than others (cf. Höhlig 2018). It was therefore not particularly surprising that disconnective actions on Twitter/ X are reflected as political actions, even if not exclusively, at least to a significant extent. Moreover, many academic studies on disconnective platform practices on both Facebook and Twitter have also repeatedly focused on political contexts (John & Dvir-Gvirsman 2015; Schwarz & Shani 2016; Bode 2016; Yang et al. 2017; Zhu & Skoric 2022). At the same time, however, studies on temporal discontinuance have indicated that additional motivations could also play a role in tie dissolution beyond politics (Dremljuga 2018: 88-89; Franks et al. 2022). Against this background, it seems reasonable to assume that although a political context and justification of disconnective actions can be expected as the norm, there might also be less political contexts in which disconnective actions are rendered visible. A central concern of the network analysis presented below is therefore to follow up on these tentative expectations by means of a more quantitative overview that also takes the structure of the interaction networks into account. In fact, among the two network studies presented below, the initial one suggests that the political use of disconnective actions can also be identified in the network structure of the discourse. The retweet graphs of the first study display a rather strongly polarized interaction pattern, where antagonistically opposed political camps share their opinions about unfollowing, blocking or muting certain accounts from the other camp. However, while on the one hand relatively clear affiliation clusters seem to emerge in the retweet networks, there still remains a lively border traffic at the level of cross-cluster mentions on the other hand. An additional concern of the network analyses presented below is therefore to be able to quantify this border traffic more clearly.

Beyond these two interests of, on the one hand, testing the thesis of a particular visibility of disconnective practices in political discourse networks and, on the other hand, examining the traffic between them, the following presentation is also intended to clarify in more detail which methods were used, identify gaps and inform future detailed qualitative analyses. The main emphasis of the article is therefore rather descriptive than theoretical. After a brief contextualization of the case study, I begin with a detailed presentation of the methods and guiding research questions of two network analyses conducted in late 2022 and early 2023. The first study focused on affiliation networks in the discourses on disconnective action based on retweet relationships and also studied @-mention links between these clusters. The second study extended the network data to include reply relationships in order to be able to identify mutual interactions more clearly. Both studies were also supplemented by semi-automatic content analyses of selected tweets or accounts per cluster, searching for outgroup markers, political expressions and patterns of justification. Following the methodological overview, the results of the two network studies are presented along the lines of the research questions formulated at the beginning, as well as the respective intersections between the two studies. In the conclusion, I will then summarize the central findings and provide an outlook on where I believe further qualitative and quantitative research is necessary.

2. Theoretical and empirical context of the case study

Existing research about disconnective action in the field of communication studies in the recent ten years has shown a particular interest in studying the political meaning and embeddedness of disconnectivity. To a name few: John & Dvir-Gvirsmann (2015) focused on "politically motivated unfriending" among Facebook users in the context of the Israel-Gaza conflict in 2014. Bode (2016) used survey data from 2012 of social media users in the US to study the extent to which they mobilize political reasons for unfriending and unfollowing. Similarly, Yang et al. (2017) used different US survey data from the same year to test the relationship between exposure to political disagreement and unfriending. The results of the latter two research examples were ambivalent insofar as Bode contended that "perceptions of political disagreement […] increase the likelihood of unfriending" (Bode 2016: 6), whereas Yang et al. did not find such a relationship and concluded their research with a "relatively optimistic picture of the potential for social media to diversify public opinion" (Yang et al. 2016: 27). In a series of different articles, Zhu and Skoric investigated politically motivated unfriending in Hong Kong and Taiwan (Zhu, Skoric & Shen 2017; Skoric, Zhu & Lin 2018; Zhu & Skoric 2022), finding evidence for cultural differences and that users might still consume a variety of information despite politically motivated unfriending.

Even though the reasons for this scholarly interest in the political aspects of disconnective behavior may vary from case to case, it seems to correspond with larger questions in political and democratic theory. On the one hand, authors might have been tempted to test whether disconnective behavior exemplifies or at least resonates with the diagnosis of a larger shift in the style of political discussions and cross-cutting communication, where conversations among opposing political camps are presumably decreasing. In this perspective, disconnective action on social media stands at the crossroads of two trajectories potentially threatening democracy: one of which is specific to online culture and describes the risk of increasing "echo chambers" and selective exposure through algorithmic content filtering (see e.g. Sunstein 2018; cf. Bruns 2019 and Dahlgren 2021); and the other trajectory describes a more general transformation towards less cross-cutting exposure and network bridging in late modern societies that might threaten societal cohesion (see e.g. Putnam 1995). On the other hand, authors might have been interested in disconnective behavior as culturally significant symbolic acts that speak to changes in the registers of political communication and in identity formation online. In this perspective, politically-motivated disconnective behavior may be evidence for an increasing politicization of formerly less politically charged settings of everyday communication, and they might mirror larger cultural developments in political sorting and identity signaling (see e.g. González-Ballón & Lelkes 2023: 169f).

The latter perspective is more closely related to the one taken in this article as it emphasizes not the disconnective act on its own but its symbolic representation. In a previous study, we have investigated different ways of how users speak about the disconnective practice of blocking, be it performed by themselves or others (Krämer & Otto 2023). We found that such acts are indeed regularly discussed in the context of controversies over ideological differences, marked by identity signaling and justified by political reasoning. However, neither in our own study, nor in the research on politically motivated unfriending mentioned above, was politics the only reason for disconnective behavior. Political reasoning ranked high on the list in our own study of blocking, but was accompanied, for example, by the motivation to regulate one's emotional wellbeing. Or in the study by Bode, users considered political motivations as less important for unfriending than simply to control for "volume" (Bode 2016: 6).

With the following analysis, I therefore attempt to further contour the scope of a political interpretation of disconnective action by means of a quantitative keyword and network analysis. I will go less into the details of individual tweets, but rather try to discern discourse patterns on the level of larger network clusters. More specifically, I will concentrate on German-language tweets published in 2021 and early 2022 that make reference to different forms of disconnective behavior, especially blocking, unfollowing and muting. During the time of study, public discourse in Germany was dominated by the COVID-19 pandemic. Thus, in the presentation of the results further below, there will be at times references to the political demarcation line between pro-vaccine and anti-vaccine activists. Moreover, Germany has witnessed a significant rise of the far-right party Alternative For Germany (AfD) over the recent ten years, and battles between Anti-AfD activists and AfD sympathizers have equally increased enormously on Twitter. Both ideological cleavages have had a significant impact on the discourse about disconnective action on Twitter at the time of study. In terms of relative participation, Twitter was estimated to be the fifth most-frequented social media platform in 2021 with about 4% of the German-speaking population over 14 years using Twitter at least one time per week and a higher participation number of 9% in the age group between 14 and 29 (Koch 2022; Beisch & Koch 2021). For some time, Twitter in Germany had been perceived as an "elite platform" whose active users were dominated by journalists, politicians, celebrities, political activists and academics (Höhlig 2018: 145). However, it is questionable whether this still holds true or if a generational shift has diversified the picture.

3. Methods and research questions

The tweets for the following analyses were collected in the period from January 2021 to March 2022, by the author in cooperation with Benjamin Schäfer and with the help of the software DMI-TCAT (Borra & Rieder 2014). More specifically, we collected German-language[i] tweets that explicitly refer to disconnective behavior in their text. On the one hand, this included tweets that addressed options for disconnective action provided by the platform, such as blocking, muting or unfollowing. On the other hand, we also collected tweets which named acts of omission that are related to the possibility and perceived mechanics of the platform for disseminating content, but are not provided by Twitter as a formalized options for action: these included, for example, calls for users not to share or retweet certain content, or announcements not to give this or that content additional attention or reach. The possibility offered by the platform to 'report' content or users, i.e. to report them to Twitter, authorities or specialized organizations as being in breach of contract or the law and to work towards its deletion, was excluded from the investigation.

The various tweet collections were keyword-based and retrieved using the Stream API provided by Twitter. Tweets containing German inflections of the basic words block, mute and unfollow were collected automatically. For the remaining disconnective actions, the collection was based on phrases, e.g. "do not share", "do not spread", do not retweet", "no attention" or "no reach". For all collections, random samples and the most shared tweets were reviewed, followed by further revision of keywords or phrases where necessary. In this way, for example, we found the keyword “block recommendation” and created an additional collection for it. We also identified stop words during the review process that we would revisit later for the subsequent filtering of the data. For example, the German word “blockieren” was used disproportionately often to refer to 'offline' blockades, such as road blockades or the blocking of a parliamentary bill, and was therefore excluded from the network analysis presented below. Overall, the clean-up effort in the samples for blocking, muting and unfollowing was limited, which is why these three collections were included in the network analysis as complete data sets, only excluding tweets with the mentioned stop words. The smaller, phrase-based collections required far greater cleaning effort, as expected. Among the collections of tweets with calls to ignore or to not share certain accounts or posts, we manually checked between 1,000 and 3,000 tweets per collection for relevance. Even though these results were also included in the initial construction of the network graphs below, I eventually excluded them from further analyses because their size fell regularly below the threshold of 1% of the overall network.

Based on the datasets just described, I used the software Gephi to create various interaction graphs, both for the individual collections and in combination. In an initial study at the end of 2022, retweet graphs were created for all collections and, using the software's modularity algorithm and visual inspection of the graph layout, two distinguishable main clusters of users were identified who frequently share their tweets with each other.[ii] Retweet graphs were used as a proxy for the representation of affiliation relationships on the assumption that people who share content from others tend to be sympathetic, or at least not antipathetic, towards them. In a second study in spring/summer 2023, a further network analysis was carried out with combined data from the various tweet collections, this time mapping not only retweet relationships but also reply relationships between users. Once again, cluster assignments were calculated using Gephi’s modularity algorithm and this time further sub-clusters were differentiated. Roughly speaking, the difference between the two studies can be described as follows: in the first, *topic-specific affiliation clusters* were studied and in the second, *topic-specific interaction clusters.*

Since both network analyses were based on partially different graph information and in the first case a visual inspection of the graph was also used to identify the clusters, the assignments of users to clusters differ in both cases. Nevertheless, there are also clear overlaps between the two studies, as they both build on the same base data, except that the second study has expanded the scope of the data presented. The following analysis refers to both studies and, in some places, also to the common intersection of the cluster assignments from both studies. Specifically, three research questions are pursued:

> *RQ1*: Which cluster formations can be observed per disconnective action topic and across topics?
> *RQ2*: Can differences be identified between the clusters in which disconnective actions are thematized? *RQ2a*: Are certain topic clusters, for example, more or less politically active or expressive?
> *RQ3*: Is there an exchange between the clusters?

To answer *the first research question,* I will describe the network graphs created with Gephi in more detail and present the results of the cluster assignment using the software's modularity algorithm. Although modularity is an often-used method for cluster detection (but cf. Guerra et al. 2013), it does not leave any gaps between adjacent clusters. For the first network study, I therefore combined the automatic cluster detection by modularity calculation with a manual selection of cluster cores based on the visual layout of the graph. I used the layout algorithm Yifan Hu to visualize the network graphs in the first study and the Force-Layout2 algorithm in the second study (Hu 2004; Jacomy et al. 2014).

For answering the *second research question,* I will use the results of two content analyses, which both used a slightly different approach: In the first study, the focus was from the outset on the more specific research question 2a, i.e. whether the content in the two main clusters of the network was more or less political. After selecting the most frequently shared accounts in both clusters, their tweets with at least ten retweets were anonymized and analyzed. The selection comprised 126 tweets in one and 84 tweets in the other cluster. The analysis was carried out by comparing the differences and similarities between the most frequent retweets in both network clusters and iteratively developing coding categories. Finally, tweets addressing political institutions (such as parties, authorities or politicians), expressing a media activist stance (e.g. against certain publishers or hashtags), or presenting themselves as victims of censorship were categorized as explicitly political statements. In the next step, implicitly political tweets were added that address group behavior and at least hint at a distinction between ingroup vs. outgroup. By contrast, the approach in the second network study compared all clusters and subclusters of significant size and used two sources of information: on the one hand, the frequency of certain outgroup markers in the clusters, which were determined using word frequency analyses (see below for details); on the other hand, the information that the five to seven (depending on the size of the cluster) most central users in the respective clusters had given in their profile descriptions. The centrality of users in a cluster was determined by using Gephi to calculate their betweenness centrality value. Some users stated explicit political attitudes in their profiles (in relation to parties or other political orientations), or they referred to computer games, soccer clubs or musicians. Some also made statements about their family status (e.g. married or their role as a mother or father) and their age, which we[iii] anonymized and noted as relevant data for answering the second research question.

To answer the *third research question,* a combination of retweet and mention networks served as the basis for the data in the first study and a combination of retweet and reply networks in the second study. A connection between members of different clusters can take place in different ways and not in all cases these connections can be described as communicative exchanges. It was therefore important to consider the particularities of the different modes of connection (retweet, @-mention, reply) and the network graphs they construct. Mention relationships between two users can arise simply because they are part of a shared conversation, even if they participate in the conversation at different points and do not respond directly to each other. In these instances, one could speak of an indirect interaction or active exposure between the members of the clusters; i.e., even though they are active participants in the conversation, they are only confronted with statements from members of the other cluster outside of a direct interaction when reading the rest of the conversation. Such forms of indirect confrontation take place, for example, when members of the different clusters react to the tweets of prominent third parties, such as politicians and celebrities. It might also be the case that the mentions from the two cluster were made in the context of two different conversations but directed at the same user, in which case they would equally appear as indirectly linked via the mentioned third party. We can only assume that in these latter cases the members of the two clusters would still be exposed to members from the other cluster during their participation. Furthermore, even in the case of more direct reply relationships between members of different clusters, a large proportion of responses remain unanswered and replies, which did not mention a disconnective act explicitly, were not collected by us. Thus, the closest indication of a communicative exchange we can get from the limited dataset at hand are instances, where users from different clusters *reciprocally* respond to each other with a tweet mentioning a disconnective act explicitly. Altogether, the analysis of cross-cluster interactions was therefore guided by a heuristic of three distinct types of interaction: single reactions between members of different clusters; indirect interaction or exposure between the clusters via third accounts and reciprocal reactions. In the first study, indirect exposure was measured via mention relationships and the visual inspection of prominent nodes that were outside the two main clusters and which were mentioned by both clusters. In contrast, the second study focused on single and reciprocal reply relationships within and between the clusters.

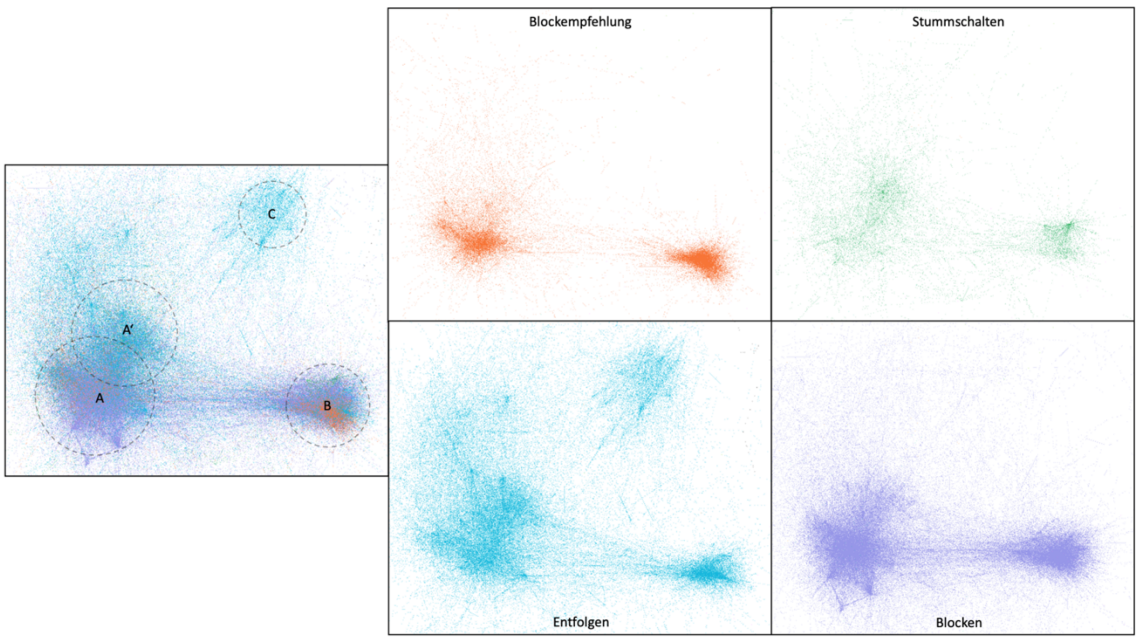
As briefly mentioned above, the second study was preceded by a lexicon-based word frequency analysis of the different tweet collections, the results of which were then also incorporated into the network analysis (see also the article's supplementary files). The lexicon was created on the basis of two qualitative studies on blocking and on calls for strategic ignorance, which had identified different types of justifying or criticizing disconnective action and repeating types of outgroup markers. For the semi-automatic content analysis, typical word patterns of the identified types were transferred into a keyword lexicon in MAXQDA in order to search the complete data sets for the frequency of keywords and phrases typical of the justification patterns and outgroup markers. More complex forms of topic modeling and classification based on machine learning were beyond the scope of the project at the time. On the level of justification patterns, the analysis made a distinction between justifications/ critiques of disconnective behavior that a) appealed to social institutions such as morality, freedom of expression, tolerance or anti-discrimination, b) justifications that referred to the collective danger or personal gain of generating publicity and reach for unwanted content, c) a type of reasoning that justified disconnective action against the risk of collective emotions such as hatred and provocation or personal feelings, and d) justifications based on the discursive quality of a discussion or specific argument. Some of the results of the word frequency analyses of justification patterns are also included in the network analyses below, in particular in answering research question 2 on the differences between the identified clusters.

4. Analysis

4.1 Results of the first investigation

Which cluster formations can be observed per topic/ across topics? (RQ1)

The combined retweet graph for tweets relating to blocking, block recommendations and muting shows two separate network clusters (Figure 1), which are subsequently referred to as *Cluster A* and *Cluster B* below. The bipolar structure is particularly striking in the case of block recommendations, but this structure also remains recognizable to some extent in the case of general comments on blocking and muting. In the case of unfollowing, however, the bipolarity of the network is less clear. Instead, cluster A frays and smaller, more independent clusters also emerge. The fraying area of cluster A is referred to below as cluster A' and the almost independent interaction cluster in the unfollowing network as cluster C.



Retweet graphs of the main topical collections in the first network study; Left panel: combined RT graphs with overlaid cluster IDs; Middle and right panels: Retweet graphs per topics with purple = blocking, orange = block recommendation, green = muting, blue = unfollowing.

Figure 1

Graph	**Number of nodes (accounts)**	**Number of edges (retweets)**
Combined RT graph	50.900	106.760
Block	33.570	58.350
Follow	21.620	28.760
Block recommendation	6.870	15.360
Mute	4.650	4.290

Table 1: Number of nodes and edges of the individual graphs in Figure 1, rounded to ten digits.

Can differences be identified between the clusters in which disconnective actions are thematized? For example, are certain topic clusters more or less politically active or expressive? (RQ2)

In each of the two main clusters A and B, around one third of the most frequent retweets were recognizable as political statements in the sense described in the methods section: i.e. they were directed at or against political institutions and politicians, the authors presented themselves as censorship victims or expressed a media-activist stance. If we also add the statements that were described above as 'implicitly political', characterized by the marking of ingroup vs. outgroup boundaries, the number of politicized tweets in both clusters increases further to 70 percent each. In Cluster A, typical outgroup tags included "right-wing extremists", "nazis", "antisemites", "AfD" (German right-wing party) or "AfD voters", different names for anti-vaccination activists during the COVID pandemic, as well as "Springer press"[iv]. In Cluster B, on the other hand, the most frequently used outgroup markers were "Fridays for Future", "left-wing" or "left-wing extremists", "Antifa", "islamists", "the Green Party" and "red dots" (a Twitter-typical term for vaccination advocates during the Covid pandemic). In political-sociological categories, it could therefore be assumed that Cluster A tended to unite liberal-progressive users and Cluster B tended to consist of more conservative users. When categorizing these outgroup references during analysis, I also noted a distinction as to whether the outgroup was clearly named (e.g. "Block nazis!"), if users used a more vague or behavior-oriented group denominator (e.g. "From now on, I will unfollow everyone who uses the hashtag #__!"), and whether the individuals addressed in the tweet were assigned to a group (e.g. "Do not share content from person X. This is a right-wing account!"). There were slight differences between the two clusters: While the assignment of addressed individuals to clear groups was more frequent in cluster A, the retweets from cluster B showed a stronger tendency to address individuals as members of a group without a clear group label based on typical behavioral criteria. One of the most recurring behavior out-called by members of Cluster B was the use of blocklists by their perceived opponents.

For further distinction, the retweets of the two main clusters were compared with prominent retweets in the unfollow network that lie outside the two bipolar clusters. In the fraying cluster A' of the unfollow network, all retweets shared more than ten times were announcements that the author would unfollow users who vote or have voted for a particular party. Thus, according to the most prominent retweets, it seemed that Cluster A' could equally be categorized as a politically active or expressive cluster. In the independent cluster C, by contrast, all of the prominent retweets were announcements that the authors of the tweets would unfollow passive followers who did not comment, like or retweet. Thus, of all the clusters examined, cluster C was the only one where the most prominent retweets did not contain political statements.

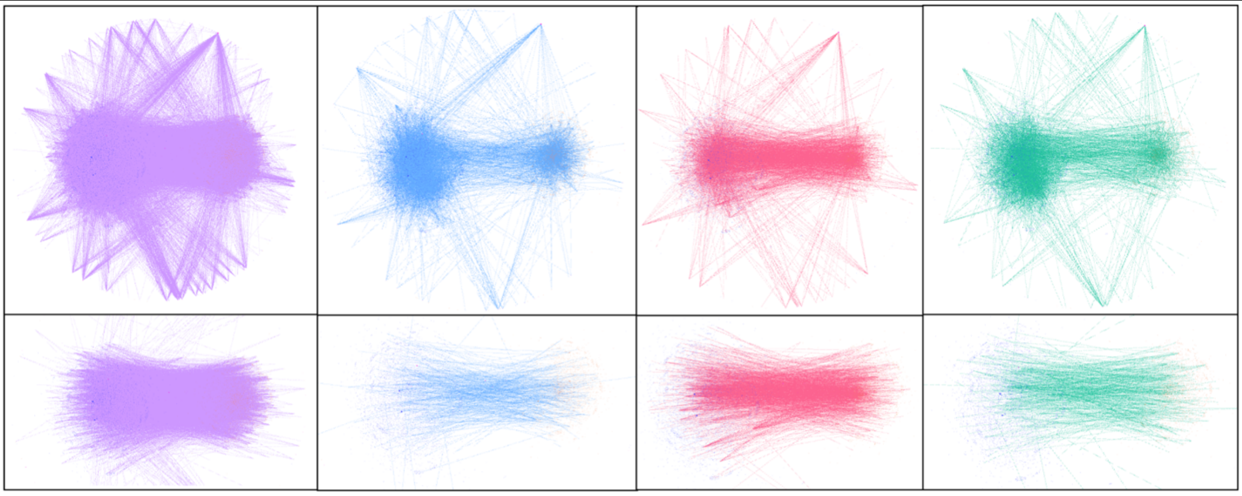
Is there an exchange between the clusters? (RQ3)

For answering RQ3 I only focused on the exchanges between the two main clusters A and B with seemingly different political orientations, at first by studying potential 'bridging accounts' mentioned by both clusters. In the case of the blocking network, two politicians from the Social Democratic Party (SPD) and one politician from the Christian Democratic Party (CDU), an activist from the German Fridays for Future movement and a journalist from WELT were particularly often mentioned by members from both clusters A and B. Some of these bridging accounts had published posts referring to high-reach and controversial accounts that were of central importance in Cluster A or B, and both supporters and opponents from the respective clusters commented on their reference. Two of the three politicians referred to the use of the block function by another, right-wing politician, while in the case of the third politician, other users raised the issue of blocking in the first place. In the case of the activist, s/he addressed the work of a popular online news collective that tends to be supported by accounts read as left-wing and regularly attacked by users read as right-wing. In the case of the journalist of the newspaper WELT, it was the journalist herself/ himself who reflected upon the use of the block function in general and which received mentions from both clusters. Altogether, particularly the timelines of the politician's and activist's accounts provided the platform for proxy battles between the two main clusters.

In the overall smaller collection of tweets about unfollowing, the number of indirect interaction or exposure between clusters A and B via mutual third-party mentions was also significantly lower and the network pattern not as concise as in the case of the blocking network. Here, only the frequent mentions of a post by an SPD politician stood out as an indirect connection between the clusters. In addition, there were isolated posts by private individuals in the transitional area between the clusters that did not convey any political content, but whose comments also radiated into both clusters. A similar picture emerged in the case of indirect connections between the clusters in the discourse network about muting:

there, it was primarily a post by an SPD member of the European parliament that received more reactions from cluster A and isolated comments from cluster B.

In order to focus more closely on the *direct* cross-cluster mentions between members of cluster A and B, the before-mentioned origins of potential indirect interactions or exposure between the clusters were temporarily excluded from the analysis. Because the majority of these bridging accounts were politicians and political institutions such as parties and authorities as well as news organizations, all accounts falling into this category with more than one hundred mentions were also temporarily excluded from the mention network, with a few exceptions.[v] The removed accounts added up to roughly 50 accounts (in the following referred to as 'top-50 bridging accounts'). For the remaining connections, I then checked the number of direct @-mentions between accounts from Cluster A and Cluster B and compared them with the number of indirect interactions or exposure via the mention of the top-50 bridging accounts. About 15% of all users in cluster A or B are indirectly connected via mentions of the top-50 most prominent bridging accounts in the area between the clusters such as the ones mentioned above (see Figure 2 top and Table 2). By contrast, about twice as many users in Cluster A and B mention each other directly (Figure 2 bottom). On the one hand, the results showed that mentions between the clusters exist to a considerable extent. However, there are significant differences between the different topics. The majority of inter-cluster mentions occur in the context of the discourse about blocking, followed by mentions of the other cluster in the context of block recommendations. Cross-cluster mentions relating to muting or unfollowing, on the other hand, were much rarer. Taking into consideration the overall number of tweets in the respective tweet collections, cross-cluster mentions in the course of block recommendations are remarkably frequent, while they are relatively rare in the course of comments on unfollowing, despite the large size of the network.



Top row: Mentions in clusters A and B per topic including mentions to the top-50 bridging accounts between the clusters; Bottom row: Cross-cluster mentions between the cluster A and B excluding mentions of the top-50 bridging accounts; Colors/ columns from left to right: purple = block, blue = unfollow, red = block recommendation, green = mute.

Figure 2

Relationships between Cluster A and B	**Number of Edges**	**Number of Nodes**
Total mentions in cluster A and B incl. top-50 bridging accounts	120474	14473
Connections between cluster A and B via the top-50 bridging accounts	8083	3357
... of which are mentions	7747	3169
... of which are retweets	336	324
Total mentions in cluster A and B excl. top-50 bridging accounts	112722	14322
Total number of users in cluster A and B		24735
Total cross-cluster connections	18112	7341
Total mutual cross-cluster connections*	1414	690
... of which are mentions*	1399	690
... of which are retweets*	15	26
... of which are tweets about blocking*	1250	652
... of which are tweets about unfollowing*	64	73
... of which are tweets about block recommendations*	53	56
... of which are tweets about muting*	47	66

*Table 2: Number of mentions and cross-cluster connections depicted in Figure 2. *Due to the filtering process of Gephi and the construction of the graph, the results show nodes that have a mutual connection but which may consist of connections from different topical collections or types of relationship (mention or retweet). For more statistics see Supplementary File 5.*

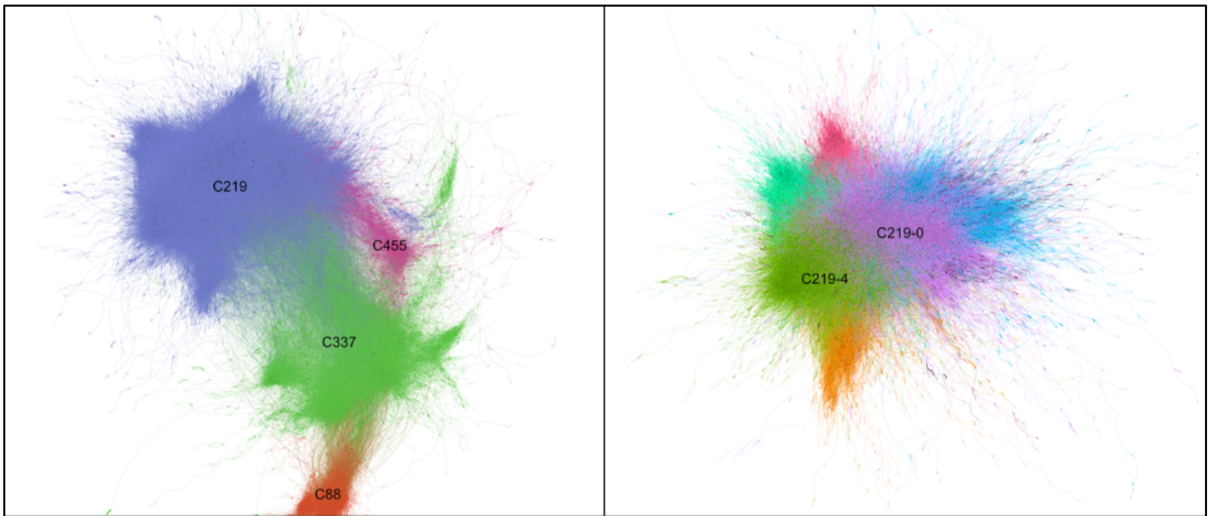
It needs to be mentioned at this point, however, that especially in the context of the blocking discourse, there also exists the practice of decidedly dispensing with @-mentions in tweets, e.g. by using screenshots, by removing the @ sign in front of the name or by inserting a space in between. On the one hand, these tactics can be read as signs of activist and political practice: They are suggested by users as attempts to avoid giving the people mentioned even more measurable attention. Thus, they once again add to the impression that the exchange about blocking is a politicized discourse. On the other hand, users also ask other members of their community to use screenshots if they have already been blocked by a person they are talking about and to still participate in the conversation in an informed manner. The amount of cross-cluster mentions via screenshots beyond the use of @-mentions shown in Figure 2 can therefore be estimated to be much higher.[vi]

Finally, the same graph that was previously used for the analysis of cross-cluster mentions also served as the basis for the analysis of *reciprocal mentions.* However, the amount of cross-cluster, reciprocal mentions is just under 1,400 tweets, which is only about five percent of the total amount of reciprocal mentions within and between the clusters. The majority of the reciprocal mentions between the clusters took place in the context of the blocking discourse. As described at the beginning, reciprocal mentions do not yet indicate whether it is merely a matter of joint participation in a conversation or a direct reaction between the parties. Only in the second study below I mapped and examined reactions between members of different clusters directly.

4.2 Results of the second investigation

Which cluster formations can be observed per topic/ across topics? (RQ1)

In contrast to the first study, the second study was based on a combined network graph of all data sets, in which author IDs and replied-to-user IDs were represented as nodes, and the connections between the nodes represented either a reply or a retweet. The differentiation of the clusters was carried out in several steps, moving from a coarse differentiation of main clusters to a finer distinction of subclusters. Nevertheless, there are also recognizable overlaps between the cluster assignments from the first and second study. A comparison showed that clusters A and B from the first study had a large overlap with cluster 219, in particular with subclusters 219-0 and 219-4, in the second study.[vii] Cluster 219 and the two subclusters 219-0 and 219-4 are therefore highlighted separately in *Figure 3.* Members of the originally identified cluster A were mainly found in subclusters 219-0 (68%) and 219-1 (12%) and members of the original cluster B in subcluster 219-4 (88%). The overlap between the affiliation cluster B and the interaction cluster 219-4 is particularly striking. However, around 1000 users who were originally assigned to cluster A also fell into subcluster 219-4 in the second study. This can be seen as a first indication that, beyond retweet relationships, there seems to be a significant amount of response relationships between the two political clusters that were originally identified. As a result, nodes from previously separate affiliation clusters appear closer to each other in the interaction network and might have even received the same cluster id by the modularity algorithms of the second study.



Network graphs from the second study – Left panel: Main clusters, which together make up 88% of all nodes and 94% of all edges (blue = C219, green = C337, pink = C455, red = C88); Right panel: Cluster 219 with subclusters that are larger than 1% and together account for 99%.

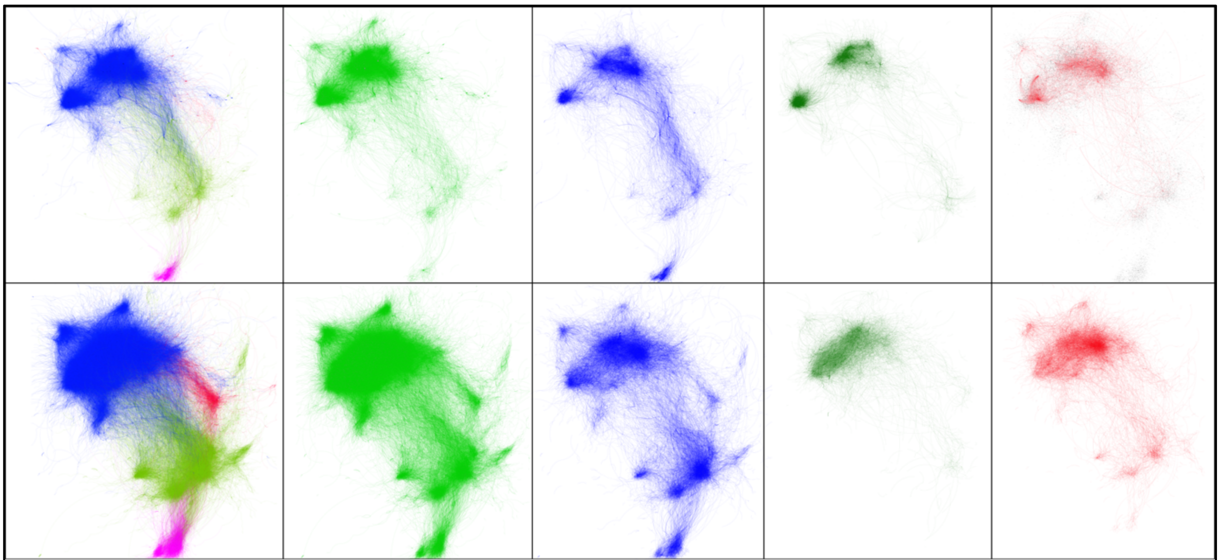
Figure 3

Cluster	**Number of nodes**	**Subcluster**	**Number of nodes**
C219	389,520 total, 92,840 users, 296,680 tweets	C219-0	185,420 total, 43,660 users, 141,750 tweets
		C219-4	116,390 total, 28,780 users, 87,610 tweets
C337	113,960 total, 27,530 users, 86,440 tweets		
C455	12,790 total, 3,370 users, 9,420 tweets		
C88	30,300 total, 8,210 users, 22,090 tweets		

Table 3: Number of nodes of the individual clusters in Figure 3, rounded to ten digits.

If we focus solely on the retweet relationships in the network graph of the second study (Figure 4 top), the patterns of the first studies are supported, albeit somewhat less concisely due to the above-mentioned transformation of the graph layout: the retweets about blocking are concentrated primarily in cluster 219, for which only a vague bipolar structure can be recognized, but which becomes all the clearer in the case of retweets about block recommendations, unfollowing or muting. In the case of unfollowing, there are also indications of radiating relationships in other clusters that lie outside C219. These additional clusters become more concise if the response relationships are also mapped (Fig. 4 bottom).

Then, in the case of blocking, unfollowing and muting, further interaction cores become apparent, which were identified by the modularity algorithm as clusters 337, 88 and 455, while only the block recommendations remain limited to cluster 219. The differences between the reply and retweet graphs can also be interpreted in such a way that retweets are quite significant as a mode of interaction for the discourse on disconnective actions in cluster 219, while reply relationships are more influential in the other clusters. At the same time, however, the reply graphs also reveal that there appears to be a lively exchange between the various subclusters within cluster 219, particularly in the case of the discourse on blocking and block recommendations.



Retweets and replies per cluster and per topic in the second network study: Top row: Retweets; Bottom row: Replies; Column 1: Combined graphs with colors per cluster ID (blue=C219, green=C337, pink=C88, red=C455); Columns 2-5 from left to right: block = green, blue = unfollow, dark green = block recommendation, red = mute.

Figure 4

Can differences be identified between the clusters in which disconnective actions are thematized? For example, are certain topic clusters more or less politically active or expressive? (RQ2)

In the analysis of the profiles of the 5-7 most central accounts of the various subclusters of the second network study recognizable differences emerged: On the one hand, there were subclusters whose central users regularly mention explicit political outgroup markers and political positioning in their profile descriptions; and, on the other hand, subclusters whose central accounts express political positioning much less frequently in their profiles, but make references to personal interests and leisure activities such as soccer, music, games or respective streaming platforms. More specifically, the central accounts in the various subclusters of C219 overwhelmingly contained political keywords in their profile descriptions, while the central accounts in C317, C88 and C455 made references to sports teams, celebrities, anime or specific computer games in their profiles. Moreover, within these latter clusters, I also found other outgroup markers than in the more explicitly political cluster 219. These included, for example, the condescending outgroup markers "kek" and "hs" (short for "hurensohn"/ “son of a bitch”). It is possible that these particular invectives are more common among younger internet users, allowing for the hypothesis that the leisure activity-oriented clusters tend to have an overall higher proportion of younger members than the explicitly political ones described before. This generalization is tentative at most, however, but it does correspond with the age information in some of the profiles of the clusters’ central users.

Additionally, we also see content-related differences between the interaction clusters in terms of which disconnective actions are primarily discussed. Tweets about unfollowing are proportionally more often in the clusters 455, 337, and 88, which tend to be oriented towards leisure activities, are less politically explicit and potentially younger. Conversely, the proportion of tweets about blocking is comparatively higher in the more political clusters 219-0 and 219-4, even though blocking is the most frequently discussed form of action in all clusters in terms of quantity. Block recommendations also appear to be a more characteristic topic in the political clusters and fall significantly in the leisure-related clusters.

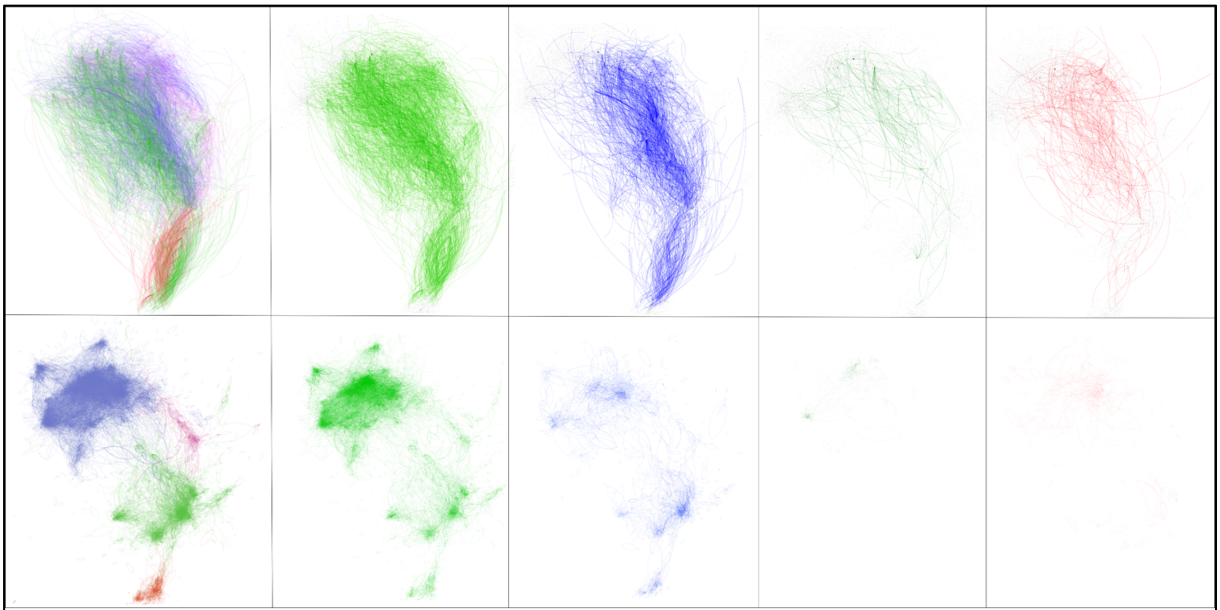
As described at the beginning, I also carried out a word frequency analysis for the different clusters, based on a lexicon of keywords indicating different ways how users justify or criticize disconnective behavior. As a result, two main trends emerged: *Firstly*, of the four[viii] originally differentiated justification patterns, all were found proportionately more often in the more political than the less political clusters. One possible explanation is that the categorization of the justification patterns was tailored to politically relevant justifications from the outset. This is contradicted by the fact that the typology also included recourse to emotions. However, it is also possible that the emotionally reflexive justifications were categorized and keyworded without being sufficiently sensitive for the emotional repertoires of younger users and the socialization around music, gaming and sports. *Secondly*, in the more politically expressive cluster 219-4 with heterogeneous subclusters, the reference to ‘emotion and provocation’ is over-proportionally frequent even in the context of block-related tweets, although in the overarching semantic cross-comparison this category only had average significance in the context of blocking. An example of this is the frequent justification of blocking due to alleged "left-wing agitation" in a subcluster with central accounts that appear to be conservative in orientation. Finally, the contrast between the more explicitly political and less political clusters can also be seen in relation to another pattern of justification: Tweets that justify disconnective actions as a means to intervene into the public reach of unwanted content or users occur more frequently in the context of the supposedly political clusters and very rarely in the less political clusters.

Is there an exchange between the clusters? (RQ3)

Before this research question can be answered, it is important to recall two particularities of the second network analysis. Firstly, the graph is based on communicative reference (reply) *and* affiliation (retweet), which affects the proximity of nodes and subsequent identification of clusters. Thus, whether a communicative exchange takes place between affiliation clusters can only be answered to a limited extent. Of course, it can be assumed that a close-knit reply relationship between different users also indicates a certain degree of affiliation. However, it is also conceivable that users respond to each other with little mutual affiliation and without strong involvement in the surrounding networks. Nevertheless, in the graph shown here, they would appear close to each other at the start of the investigation and possibly be assigned to the same cluster by the modularity algorithm. The question of an exchange between *affiliation clusters* must therefore be limited to the members of the two clusters A and B that were identified in the first study and which mainly fall within cluster 219 in the present study. Secondly, the reply relationships represented here refer exclusively to links between a tweet that explicitly names a disconnective action and the tweet or user to which it is in response. However, it is also possible that the tweet naming a disconnective action received a response itself, but this response won't be part of the present dataset. In other words, the graph only displays the communicative proximity and distance of users who explicitly comment on disconnective behavior and those who are addressed with this statement. Because the latter may also have commented on disconnective action during the study period, the more complex discourse network depicted here gradually emerges, but it only covers a fragment of actual communicative exchange.

Looking at the four main clusters of the second network analysis, we can see a total of 7400 cross-cluster connections between almost as many users (Figure 5 top, see also supplementary files). However, these are only one-way relationships, of which almost 80% are replies and 20% are retweets. As could be expected, most of the cross-cluster replies occurred between neighboring clusters, mainly between C219 and C337 (56%), between C219 and C455 (19%), and between C337 and C88 (15%). The same pattern can be found in the case of cross-cluster retweets, although the connections between C219 and C337 (76%) and between C219 and C455 (13%) stand out in particular. These retweet connections can be seen as an indication that there are also some ambivalent cluster assignments for users who might have appeared as members of the same cluster in an otherwise different clustering method solely based on retweets.

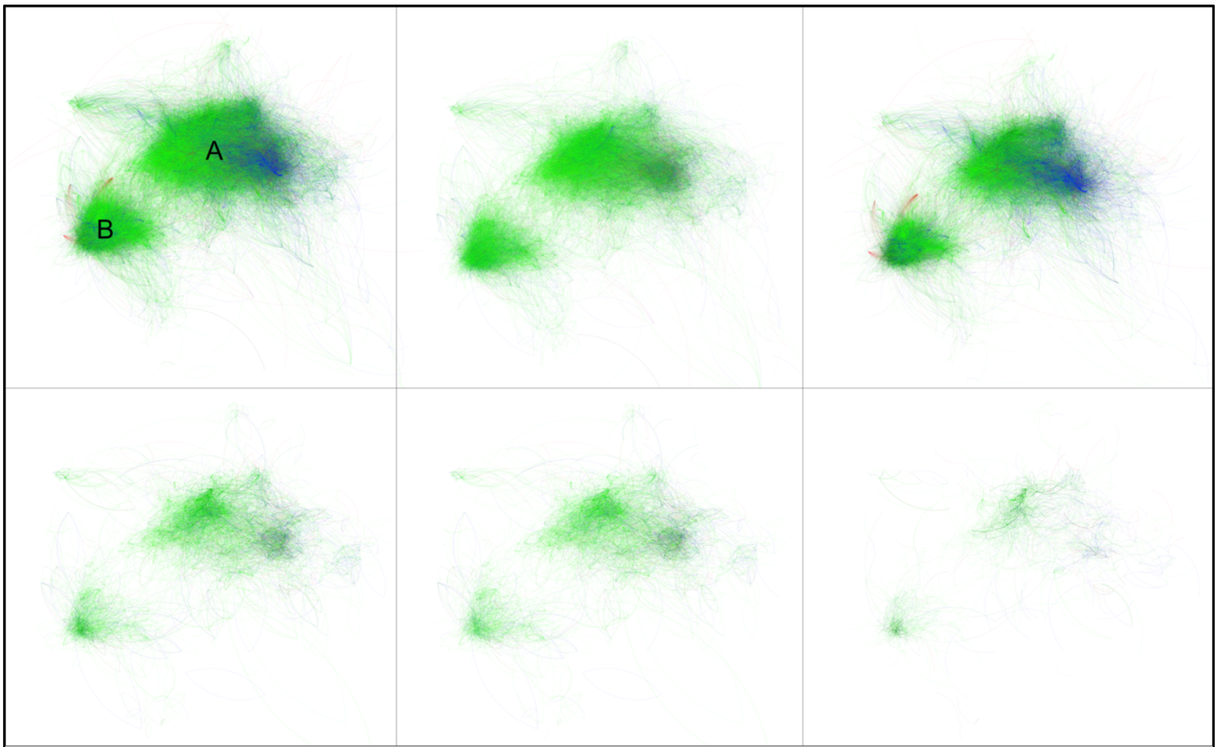
If we move from the one-way relationships to the reciprocal references between members of different clusters, the frequency of interaction decreases enormously. As written above, only a very selective picture of exchange is depicted here, which is based on explicit thematizations of disconnective behaviour. Nonetheless, it can be assumed that a discourse about disconnective actions also repeatedly mentions precisely these actions explicitly and the more frequently such mentions are mutually linked, the more likely I can assume an active exchange about disconnective actions between the accounts involved. Between the four main clusters of the second network analysis, however, there were only about 370 reciprocal connections between members of different clusters, the majority of which (96%) were replies.[ix] Just over half of these are reciprocal connections between the neighboring cluster 219 and 337. For comparison: the reciprocal links *within* the four main clusters added up to slightly more than 24,000 and thus to around 65 times the number of reciprocal connections between the clusters (Figure 5 bottom). Moreover, I also checked whether the nodes identified as cluster A or B in the first network analysis were in a reciprocal response relationship in the graph of the second analysis. However, since most of the nodes that were assigned to clusters A or B in the previous study are located in cluster 219 in this study, only three cases of reciprocal links between clusters A or B could be found at this level of observation.



Cross-cluster single connections and within cluster reciprocal connections per cluster and per topic in the second network study; Top row: Cross-cluster single connections; Bottom Row: Within-cluster reciprocal connections; Column 1 top: Combined graphs with colors per cluster origin (blue = connections originate from C219, green = from C377, pink = from C455, red = from C88); Column 1 bottom: Combined graphs with colors per cluster ID (blue=C219, green=C337, pink=C88, red=C455); Columns 2-5 from left to right: block = green, blue = unfollow, dark green = block recommendation, red = mute.

Figure 5

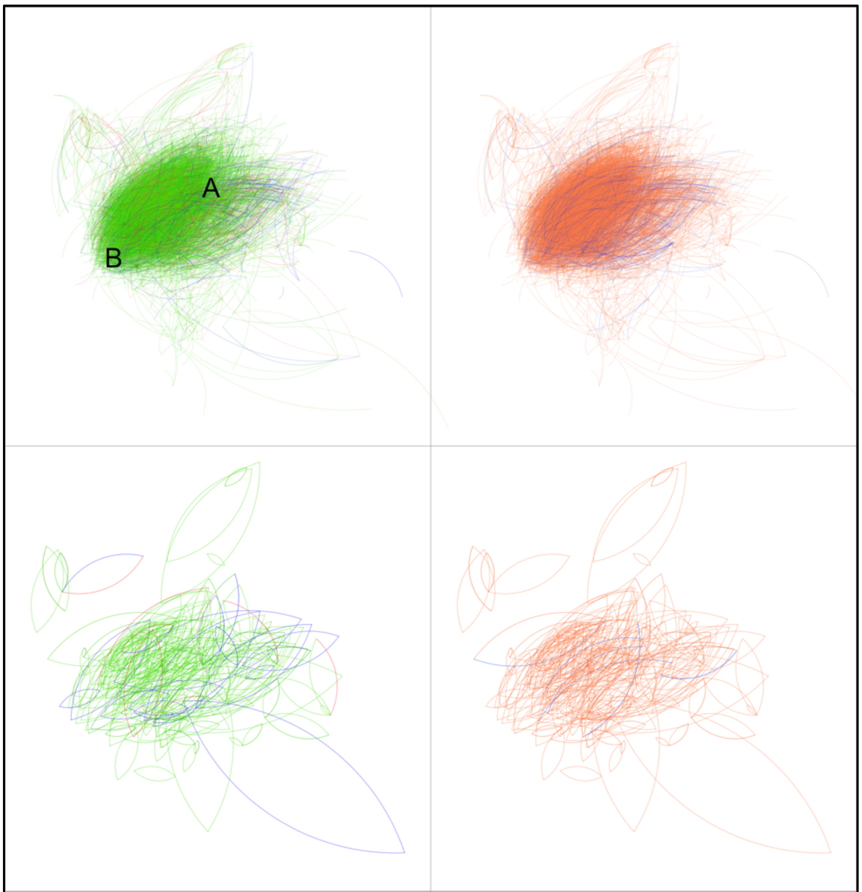
If we zoom one level further in and look at the reciprocal links between the subclusters of C219, which contains the majority of the members of the clusters A and B from the first study, the overall picture of reciprocal exchanges between subclusters increases significantly to 1900 if one considers all nodes in the network. The most reciprocal replies or retweets take place between the subclusters 219-4 and 219-0 (36%), as well as between 219-4 and 219-1 (34%), which were identified above as political or politicized interaction networks. However, combining the cluster assignments from the first study with the results of the graph analysis of the second study shows that that the number of exchanges between the nodes of the two affiliation clusters A and B remains extremely low. Of the total of 26.500 accounts with a Cluster A or Cluster B assignment, around 24.500 fall into Cluster 219. At the same time, however, the second study reveals that there are only 95 reciprocal reply relationships between members of Cluster A and members of Cluster B within C219 (involving 170 users and duplicate edges counted only once; see Figure 7 bottom). This number is even smaller than the cross-cluster mentions that were examined in the first study, suggesting a very limited amount of exchange about disconnective behavior between the two political affiliation clusters. By contrast, *within*-cluster mutual reply relationships are much more common for both clusters A and B (see Figure 6 bottom), suggesting that topical exchanges about disconnective behavior is rather occurring within respective affiliation groups.



Top row: within-cluster connections between members of cluster A and B in C219; Bottom row: Within-cluster mutual connections between members of cluster A and B in C219; Column1: all connections; Column2: only replies; Column3: only retweets; Colors: green = block, blue = unfollow, red = Mute.

Figure 6

Despite the rare occurrence of cross-cluster mutual replies, the first study had shown that there are nevertheless frequent single mentions between the clusters, especially in the context of indirect conversations via prominent third parties. Similarly, on the level of reply patterns between members from cluster A or B in the second study, we can see that *non-reciprocal* replies do indeed occur to a substantial extent (Figure 7 top). Roughly 4700 single cross-cluster reply relationships exist between 4100 users of cluster A and B (duplicate edges removed). Similarly to the mention network, these replies occasionally concentrate in relation to prominent accounts such as politicians, journalists or news organizations. But there are also many single cross-cluster replies between both affiliation clusters directed at users whose popularity is limited to Twitter as well as towards lesser-known accounts.[x]



Top row: cross-cluster connections between members of cluster A and B in C219; Bottom row: cross-cluster mutual connections between members of cluster A and B in C219; Column 1: colors per topic (green = block, blue = unfollow, red = mute); Column 2: colors per relationship type (orange=reply, blue=retweet).

Figure 7

5 Summary and conclusion

Disconnective actions and events were common everyday topics on the platform Twitter during the time of the two studies. In a direct comparison between the different types of disconnective action, blocking dominated as the most frequent topic. Moreover, the largest cluster within the discourse network on disconnective actions could be identified in both network studies as a political cluster based on the most frequent retweets and the self-descriptions of the most central accounts. However, besides the dominance of the topic of blocking and of the political clusters within the overall network, it was also shown that discourses about unfollowing play a significant role in clusters that appeared to be less political and which may revolve around sports, games or music, among other things. Thus, while the focus of many earlier disconnectivity studies was on the political significance of unfriending and unfollowing, the practice of blocking appears to be comparatively more suitable for political articulation on Twitter.

One of the reasons of the symbolic-political popularity of blocking on Twitter may be that block events can be documented using screenshots, whereas unfriending events are more difficult to represent. Another one could be that block experiences can be embedded more intuitively into narratives and controversies about communicative freedom, framing blocking as the opposite of norms of communicative accessibility and openness, and capitalizing on a perceived political cleavage along the lines of attitudes towards free speech. Future qualitative studies could zoom in more detail on the differences between the political reasoning of unfollowing and blocking, while also expanding on the particular justifications of disconnective practices in contexts that are seemingly less political. Moreover, what both studies unfortunately could not problematize, is whether the association of a disconnective platform function with political meaning is due to an already existing politicization among users, or whether a certain habitus of Twitter has encouraged such a politicization of disconnective action. In the latter case, it would be interesting to follow diachronically whether members of originally less politicized clusters increase their political reflection of disconnective action over time, and whether seemingly less political forms of disconnective action become increasingly politicized.

The two studies also sought to describe in more quantitative terms the amount of communicative exchange between different affiliation and interaction clusters in the discourse about disconnective action in Twitter. On the one hand, the first study found out that there is indeed a significant number of cross-cluster connections. To a considerable extent this is due to connections via bridging third-party accounts outside the cores of the two affiliation clusters; where the most commonly mentioned bridging accounts were politicians, prominent activists, journalists and news organizations. Yet, also the level of direct mentions between the two affiliation clusters after excluding the accounts of prominent public figures from the network analysis remained high. On the other hand, *mutual* mentions between members of these clusters, and which were not channeled through indirect connections with the aforementioned 'bridging accounts', only took place to a very limited extent. The second study was able to provide additional support for this finding, as only in less than 100 cases did members of the two most prominent retweet clusters respond to each other directly. However, it must be pointed out that only those interactions could be considered in which the participants explicitly named the disconnective action under question. Future studies are thus encouraged to expand this scope by considering the exchange between the members of different clusters before and after a specific disconnective action is being made explicit.

Overall, the results suggest that a more substantial communicative exchange about disconnective actions in the form of a reciprocal dialogue about the action in question is more likely to take place *within* groups, albeit with regular mentions of potential members of an 'outgroup' against whom a disconnective act is announced or called for, or who are criticized for their action. The existence of regular inter-cluster mentions confirms what Bruns & Highfield (2015) have noted almost ten years ago: that despite means for personal content curation, among politicized Twitter users there remains to be an exposure to content from other groups. Even more than that, statements about disconnective acts are regularly used to signal political identity claims towards both affiliates and opponents, maintaining a form of connection precisely through the communication of disconnection.

Acknowledgments

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Notes

[i] The language recognition was carried out by the platform operator. Twitter offers various filter options when using its API, including filtering according to the language of the tweet.

[ii] The modularity algorithm was performed with a resolution index of 10 and without taking edge weights into account, as the edges were not merged when the network was created. For the visual identification of clusters, the layout method of Yifan Hu (Hu 2004) was used and a selection of the two main clusters was carried out based on the visual shape of the graph; i.e. I manually selected nodes within a radius from the respective centers of the two main clusters and assigned them to one or the other cluster. The idea was to limit the selection to the visually denser centers of the two clusters and to ensure a concise distance between the two selection areas. Only those nodes that were assigned to one or the other cluster according to both methods (manual selection *and* modularity algorithm) also received the final assignment to cluster A or B.

[iii] The coding of the profile descriptions of the most central users per clusters was performed by a team of two coders including the author and one student assistant.

[iv] Overall, the following categorizations, clearly recognizable as outgroup markers, were used in Cluster A: "anti-vaccinationists", "querdenker", "covidiots", "right-wing extremists"/"right-wingers", "Nazis", "Holocaust relativizers", "fascists", "anti-Semites", AfD and AfD voters, "Sifftwitter", authors of misogynistic content, "trans enemies", disseminators of fake news, cannabis legalization opponents, "Springer press", "Bild".

[v] The accounts of the parties AfD and Die Linke were not included, as both also played a central role in the respective retweet clusters. The same applied to journalists, unless they were already in the transition area in the retweet clusters.

[vi] A test analysis of tweets with the keywords "screen" or "screenshot" revealed that around 4 percent of accounts from cluster A (700) and around 3 percent from cluster B (290) addressed the use of screenshots in the context of disconnective actions (demanding, criticizing, etc.) during the survey period. It can be assumed that the use of screenshots to address members of the other cluster, which was not explicitly mentioned, is significantly higher.

[vii] Of the approx. 26,600 nodes originally assigned to clusters A or B, 92% (or 91% in the case of cluster A and 95% in the case of cluster B) belong to cluster C219 in the second study. Approximately 5% are found in cluster 337, whereby this mainly concerns nodes from the original cluster A.

[viii] In the original content analysis of tweets about blocking and strategic ignorance, I distinguished five patterns of justification. The fifth justification pattern comprised tweets that referred to the limited energy, strength or time resources of users as the basis for justifying a stronger curation of contact opportunities. Due to the low use of this type of justification in the cluster analysis, it was excluded from further interpretation in the present network study.

[ix] The calculation was as follows: one connection between 219 and 337 and one between 337 and 219 together result in *one* reciprocal connection between these clusters.

[x] Among the top 100 users who have most often been replied to from the other cluster, only about every fifth entry was a politician, journalist, news organization, spokespeople of an NGO or a popular YouTube influencer.