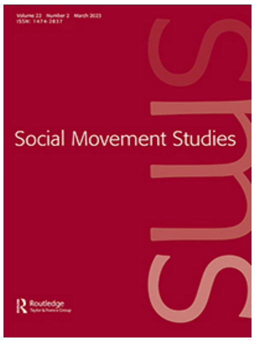

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Diffusion dynamics and digital movement: The emergence and proliferation of the German-speaking #FridaysForFuture network on twitter

Xixuan Zhang

Institute for Media and Communication Studies, Freie Universität Berlin, Berlin, Germany

ABSTRACT

Diffusion is a long-established concept that deals with the mechanisms explaining the prevalence of social movements. However, previous empirical studies on digital movement merely used diffusion as a term referring to increasing numbers of posts or public attention, without distinguishing what is diffused nor asking how information is diffused. Studies applying social network analysis have restricted themselves to retweet networks from a static perspective and emphasized the main actors and critical messages driven by the crowds. While the previous studies examined information diffusion as an outcome, they were unable to reveal the underlying processes that define how digitally networked movements spread over time among crowds embedded in different communities. As a case study, this paper investigates how the German-speaking network #FridaysForFuture was facilitated and contested through different diffusion dynamics. By inferring a diffusion network based on 237,892 retweeting sequences and the following/follower relationships of the 51,803 engaged actors in the early stages of #FridaysForFuture, it quantifies the digitally networked movement from a top-down perspective: the network, the tweets, and the retweets, concerning aspects of both actor and content. The findings suggest the development of digitally networked movements depends on their ability to influence and spread among different networked publics. The diffusion mechanisms of information, discourses, and beliefs of digitally networked movements were mainly enabled by, and flowed through, pre-existing networks rather than situational spontaneity. However, they varied according to issue salience and were distinguished by the network structures, political positions, ideological lines, and geographical proximities of the involved communities.

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Information diffusion; diffusion dynamics; digital movement; online discourse; networked publics; computational methods

Introduction

The environmental movement Fridays For Future (FFF) has proven to be one of the most influential of its kind in gaining unprecedented social impact and political attention (Haunss & Sommer, 2020). Launched on 20 August 2018, the movement was initiated and organized by Greta Thunberg, specifically engaging school students who skip school every Friday to publicly call for climate justice and efficient climate

CONTACT Xixuan Zhang x.zhang@fu-berlin.de Freie Universität Berlin, Garystraße 55, Berlin 14195, Germany

politics that will safeguard their future. On 15 March 2019, the movement's first global strike mobilized more than 1.6 million people and received worldwide public attention (Wahlström et al., 2019). On social media, #FridaysForFuture emerged as a hashtag that flourished in receiving both positive recognition and criticism. The FFF network now serves as a facilitator of both online and offline movements, providing a public arena for political discourses, revealing the independent and interdependent trajectories of collectives[1] and their interactions with ideas, beliefs, and messages throughout cycles of demonstrations.

Social movements emerge, persist, flourish, and fall for a variety of reasons. Information diffusion, associated with mobilization and participation, is a long-established concept referring to the mechanisms that explain the prevalence of social movements and the spread of related symbols and tactics (Easley & Kleinberg, 2010; Strang & Soule, 1998). Though a growing body of studies examined diffusion processes of social media movements, they used diffusion merely as a term when referring to increased post volumes. Studies applying social network analysis have attended only to retweet networks from a static perspective, with attention to the main actors and to critical messages. However, they neglected the networked publics that promote particular frames and belong to different communities and overlooked the underlying diffusion processes of social movements. Based on the diffusion network resulting from 237,892 retweeting sequences and following/follower relationships of 51,803 actors, this study analyzes how #FridaysForFuture was facilitated and contested through different diffusion dynamics of the networked publics. It traces the information flows, quantifies diffusion patterns, and reveals the interplay between information, communities, and movement.

Social movements in the digital age

Considering the prominent concept of 'connective action,' Bennett and Segerberg (2013) distinguish between connective action and the conventional concept of collective action. They show how each differently relates to the role of formal organizations and communication technologies in accommodating political action. Compared to collective action that is organizationally brokered, connective action features inclusive networks with personalized action frames and loose or limited organizational coordination. This applies to both variations of connective action, i.e., crowd-enabled connective action and organizationally enabled connective action. Social media, as the technical infrastructure enabling large-scale engagement, connects diverse actors through cross-cutting mechanisms. The multi-layered networks serve as 'organization agents' that negotiate the interests and values of different actors for a contested goal (Bennett & Segerberg, 2013; Castells, 2015).

Nevertheless, social movements are more than connective action networks that can be self-organized, stabilized, and maintained in digital space (della Porta & Diani, 2020; Dolata, 2018; Kavada, 2015). Technological infrastructures typically support the spontaneous emergence and operation of non-organized formations under inclusive frames such as 'We Are the 99%,' coined in 2011 during the Occupy movement; however, a successful transition from non-organized formation to a strategically oriented and persistent form of collective beyond the individual level depends on institutionalization processes and social conditions, which mainly happen during (large) group protests and demonstrations on the ground (Dolata, 2018, pp. 48–51). In movements' social media activities, actors do not simply become substantial social formations; the identity-building processes of movements are less coherent due to actors intensely exchanging individual perceptions and exhibiting highly personalized protest behaviors (Dolata & Schrape, 2018b, p. 24; Dolata, 2018, p. 50).

Concerning the coexistence of multiple mechanisms and their mutual influence in digital spaces, the coherence of collective action is influenced by the scattered ideas circulated in multiple loosely structured networks and via different agendas of various organizations (Bennett et al., 2018). In protests and social movements, it can be necessary for the core to stabilize the periphery, as understandings on the periphery can take over the intentions of the core – crowds, even of like-minded people, can change their opinions when moving from one network to another (Bennett, 2020, p. 52). Increased flexibility of networks brings crowd-enabled connective action that entails not only large-scale mobilization, but also large-scale weighing of contending ideas. In such circumstances, organizations can lose control over their agenda by individual actors' personalized action frames taking organizationally enabled action (Bennett & Segerberg, 2013). According to Bennett (2020), the political outcomes of social movements are primarily influenced by how ideas can be produced and packaged to traverse through different social and political networks (pp. 54–55).

Information diffusion in digitally networked movement

Diffusion is a key term that describes the process of spreading and adopting ideas, symbols, tactics, and frames in social movement research, thereby enhancing our understanding of social movements' prevalence (della Porta & Diani, 2020; Easley & Kleinberg, 2010; Snow et al., 2018; Strang & Soule, 1998). In the classic sense, social movements aiming to spread collective behaviors, require social affirmation and reinforcement from multiple sources and connectivities (Barash et al., 2012; Centola & Macy, 2007; Easley & Kleinberg, 2010). Because participation in a social movement is an inherently risky undertaking, these movements need first to build and maintain momentum within neighborhoods and small communities before forwarding political mobilization to the other parts of their networks (Easley & Kleinberg, 2010). Thus, many movements scale up slowly when building communities for information transition and coordination in their respective local networks (Barash et al., 2012; Easley & Kleinberg, 2010). Weak communication ties carrying non-redundant information between different densely connected communities are less useful since they do not enable communities to get connected with a view to large-scale coordination in a social movement (Krinsky & Crossley, 2014).

The advent of ICTs has generally prompted the diffusion processes of social movements by creating interpersonal connections, enabling multichannel communication, and facilitating horizontal coordination (Castells, 2015; della Porta & Diani, 2020; Krinsky & Crossley, 2014). Meanwhile, a plentiful of networked (counter)publics that produce disruptions or interruptions of dominant political narratives assemble and organize diverse forms of communities around various issues (Foucault Welles & Jackson, 2019; Papacharissi, 2016). Bypassing the traditional media gatekeeping, they can amplify particular frames to prominence and influence mainstream public sphere, by actively participating in repetitive conversational practices and collaborative filtering through platform features (Meraz & Papacharissi, 2013). Concerning the discursive contestation between the divergent publics, ideas and beliefs of movements may not be able to bridge networks of competing ideologies, where homophiles and selective exposures restrict information exchange across ideological frames (Foucault Welles & Jackson, 2019). As a result, it is still difficult for digitally networked movements to gain and retain momentum within and across different communities.

Quantifying diffusion dynamics

The networked environment brings together actors with similar goals and agendas, close organizational properties, or the same frames and identities (Diani & Mische, 2015; Gomez-Rodriguez et al., 2012). The groups' trajectories are delimited by individuals' intersections (Diani & Mische, 2015, p. 15). Additional to this insight, key features in understanding how information is diffused through social media and how large numbers of actors move throughout the networked movement, are collectives with shared values and their cohort trajectories (Diani & Mische, 2015; Gomez-Rodriguez et al., 2012). Regarding actors, we crucially need to understand how those impacted by their local networks decide to act, how they pick up trends before a peak, and how they reach other influenceable actors, turning them into amplifiers through their networks (Cha et al., 2020; Easley & Kleinberg, 2010). Concerning the messages, to understand meaning construction, organizational structure, and diffusion processes, we need insight into the existing ties between actors, the content of messages, and patterns (Krinsky & Crossley, 2014).

Empirical diffusion studies on digital social movements and their related online discourses are mostly issue-centric and Twitter-based, with a descriptive focus on a small number of influential actors and messages circulated in retweet networks of online protests and activism (e.g., Klinger et al., 2022; Theocharis et al., 2015; Tremayne, 2014; X. Zhang, 2021). These studies examined information diffusion as an outcome; however, they did not reveal the underlying processes that explain how messages, beliefs, and frames that evaluated and revised by networked publics, spread across communities. Previous research, shaped by networks modeled through mentions, replies, and retweets, could have overemphasized the connections between original tweeter and retweeters. On Twitter, actors are embedded in different follower networks that deliver content to the actors' followers and eventually drive them to create narratives, reshape opinions, and push the ongoing activism forward. Therefore, actors do not necessarily obtain new information from original tweeter who first posted it, but from those whom they follow. In contrast to the previous studies, this paper aims to reveal the diffusion dynamics of a digitally networked movement and its discourse in a temporal dimension. I investigate and present as a case study, how the networked #FridaysForFuture movement was facilitated and contested through different diffusion dynamics in its emergence and proliferation on Twitter. I quantify the diffusion dynamics by modeling and analyzing (1) the diffusion network, (2) the diffusion cascades, and (3) the diffusion paths between actors from a top-down perspective.

Correspondingly, four research questions guide this study on the level of the network (RQ1), tweets (RQ2), and retweets (RQ3.1, RQ3.2).

RQ1: Which topics and communities constructed the diffusion network of #FridaysForFuture, and how did they contribute to the dynamic #FridaysForFuture diffusion processes?

Researchers have found different communities and discursive frames, and particularly the complex dynamics behind different forms of power competition between right-wing and left-wing networks (Gallagher et al., 2018; Knüpfer et al., 2020; Martini, 2020; Suk et al., 2019; Xu, 2020). In spite of studies that descriptively investigate cascades based on different sets of information (e.g., Cha et al., 2020; Goel et al., 2015; Vosoughi et al., 2018) and statistically test the cascade structure's impact on information sharing (e.g., Liang, 2018), diffusion dynamics that aggregate both actors and messages at a network level are rarely examined. Additionally, only a small number of the studies examine network changes of communities. By answering RQ1, I provide an overview of the topics and communities in the #FridaysForFuture diffusion processes at a network level. I hypothesize that multiple frames and communities have differently contributed to the structuring and formation of #FridaysForFuture.

RQ2: How were tweets, as well as their diffusion dynamics, varied according to topics and communities, and what did these differences mean for the coherence of the movement?

Information diffusion is varied across different community networks, types of diffused information, and digital platforms' technological affordances (Gomez-Rodriguez et al., 2012). Actors who are well networked in an online community have homogeneous opinion patterns and similar characteristics, such as a common political ideology (Barberá et al., 2015; Y. Zhang, 2020). On Twitter, messages are spread more widely than deeply (Cha et al., 2020; Goel et al., 2015). However, getting messages shared cross-cuttingly is more likely if information is deeply spread through different generations of actors in multiple steps (Liang, 2018). RQ2 analyzes the diffusion cascades from the perspective of each retweeted tweet and its original tweeter. In the case of #FridaysForFuture, I hypothesize that tweets created by different communities and focusing on different topics would have distinct political frames, opinion patterns, and diffusion capacities.

RQ3: In the #FridaysForFuture movement, what triggered retweets, and what do such triggers imply for the development of the movement concerning contestation and coordination between communities?

On Twitter, the actors' decision to share particular information depends not only on the original tweeter but also on what is posted and who in their local setting reposted it concerning the positionality of actors and their peripheral networks. At the level of retweets, RQ3 and its sub-questions serve to determine how ideas, beliefs, and frames persuaded across different communities that contested and coordinated in #FridaysForFuture from the perspective of each actor, the diffusion paths, and the actor's contacts.

RQ3.1: How were #FridaysForFuture content retweeters influenced by the potential exposures[2] mediated by their neighboring contacts?

Activism discourses can originate in vastly different Twitter communities (Y. Zhang, 2020). Still, solidarity and togetherness can arise in social movements as a result of geographic location and shared interests (van Haperen et al., 2018). Liang and Fu (2016) showed the likelihood of retweeting is positively related to tightly connected networks with abundant contacts. In different communities, diffusion is more likely to occur between homogenous actors, while the spread of opposing opinions becomes difficult (Liang & Fu, 2016). Gallagher et al. (2019) observed how network-level reciprocal disclosures contribute to networked narratives growing. However, only a few empirical studies have investigated sharing behaviors in digital movements.

RQ3.2: Which kinds of messages circulated in one community could trigger further diffusion into other communities, and vice versa?

A number of studies have already raised questions on which factors drive the proliferation of digital movements regarding issues, frames, and communities. Haßler et al. (2021) confirm the strong influence protest events in the #FridaysForFuture have on the increase of related tweets over time, until the pandemic lockdown. Suk et al. (2019) show how #MeToo was mainly driven by networked acknowledgment and news frames related to politicians. Freelon et al. (2018) distinguishes different communities in #BlackLivesMatter, finding the unaligned mainstream news community, influenced by the social movement community, greatly affected the political elite's response. Still, there is little empirical evidence on the role of information frames in diffusion between Twitter communities.

Methodology

Data

I used Twitter API for data collection, gathering 287,865 tweets by searching for all German-language tweets containing the hashtag #FridaysForFuture, from Friday, 14 September 2018, to Monday, 18 March 2019 to investigate the emergence and expansion of the networked movement. This period covers all critical issues ranging from Greta Thunberg's action against climate change, the first national climate change strike in Germany on 20 August 2018, to the first global climate strike on 15 March 2019. I decided to focus on German-language tweets because the climate movement is prominent and well established in Germany and German-speaking countries. To study diffusion dynamics and model diffusion processes, I included only retweets and the original tweets from which each retweet was generated, because quote tweets and replies that allow further interpretations to the original tweets have different logics of sharing. In contrast to quote tweets and replies that are usually linked to other than the pertinent context and do not contain this hashtag or are unrelated to the discourse, retweeting is a Twitter feature designed for large-scale retransmission without reinterpretation of the original tweets. Next, I retrieved all actors, termed 'followees' (i.e., who are on the actor's list of those s/he is 'following' on Twitter[2]) to construct a follower network among actors who posted with the hashtag #FridaysForFuture. The 'follower network' shows the engagement between actors who follow each other (see Figure 1).

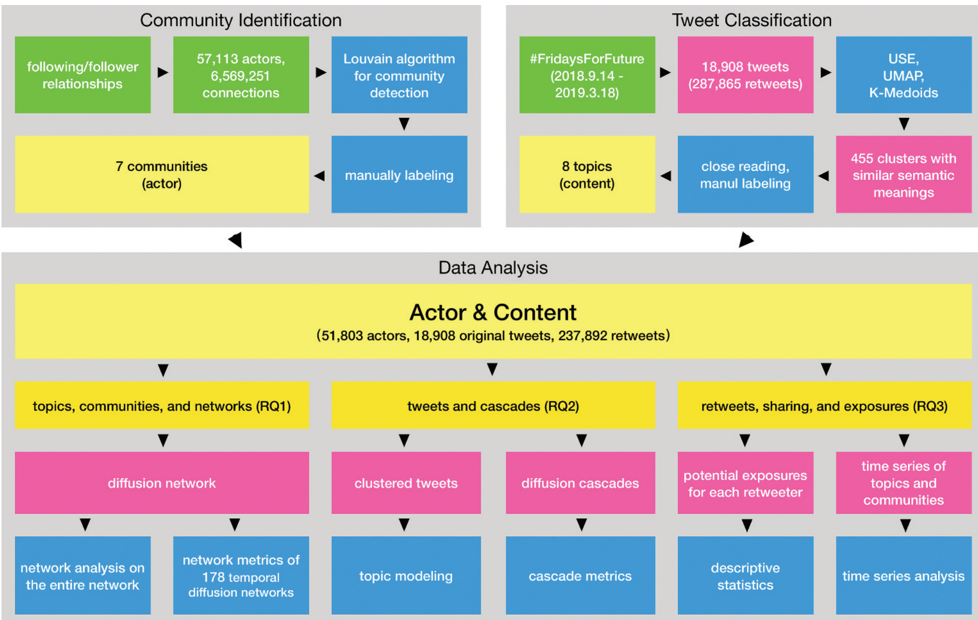

Figure 1. Overview of the data collection, preprocessing, and analysis processes of the study.

Community identification

The follower network is constructed by 558 isolated and 57,113 connected actors with 6,569,251 follower/following connections. Compared to a retweet network or mention network which joins actors through one-off interactions, a follower network is composed through stable subscription ties. I applied the widely used Louvain algorithm (Blondel et al., 2008) for community detection to the follower network, to identify the various communities in #FridaysForFuture. The algorithm maximizes modularity which measures the relative density of edges inside communities in relation to that of edges outside communities taking a bottom-up approach. In the heuristic algorithm, users need to decide on the size of communities by setting a resolution parameter. After testing different resolution values in Gephi (Bastian et al., 2009) and getting the optimal resolution value, I ran the algorithm ten times from randomized starting nodes to confirm the number of communities: seven communities presented as always significant. To label them, I reviewed the 10% most followed actors in each community.

The follower network conditions most information diets and information production[3]. Thus, the actors in each community identified through the network analysis share common patterns of allocating attention and expressing opinions (Y. Zhang, 2020). The labels such as 'political left' and 'radical right,' delimited through the follower network and indicated by the most-followed actors, do not necessarily present ideological lines of all the communities' actors. Similarly, the 'environmental movement community' does not equal the movement but is strongly characterized by activism, according to the findings given below.

Tweet classification

Because tweets are context-dependent and short, they are difficult to classify automatically. Therefore, I analyzed tweets through both embedding-based clustering approach and topic modeling. The clustering analysis has an explorative character without directly imposing categories on the data. It enables the quantitative presentation of a large dataset by reducing the workload of coding every tweet, and is open for validation. The idea is to represent tweets in a high vector space (embedding) and thus to group similar tweets together (cluster analysis), since tweets with similar semantic features are clustered together in the vector space. First, I pre-processed the data by removing links in the tweets and mapping them all into a 512-dimensional vector space, using the pre-trained multilingual Transformer of the Universal Sentence Encoder (USE) in the Google's TensorFlow (Yang et al., 2019). Then UMAP (McInnes et al., 2018), a dimensionality reduction technique, was applied to reduce the tweets into a low-dimensional representation by accessing the distance between every pair of tweets and determining how close they are in meaning through cosine similarity. Next, I grouped tweets into different clusters, applying the K-Medoids clustering algorithm (Park & Jun, 2009). This clustering process was performed iteratively on each resulting cluster for detailed discourse topics. In total, 455 clusters with similar semantic meanings emerged.

I applied close reading to label the clusters. Although a few outliers from certain clusters might fit better in other frames, I assigned the label based on the majority of tweets. During the coding process, I noted keywords of each cluster, in case new topic categories need to be established later. At the end, I merged related keywords together and considered the possibility of creating a new category. The clusters are labeled in 8 overarching topics. Finally, the tweets that originated in the same community and belong to the same semantic cluster were accumulated in 2,045 documents, where LDA-based topic modeling was conducted. Topic modeling assists in discovering and presenting latent topics distinguished by topic and community through a small number of words. In reviewing the semantic clusters with these keywords, further interpretation of crucial tweets became possible.

Diffusion path, cascade, and diffusion network

For presenting how information flows between actors through the follower network, it is crucial to find intermediaries of each diffusion path. An intermediary is a retweeter who simultaneously plays the role of spreader and activator. As spreaders, intermediaries share a (re)tweet pushed to their feed by those they follow. Activators enable further diffusion by influencing their followers to share the post. I inferred cascades of each retweeted original tweet based on the follower network and the timestamps their retweets carried, following Vosoughi et al. (2018). Generally, diffusion paths around one tweet and its retweets construct a cascade generated by the original tweeter and spread via intermediaries to further retweeters. Together, cascades compose a diffusion network.

Data analysis

To address RQ1, I first introduced the actors and messages that constructed the overall diffusion network. Then a sliding window approach[4] was applied to dynamically present how the diffusion network was formed based on retweeted topics' distribution and on each community's accumulative network metric[5]. Regarding RQ2, the tweets and their diffusion capacities, distinguished by topics and communities where the cascades originated, were explored by topic modeling and quantified by the cascade metric[6]. To answer RQ3, I measured affirmation and reinforcement by asking how often an actor's followees retweeted the post before the actor did and to which communities these followees belong (RQ3.1). Finally, I conducted a time series analysis to investigate how topic frames and different communities influence the diffusion processes between communities (RQ3.2).

Findings

Communities, topics, and diffusion network (RQ1)

Five communities are located in Germany and two communities in other German-speaking countries. They are (1) the 'environmental movement community – ENV' (22%) composed of FFF activists, environmental organizations, engaging the issue public for climate justice, (2) the 'mainstream media and parties – NEWS' (22%) following mainstream media, institutions, political parties (CDU/CSU/FDP/SPD/Green) and politicians in the middle of the political spectrum, (3) the 'radical right – RR' (8%) led by the far-right party AfD, its politicians, right-wing media, journalists, and influencers, (4) left-leaning 'digital enthusiasts – DIGITAL' (35%) with Pirates, the PARTY, satirical media, left politicians, activists and influencers on digital politics as most-followed actors, (5) the 'political left – LEFT' (7%) gathered by the Left party, its politicians, and activists for social and environmental justice, (6) an 'Austrian' community (4%), and (7) 'Swiss' actors (1%). The subnetworks[7] of the 'Swiss,' 'Austrian,' and RR are the most dense, while NEWS, ENV, and DIGITAL are the most sparse.

Most of the retweeted posts in #FridaysForFuture are about activism (56%), introducing the movement with urgent demands on climate protection, providing information on upcoming or past events, sharing individual participation experience, and calling for action. The second most retweeted topic concerns youth (15%) either praising the political youth's initiatives in fighting for their future or sarcastically commenting on the youth's activism. Schooling (9%) ranked third, discussed schooling politics and schools' reactions since the Friday demonstrations go against mandatory schooling. Critical issues on parties or politicians (7%) and politics or government (5%) also gained attention, with tweets criticizing parties and politicians, or calling for system change in discussing the 2019 EU-Parliament election, schooling politics, and digital politics. Retweets about leading activists (4%), such as Greta Thunberg and the leading German activist Luisa Neubauer were recorded, as were the relatively small number of retweets on environmental and economic issues (2%) on climate change, environment protection, energy transition, and forest protection.

The diffusion network interrogates how an actor's (re)tweet drove others' further retweeting activities. It is generated through 237,892 retweets (18,908 unique tweets) by 51,803 classified actors (49,074 retweeters and 7,212 original tweeters). Of the retweets, 60% were shared through intermediaries, and 21% were disseminated via original tweeters. Actors tended to spread messages within the networks of their

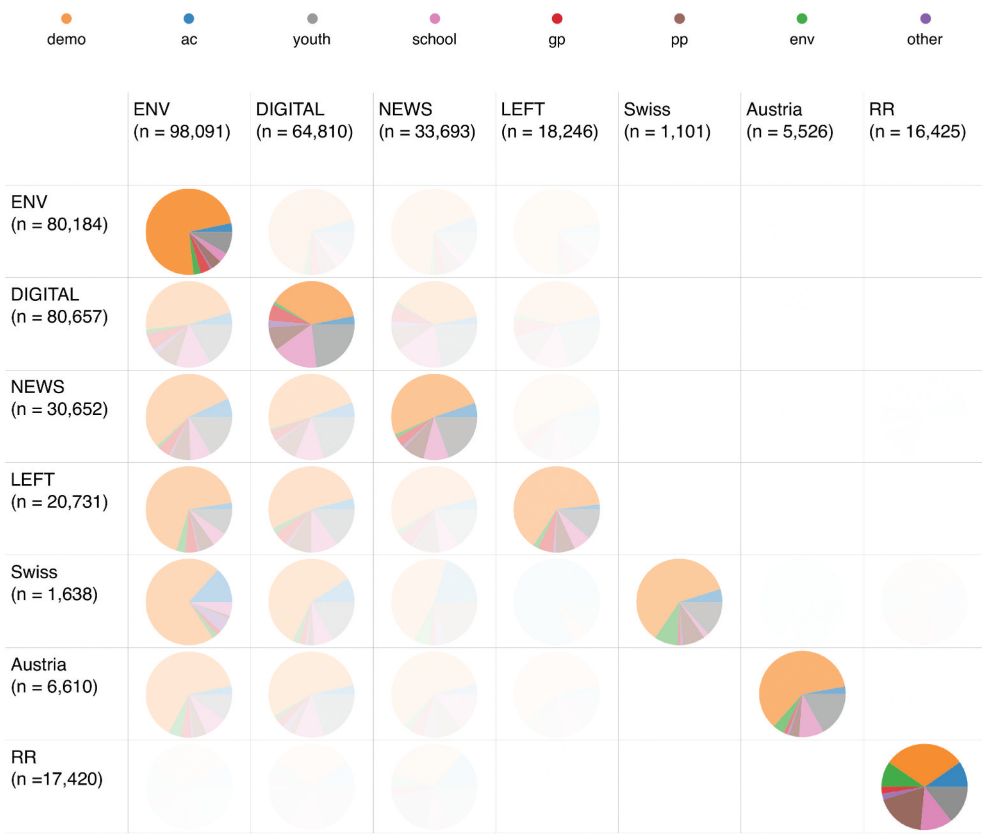

Figure 2. The proximity matrix: communities of interest. Who (row) retweeted whose (column) posts with which focus; the opacity of each pie chart is based on the intensity of in-group sharing activity relative to total sharing activity.

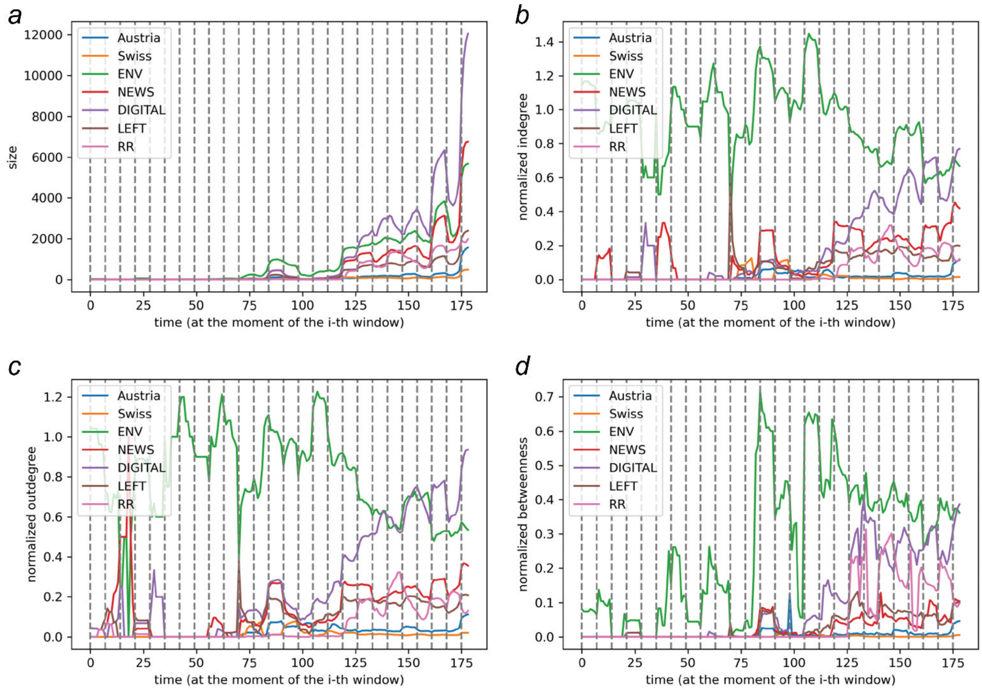

Figure 3. Network metrics of #FridaysForFuture diffusion networks created in every seven-day interval, categorized by groups of involved actors.

communities rather than across those networks. While the leading intermediaries in the communities DIGITAL, NEWS, ENV, and LEFT formed reciprocal reposting activities, RR and the other German-speaking communities were relatively isolated (Figure 2). For most of the communities, sharing information on demonstrations and taking part in activism was the central topic; however, in relation to their total retweets, the RR and DIGITAL communities had the lowest percentage of retweets on demonstration, but shared interests in topics on parties or politicians, youth, and schooling.

From a dynamic perspective (Figure 3), ENV, endorsed by NEWS and DIGITAL, enabled the movement with the most significant size, outdegree, indegree, and betweenness values during the evolution of the diffusion network. This corresponds with their roles as central contributor (measured by size), spreader (outdegree), activator (indegree), and broker (betweenness) before #FridaysForFuture got public attention[8]. After the movement's expansion, RR and DIGITAL became influential. RR obtained the third highest betweenness value in this period, indicating a polarizing trend. When the first global climate strike occurred, DIGITAL exceeded the ENV by the number of participants and other centrality values. The country-specific communities 'Austrian and 'Swiss' took part in the networked movement, but did not achieve considerable resonance according to the distribution of retweets. Regarding the four network metrics of each community, most peaks were located near Friday, thus coinciding with the mobilization

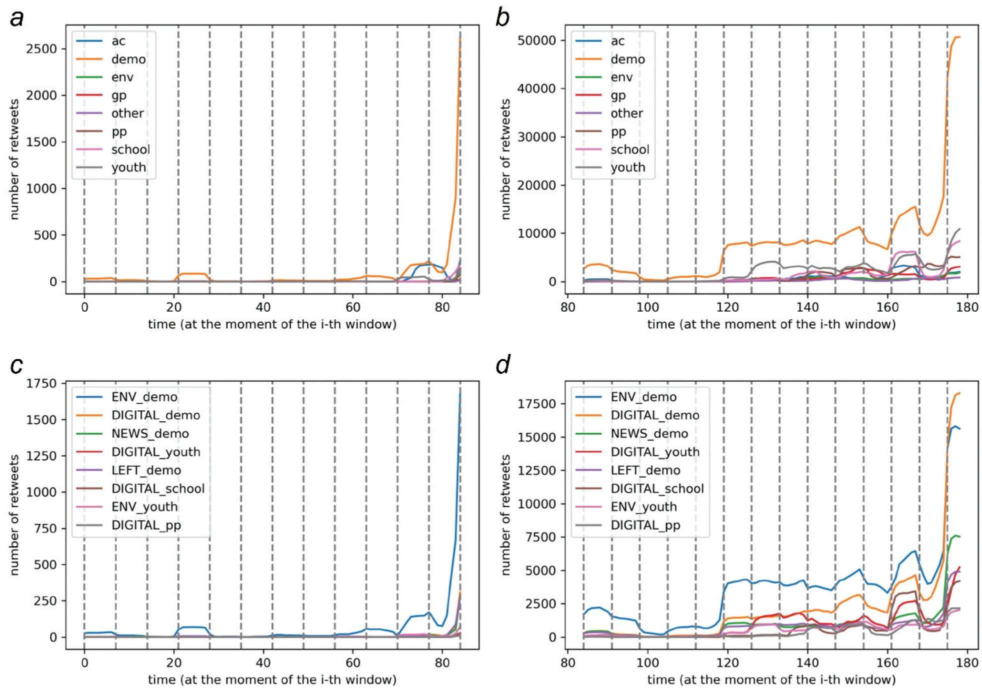

Figure 4. The number of retweets in every seven-day interval, categorized by topic.

and demonstrations. As the daily retweet volumes (Figure 4) show, retweets focusing on demonstrations significantly dominated the #FridaysForFuture information flows over time, and were mainly pushed by ENV, NEWS, DIGITAL, and LEFT.

Tweets and diffusion cascades (RQ2)

Topic models and semantic clusters of tweets provide detailed insight (see Appendix). Although the majority of tweets exhibited the same stance on demonstrations and related topics, what and how #FridaysForFuture was discussed varied across communities. ENV was strongly characterized by mobilization efforts and online participation regarding tweets about demonstrations, youth, and leading activists. In contrast, other communities mainly endorsed the movement. Addressing environmental or economic issues, ENV and the 'Austrian' community posted demands and called for concrete political solutions. Topics in the tweets of NEWS, 'Austrian,' and 'Swiss' actors were largely convergent. They did not as much distinguish between politicians or parties as focus on news sharing ('Swiss'), calling for change ('Austrian'), or addressing the central debates on mandatory schooling and the FDP party leader, Christian Lindner's statement that 'climate protection is something for professionals' (NEWS). There are unique patterns in the tweets the left-leaning and right-leaning actors posted. While most tweets asserted solidarity with protestors and recognized the necessity of climate protection, the RR actors attempted to delegitimize the movement. Their push-back focused on truancy,

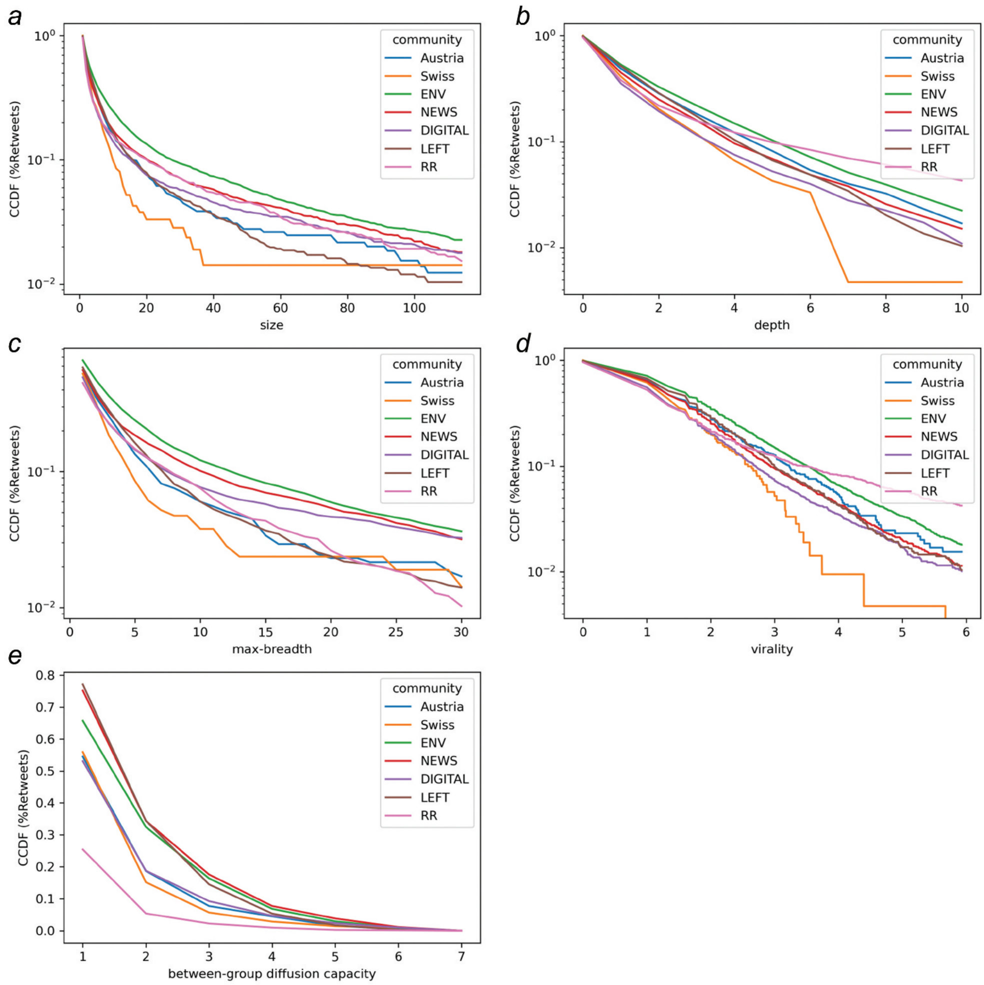

Figure 5. Complementary cumulative distribution functions (CCDFs) of #FridaysForFuture cascades, categorized by community. CCDFs show the probability x of one post from one group to have value y (size, depth, max-breadth, structural virality). In Figure 4B, the probability for one post from the 'radical right – RR' community to diffuse deeper (depth greater than 5) was higher than for other groups.

hypocritical activists, and instrumentalizing children, claiming that the climate crisis was unsolvable or even invented, and mocking politicians and governments. The DIGITAL and LEFT expressed their discontent in another way, accusing the ruling parties not only of poor climate politics but also of digital politics related to abusing the internet copyright act.

The cascade analysis presented by CCDF plots (Figure 5), considers each retweeted tweet as a diffusion cascade and each original tweeter as its source, thus shows how probably cascades (from one group or/and about one topic) are at or above a specific value. Most cascades ENV posted (90%) gained a great number of retweets (size) and

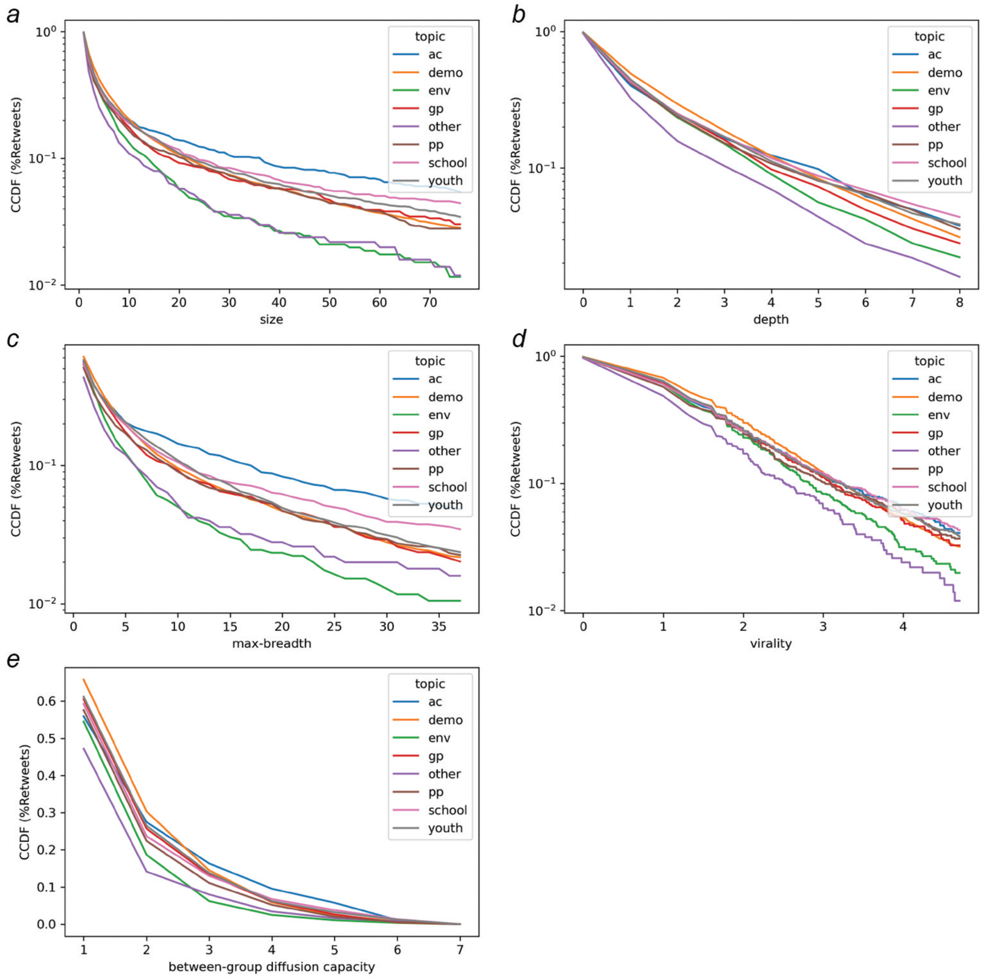

Figure 6. Complementary cumulative distribution functions (CCDFs) of #FridaysForFuture cascades, categorized by topic. CCDFs show the probability x of one post related to one topic to have value y (size, depth, max-breadth, structural virality). In Figure 6C, the probability for one post related to leading activists or schooling issues to diffuse more viral (structural virality greater than 3.5) was higher than for other topics.

spread more broadly (max-breadth) than the other communities. In volume, they were followed by NEWS and DIGITAL. Their depth values exceeded those of other communities by 5, and their structural virality values exceeded those of other communities by 3.5. The RR cascades were deeper and more viral but neither broader nor larger. It indicates chain-like diffusion patterns through single diffusion paths between actors at different depths, rather than a broadcast mode with plentiful diffusion paths at the same depth, which could reach a broader audience, retweeters, and potential retweeters. Regarding between-group diffusion capacity, the RR tweets have the lowest performance, NEWS has the highest, ENV the second highest.

Concerning the tweeted topics (Figure 6), a great number of cascades on activism and demonstrations diffused in greater volume (measured by size), more broadly (max-breadth), deeper (depth), and more viral (structural virality) than the majority of tweets on other topics. Posts that particularly diffused in greater volume (size>10), more broadly (max-breadth>5), more deeply (depth>4), more viral (virality>3), or diffused across more than one community (number of communities>2), referred to the leading activists and schooling. Although the movement campaigned for climate justice and better environmental politics, tweets on environmental or economic issues did not prompt a large number of retweets or diffuse more broadly, nor were they shared by multiple communities.

Overall, ENV mainly boosted tweets on demonstration, youth, and government or politics, while NEWS promoted tweets on leading activists, and ‘Austrian’ catalyzed tweets on schooling and environmental issues. Although RR activated the most well-diffused cascades of tweets on parties or politicians, these tweets were only well-diffused in the in-group rather than in between-group diffusion.

Retweets, in-group, and between-group sharing (RQ3)

Social affirmation within the community is crucial for actors to retweet a #FridaysForFuture post (RQ3.1). Actors were significantly affected by their followees from their own community; 63% of the retweets were shared under the in-group influence, with 45% being exclusively triggered by retweeters’ in-group followees. Many in ENV (60%) and RR (75%) were convinced by messages circulated within their community so that they would also share them later, while LEFT (23%), NEWS (31%), and ‘Swiss’ (32%) shared the least. Regarding the social reinforcement measured by the intensity of exposures, the RR actors required the most exposure before retweeting posts on #FridaysForFuture (Figure 7A). This indicates the posts were well-circulated in the RR community, as the actors had to be exposed by posts retweeted several times before they would retweet. LEFT, DIGITAL, ENV, and ‘Austrian’ demanded modest exposure, while actors from ‘Swiss’ and NEWS would retweet a post affected by fewer in-group exposures. Taking topics into account, retweeting on schooling required the least exposure, while topics on politicians or parties, environmental issues, and leading activists required

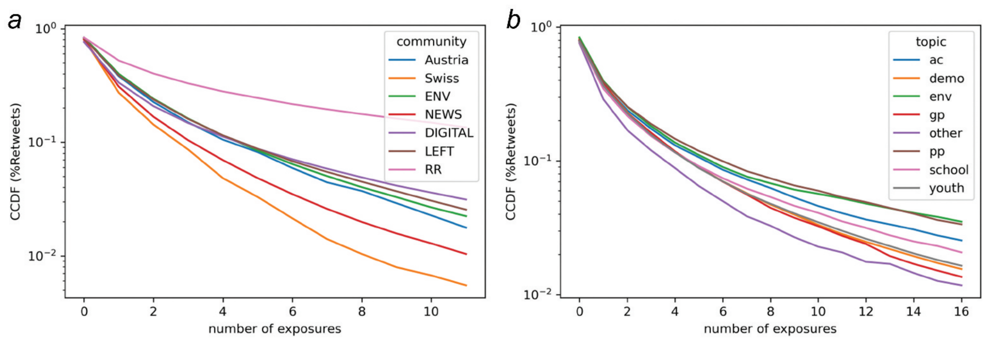

Figure 7. Complementary cumulative distribution functions (CCDFs) of #FridaysForFuture cascades, categorized by groups (A) and topics (B), regarding the frequency of the potential exposure.

the most (Figure 7B). For each topic, the community influence, which affects how many potential exposures and how different communities drive retweeting activities between neighboring actors, remained the same.

Regarding RQ3.2, Granger causality tests (one-day lag) were conducted to test whether the time series of in-group sharing could predict this between-group sharing and vice versa. For the in-group retweets circulated within one specific community and/or focusing on one particular topic, these tests examine whether in-group retweets could drive diffusion into other communities within one day. For the between-group retweets taken from other communities and introduced into another specific community and/or focusing on one particular topic, the tests determine whether they could drive in-group diffusion within one day. The findings (see Appendix) show that information diffusion within DIGITAL, LEFT, and 'Austrian' significantly drove between-group retweeting. In contrast, only retweets introduced by the NEWS, which were taken from other communities, could modestly cause in-group retweeting. Schooling was the major topic to be significantly spread through in-group and between-group sharing. Retweets on government or politics spread by RR and those on schooling diffused by NEWS drove both in-group and between-group sharing.

Additionally, I noted that retweets on demonstrations that ENV spread from other communities could only drive the further proliferation of in-group retweets within ENV at a lower significance level. This shows ENV actors' mobilization endeavors to introduce activism content that other communities generated, to the followers in their network. However, neither ENV actors (the main activators and intermediaries), nor demonstration (the central topic carried in most of the retweets) were the main diffusion driver concerning in-group or between-group sharing. After testing how ENV's demonstration-related in-group retweets influenced its between-group sharing, I found high significance in the movement's initial phase. These results indicate that the tweets on demonstration and activism were diffused regularly after the movement had gained public attention, so that the past frequencies of in-group/between-group retweets on demonstration could better predict their future frequencies.

Conclusion and discussion

This study investigates how #FridaysForFuture was facilitated and contested through different diffusion dynamics on Twitter in its early stages. The findings demonstrate that different communities, characterized by diverging interests and capacities to spread and activate diffusion, engaged the networked movement differently. On the one hand, #FridaysForFuture served as the facilitator for protest participation and movement mobilization. Tweets about topics tightly associated with the movement, i.e., activism, youth, and leading activists, were contributed mainly by ENV, and were well diffused. Nevertheless, the activism retweets promoted within ENV did not prompt diffusion regarding between-group sharing after the #FridaysForFuture's expansion when the movement was well-known to other communities. On the other hand, #FridaysForFuture featured an issue network for political discourses related to climate politics, schooling, political parties, and politicians that were discussed and modestly spread. While the ENV's posts called for system change, those by NEWS, 'Austrian,' and 'Swiss' actors were characterized by news sharing. Meanwhile, there were also right-leaning actors' attempts to delegitimize the movement, along with the left-leaning actors' engagement to condemn leading parties and bring digital politics into the discourse. Compared with the spread of tweets related to the online discourses, which were driven by critical issues and centered on schooling, the diffusion of activism tweets relied more on the movement's mobilization capacity and on individual actors' commitment.

Most of the retweets were not directly shared by original tweeters; rather, they moved between actors through the follower network and driven by in-group intermediaries. The diffusion mechanisms of information, discourses, and beliefs related to #FridaysForFuture were mainly enabled by and flowed through pre-existing networks rather than situational spontaneity. They were varied according to issue salience and distinguished by the involved communities' network structures, political positions, ideological lines, and geographical proximities. Though connective action on social media can be enabled by loosely structured networks, flexible organizational forms, and personalized action frames, the connectivity is rooted rather in the 'specific institutional and infrastructural frameworks, with action structures and behavioral effects' (Dolata & Schrape, 2018a, p. 2). Organizational forms of networks are rarely planned in their entirety, but arise as patterned and repeated interactions and decisions of a variety of groups and organizations with shared values, histories, or expectations (Diani & Mische, 2015). On Twitter, social ties can be created through temporal interactions such as retweeting and shaping actors' positioning processes in relation to the entire network. However, these one-off interactions are embedded in information flows between actors, which circulate through enduring communication infrastructures such as follower networks.

Regarding the coherence of social movements, previous studies also demonstrated left- or right-wing actors attempting to assert their political agendas by using trending hashtags on other issues (Martini, 2020; Suk et al., 2019). In the case study, the left-leaning 'digital enthusiasts' were actively involved in the discourse activating and spreading a great number of retweets; however, they were loosely connected and possessed modest to low diffusion capacity. The community of 'digital enthusiasts' should be understood as a 'partial issue public' through their collective event-related behaviors, which was 'not a result of design' (Dolata & Schrape, 2018b). Regarding the counterpublic led by far-right actors, particular tweets diffuse well through their chain-like diffusion mechanisms in the online discourse. Nevertheless, other communities isolated the 'radical right' and impeded the spread of their cascades beyond their own 'bubble.' Through the relatively high post volume and densely connected network, the hype of the right-wing pushback could raise public attention and increase the likelihood of recruiting like-minded newcomers. However, it failed to hijack the networked FFF movement since ENV, safeguarded by other communities, already had an established organizing core of activists, NGOs, and organizing actors that facilitated online and offline activism. The intense mobilization endeavors, engagement of other communities, and well-diffused messages ensured that the networked movement maintained momentum within the ENV community in the initial phase, gained momentum in expanding its influence, and stabilized the peripheries for coordination and information transition.

The findings support theoretical frameworks showing that digitally networked movements face the challenge of losing coherence in a networked environment of contending ideas (Bennett et al., 2018). As indicated in other empirical studies, the growth of digital movements depends on their ability to influence and disseminate among different networked publics with diverse interests (Foucault Welles & Jackson, 2019; Freelon et al., 2018; Liang & Fu, 2016). With the methodological approaches this paper has introduced, I expect to see generalized diffusion patterns of other influential networked movements initiated and led by organizing cores, supported by a wider public, and attracting right-leaning and left-leaning actors to join the discourse. Still, the Twitter-only perspective restricts the spectrum, thus limiting us in exploring the influence of other media channels and offline protests on information sharing processes and movement mobilization. Questions that remain, include how collective actors and the non-organized communities engaged in the observed diffusion processes, and what the different metrics of cascades meant for networked movements to achieve their political goals. For future research, I suggest analyzing Twitter publics in digital movements should not be the main focus. More salient would be to investigate how the networks are formed and shaped through interactions of knowledge, issues, actors, and movements, and to examine their diffusion dynamics in both media and socio-political contexts.

Notes

1. Collective is used as a generic term for groups, communities, publics, crowds, networks, masses, and clusters of participants. In the data analysis and results, I use the term community to refer to structurally densely connected actors (i.e., clusters in the context of network analysis) that are identified by a community detection algorithm.
2. To get the following-follower relationships between the actors who posted tweets on #FridaysForFuture, we need EITHER to know [who follows an actor by retrieving the actor's followers] OR [who is followed by an actor by retrieving the actor's following list]. The two options are equivalent since users who do not post/share comment on #FridaysForFuture but are followed by/following the involved actors are excluded.
3. Although algorithm-based feeds can also bring posts to users' timelines, online networks aggregating followees' tweets are the more prominent information source of Twitter users. Scholars (Bakshy et al. 2015; Haim et al., 2018) found the feeds delivered by algorithms have little influence on selective sharing of social media users compared to that shared by users' followees.
4. In the sliding window approach, a window with a user-defined length will move over data to get statistics of the data in this window. This paper applies the approach to construct temporal diffusion networks through 178 overlapping sliding windows with a length of seven days and a one-day time step. The first window starts from 2018-9-14 to 2018-9-20 and the second from 2018-9-15 to 2018-9-21, and so on.
5. (1) Size: the number of unique actors, (2) normalized indegree centrality: the number of an actor's retweeted posts divided by the number of all actors, (3) normalized outdegree centrality: the number of an actor's retweets divided by the number of all actors, (4) normalized betweenness centrality: the number of all-pairs shortest paths that pass through an actor's account divided by the number of paths that could connect every pair of actors.
6. (1) Size: the number of unique actors in a cascade over time. (2) depth: depth of an actor is the number of retweets from an actor, and the depth of a cascade is the maximum depth of the actors in the cascade. (3) max-breadth: the maximum number of users involved in the cascade at any depth. (4) structural virality: average distance between all pairs of actors in a cascade (5) between-group sharing capacity: the number of unique communities in a cascade.

7. The edges of a subnetwork are the follower/following relationships exclusively among the actors of this community.
8. From Friday 2018-9-14 to Friday, 2018-12-14 (determined by daily retweet volumes and the date of the first national climate strike in Germany).

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Notes on contributor

Xixuan Zhang is a research assistant and Ph.D. candidate at the Freie Universität Berlin.

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