Exploring the German-Language Twittersphere: Network Analysis of Discussions on the Syrian and Ukrainian Refugee Crises

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EXPLORING THE GERMAN-LANGUAGE TWITTERSPHERE

NETWORK ANALYSIS OF DISCUSSIONS ON THE SYRIAN AND UKRAINIAN REFUGEE CRISES

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ABSTRACT

This study conducts a comparative analysis of Twitter communication networks relating to the Syrian and Ukrainian refugee crises. Employing a network analysis approach, the study uses approximately 660,000 tweets to gain insights into the online discussion communities surrounding these crises. Tweets specifically discussing Syrian refugees were collected between 2015 and 2023, while those about Ukrainians were harvested from 2022 to 2023, utilizing the full-archive search endpoint of the Twitter API. By transforming retweets into communication networks between users, the study investigates the community structure within these networks. The findings reveal that the online anti-refugee community is smaller in size, more active, highly interconnected, and transcends national boundaries, in contrast to the opposing communities. These results underscore the need for increased social media engagement of pro-refugee voices and improved moderation practices to foster a more inclusive virtual public sphere.

1 INTRODUCTION

Migration is a central topic in political discussions across European countries, leading to polarisation (Damstra et al., 2021). Right-wing populist politicians exploit the fear surrounding migrants to gain electoral advantage and propose policies to reduce their numbers. In contrast, liberal and progressive politicians prioritise the humane treatment and human rights of migrants, advocating for integrationist policies (Bossetta, 2018). The media played a role in negatively framing Syrian refugees in 2015, particularly in countries with right-leaning governments, leading to a "systemic and persistent" de-individualisation of their image (Georgiou & Zaborowski, 2017, p. 3). People's media preferences, consumption habits, and attitudes towards migrants were found to be connected (De Coninck et al., 2019; Debrael et al., 2021). Furthermore, public opinions on migration vary significantly and are polarised across Europe (d'Haenens et al., 2019). Hence, the dynamic relationship between politicians, media, and public opinion is not fixed and evolves over time and in response to ongoing events (De Coninck et al., 2022).

Utilising social media platforms for analysing latent public opinion about contested topics, such as migration, not only provides valuable insights but also enables the detection of viral sources and the spread of information, contributing to combating misinformation and fostering a more inclusive public discourse. Twitter is frequently used in analysing social media platforms for political communication studies (Seabold et al., 2015; van Klingeren et al., 2021). Twitter data serves as a valuable and extensive information source for computational social science (Verbeke et al., 2017). By detecting viral sources and monitoring information dissemination on online social networks, it becomes possible to combat misinformation (Tambuscio et al., 2018) and to contribute to a more inclusive public discourse (Ahmed et al., 2020). Through collecting trace data from platforms like Twitter and applying computational research methods, we can gain insights into the underlying public opinion and how these opinions are communicated within online networks (Freelon, 2020).

Previous research on refugee crises has primarily focused on examining the impact of textual or visual content on social media platforms (Chouliaraki, Lilie et al., 2017; d'Haenens et al., 2019; McCann et al., 2023; Nerghes & Lee, 2019; Ozerim & Tolay, 2021; Öztürk & Ayvaz, 2018). Some network-based approaches also exist (Institute for Strategic Dialogue, 2021; Nerghes & Lee, 2018; Pöyhtäri et al., 2021). This new study adds a partition-based network analysis of the online political communication about refugees from a comparative perspective to the literature. More in particular, our research investigates the retweet networks related to Syrian and Ukrainian refugees on Twitter (from now on, N1 and N2, respectively).[1] There are several studies of political message networks on Twitter (Stegmeier et al., 2019), their temporal changes (Nasralah et al., 2022) and in different national twitterspheres (Fincham, 2019) and different languages (Smyrnaios & Ratinaud, 2017; Yao et al., 2022)). Prior research on political communication networks indicates that these networks are divided into two main camps (Galeazzi, 2022). However, these camps consist of different user clusters (Freelon 2020). Our first goal is to disclose these clusters in the networks.

RQ1: What are the community structures of retweet networks related to these refugee crises?

[1] We want to highlight here two ethical challenges for our research: 1) In this study we aim at analysing communication networks, however we do not assume or claim that both Syrian and Ukrainian refuge crises are identical events. Both have different cultural and historical dynamics that are beyond the limits of our communication-based research. 2) Although we refer to these events concerning human mobility as ‘crises’, we do not claim they should be considered as such. The narrative of crises about human mobility can have detrimental effects for social inclusion and communication (Sommer, 2022). We will nevertheless use the term ‘crisis’ for lack of a better term to refer to these events.

Additionally, the literature on social media analysis reveals that far-right parties and movements effectively use social media platforms to advance their anti-refugee agenda (Åkerlund, 2022; Schroeder, 2018).We ask ourselves whether there any differences between the two networks in this regard.

RQ2: What are the activity and engagement levels of the main pro- and anti-refugee communities[2] in both networks?

Finally, we will exploit a feature of our dataset to explain the results of our RQ2. Concretely, we will analyse the national composition of main clusters to investigate the transnationalityof the leading communities in debate (Stoltenberg, 2021). The study of interactions between similar political movements and groups across national borders in the virtual public sphere is facilitated by digital methods (Dahlberg-Grundberg et al., 2016; Merrill & Copsey, 2022). Thanks to our German-language Twitter dataset, we have the geolocation of users from mainly three countries: Germany, Austria, and Switzerland. We investigate if the communication networks are divided along national lines or if there are any cross-national collaborations in network clusters. If so, do they happen equally on each side of the polarisation?

RQ3: What is the national composition of the clusters? Which are more transnational?

2 RESEARCH DESIGN AND DATA

Social network analysis (SNA) is a method that is widely applied for the analysis of polarisation on online social media platforms (Adamic & Glance, 2005; Al Amin et al., 2017; Esteve-Del-Valle, 2022; Feller et al., 2011; Garimella, 2018; Urman, 2020). Unsurprisingly, online discussions about migration are the subject of many SNA studies (Dehghan & Bruns, 2022; Vilella et al., 2020; Yoo, 2019). We adopt a mixed-methods approach to the social networks championed by recent studies in communication sciences (D'angelo et al., 2016; Freelon, 2020; Froehlich et al., 2020, 2020; Yousefi Nooraie et al., 2020). Furthermore, we aimed to conduct SNA for communication science purposes and focused on the partitions and their interrelations (Freelon, 2020; Freelon et al., 2015, 2016). Furthermore, we used descriptive network statistics, visual analysis methods (Jacomy, 2021) and data-driven but reflective analysis of the textual features of user and tweet metadata (Dehghan et al., 2020) to understand the complex social network structures.

We will adopt an exploratory approach to find changes and patterns between these communication networks related to the Ukrainian and Syrian refugee crises. We will focus on the structure of the retweet networks as they signify positive relations between users and approval of message content most unambiguously (Ahn & Park, 2015; Freelon, 2020). Our workflow was as follows: First, we collected the dataset from Twitter API. Second, we applied custom Python scripts to our dataset to clean the data and scrape the location attribute of user data. Third, we constructed networks (graphs) and detected the communities (subgraphs, partitions) and influential users (based on indegree centrality). Fourth, we (qualitatively) labeled the communities based on the description and retweet data. Fifth, we analysed meso-level network structures using 1) community size, 2) the internal ties as an

[2] Given the strong anti-refugee disinformation and propaganda in online social networks, we will refer to any group and tweet that does not explicitly aim at expanding this agenda as pro-refugee in this research. Pro-refugee in this study should not be understood as an ideological position but rather as a non-anti-refugee position.

indicator of retweet activity and connectedness of the community and 3) subgraph average degree to quantify the level of engagement per user of a given cluster. Finally, we exploited the user geolocation data to investigate the national composition of the communities.

Our analysis of retweet networks involved the utilisation of various tools and techniques. Firstly, we constructed the networks by representing users as nodes and retweets as directed and weighted (the number of retweets between users) ties. To conduct partition-based network analysis, we used Python and its Pandas, NetworkX, and TSM packages (Freelon, 2020). Subsequently, we visualised the networks using Gephi, a widely adopted tool for visual network analysis (Bastian et al., 2009). Gephi facilitates the transformation of networks into visual maps, employing force-directed layout algorithms to position related nodes in close proximity (Jacomy et al., 2014). Community detection is a vital part of network analysis of political communication (Münch, 2019). Our study employed the "Louvain" algorithm, renowned for its efficiency (Blondel et al., 2008). The algorithm works based on detecting sets of nodes (users) exhibiting dense interconnections, indicating homophily. To identify influential nodes, we employed the weighted indegree centrality measure.

Considerable deliberation was invested in formulating our tweet dataset construction methodology. We deliberately extended our investigation beyond 2015 for the Syrian Refugee Crisis, considering the enduring impact and ongoing debates surrounding this issue. Therefore, our data collection encompassed the period from 2015 to 2023 for this event. We focused on gathering data from 2022 to 2023 for the Ukrainian case. To ensure the inclusion of relevant tweets concerning each refugee debate, we adopted a filtering method that entailed capturing tweets containing keywords associated with human migration, coupled with ethnic markers such as 'Syrian' or 'Ukrainian,' all in the German language. The query strings used for data collection were made accessible through the GitHub repository of the first author.[3] These refined queries specifically targeted data directly relevant to our study, excluding indirectly related events such as the Syrian Civil War or the invasion of Ukraine.[4] The collected dataset is presented below for reference.

	SYRIAN CASE	UKRAINIAN CASE	TOTAL
TOTAL MESSAGES	318,338	342,634	660,972
RETWEETS	214,683	238,934	453,617
USERS	92,673	101,192	193,865

Table 1. The collected dataset

The dataset is used to generate a retweet network as described below:

	SYRIAN-NETWORK (N1)	UKRAINIAN-NETWORK (N2)
NODES	55,160	66,885
EDGES	213,031	237,378

Table 2. Node and edge sizes of the generated networks

[3] https://github.com/sercankiyak/GermanTwittersphereMigrationSNA

[4] It is important to acknowledge that our commitment to explicit and stringent criteria implies that our dataset does not capture all Twitter communication on the topic. It is possible for users to allude to these groups without explicitly mentioning ethnicity or referring to migrants. In fact, they can do it without any words such as visuals or gestures or emojis. In short, our keywords generated an amalgamated dataset of political communication that is limited in size but highly accurate.

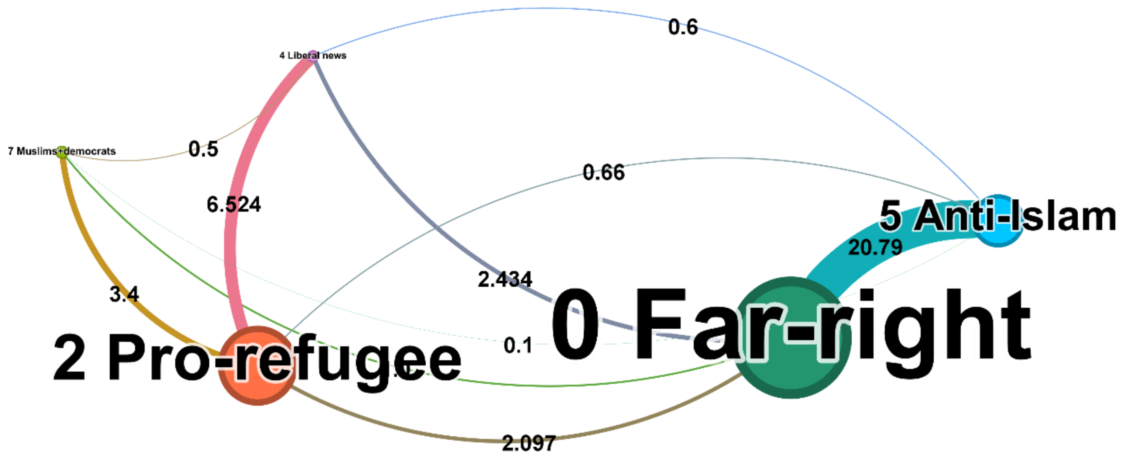
3 RESULTS

Our analysis of N1 resulted in Tables 4 and Graph 1 below.

COMMUNITY	POPULATION	INTERNAL TIES	AVG. DEGREE
PRO-REFUGEE (2)	<u>14,181</u>	36,558	2.58
FAR-RIGHT (0)	10,080	<u>54,025</u>	<u>5.36</u>
ANTI-ISLAM (5)	8,579	25414	2.96
MUSLIMS+DEMOCRATS(7)	7,079	8731	1.23
MEDIA (4)	6,001	8400	1.40
AFD+NEWS (11)	2537	4,207	1.66
SOLIDARITY+NGOS (21)	2026	3371	1.66
INTERNATIONALIST(38)	1863	3369	1.81
ACTIVIST (13)	1416	1461	1.03
MIXED (25)	1398	1809	1.29

Table 4. Size, internal ties and average degree scores for the top 10 detected communities in N1. Community labels consist of two parts: 1) Label assigned by the researchers and 2) the arbitrary number assigned by the algorithm (kept for future reference and convenience). The communities are listed from the largest to smallest in terms of their user population. The internal ties represent the volume of internal retweeting activity. The average degree quantifies the (internal) retweet per user. It shows the average user engagement and promotion of their community by users (irrespective of the community size). The highest numbers in each column are highlighted.

Regarding community sizes and identifying central nodes within N1, our analysis reveals several notable findings. Firstly, the pro-refugee community (2) emerges as the largest group within the network, encompassing pro-refugee NGOs, media outlets, politicians, and their respective supporters. In contrast, community 0 primarily consists of the anti-migrant populist party Alternative für Deutschland (AfD), alongside other nationalist and conservative opinion leaders. Interestingly, the third largest community (5) exhibits a distinct anti-Islam stance that parallels the nationalist community (0). Community 5 also shows a significant average subgraph degree, indicating strong per-user engagement. Unsurprisingly these communities exhibit a similar stance against Syrian refugees. Community 7, conversely, consists of influencers who are Muslims, individuals from migrant backgrounds, and politicians who express empathy toward them. Notably, within the fifth largest community (4), central accounts predominantly belong to liberal or left-wing media entities. After the 5th community, the population size dips significantly (from 6000 to 2500). Consequently, we decided to focus on the top 5 communities in N1. The external ties among communities can be as informative as internal ties. They are visualised below as Graphs 1 and 2.



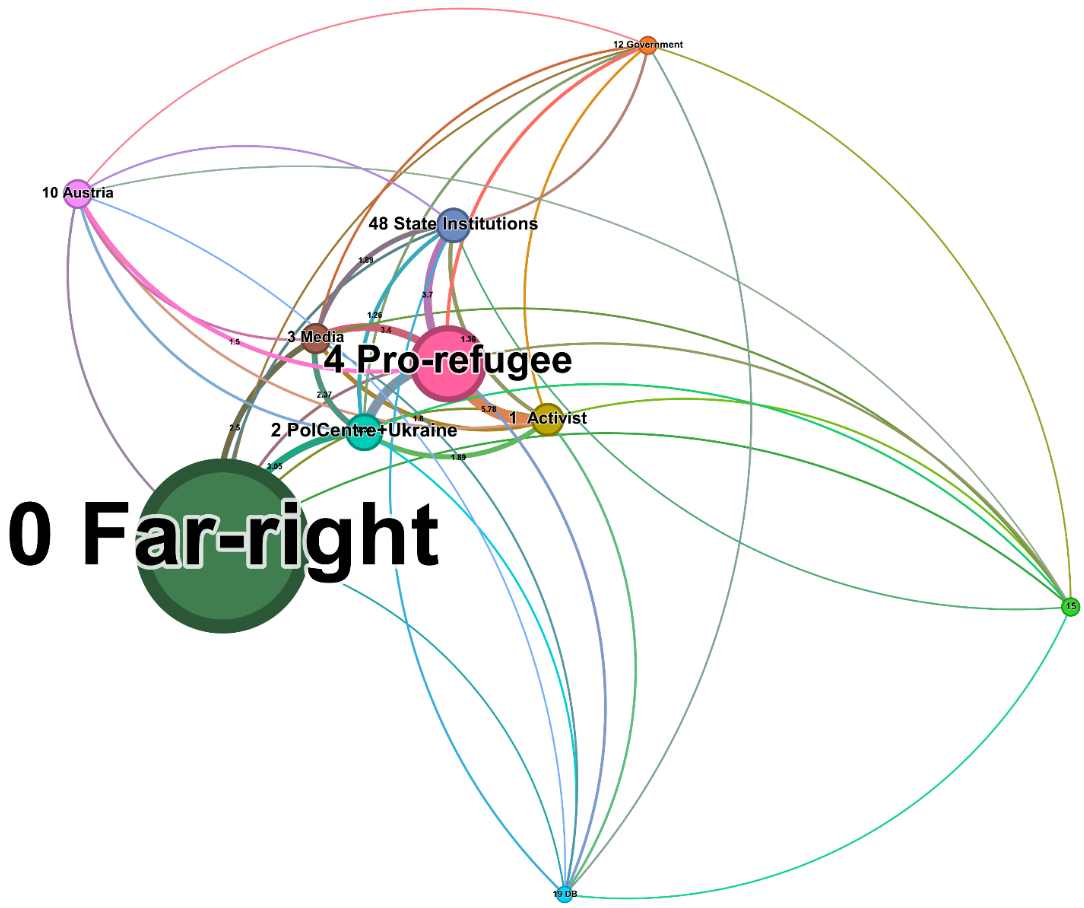
Graph 1. The community network structure of the top 5 communities in N1. The size of each node, representing a community, is determined by its internal ties rather than the number of nodes within the community. Consequently, larger nodes correspond to communities with higher rates of retweeting among their members. The thickness of the edges connecting nodes indicates the strength of connections between two communities (number of connecting edges divided by all edges).

The strong tie between the anti-refugee communities (far-right (0) and anti-Islam (5)) indicate a strong connection and retweet activity between these communities. The retweet activity of pro-refugee communities on Twitter is relatively weak compared to their opposition in the case of Syrian refugees in terms of both internal and external ties. Table 5 and Graph 2 below concern the N2.

COMMUNITY	POPULATION	INTERNAL TIES	AVG. DEGREE
FAR-RIGHT (0)	17,283	85,560	4.95
PRO-REFUGEE (4)	14,703	33,787	2.30
UKRAINIAN+POL.CENTRE(2)	7,560	12,803	1.69
ACTIVIST (1)	7,057	10,522	1.49
GOVERNMENT (48)	5,869	11,433	1.95
MEDIA (3)	4,939	9,159	1.85
AUSTRIAN (10)	3,693	8,483	2.30
GOVERNMENT (12)	2,089	2,803	1.34
SWISS (15)	1,896	2,945	1.55
PUBLIC INSTITUTION (19)	1,796	1,955	1.09

Table 5. Size, internal ties and average degree scores for the top 10 detected communities in N2. See Table 4 above for the explanations.

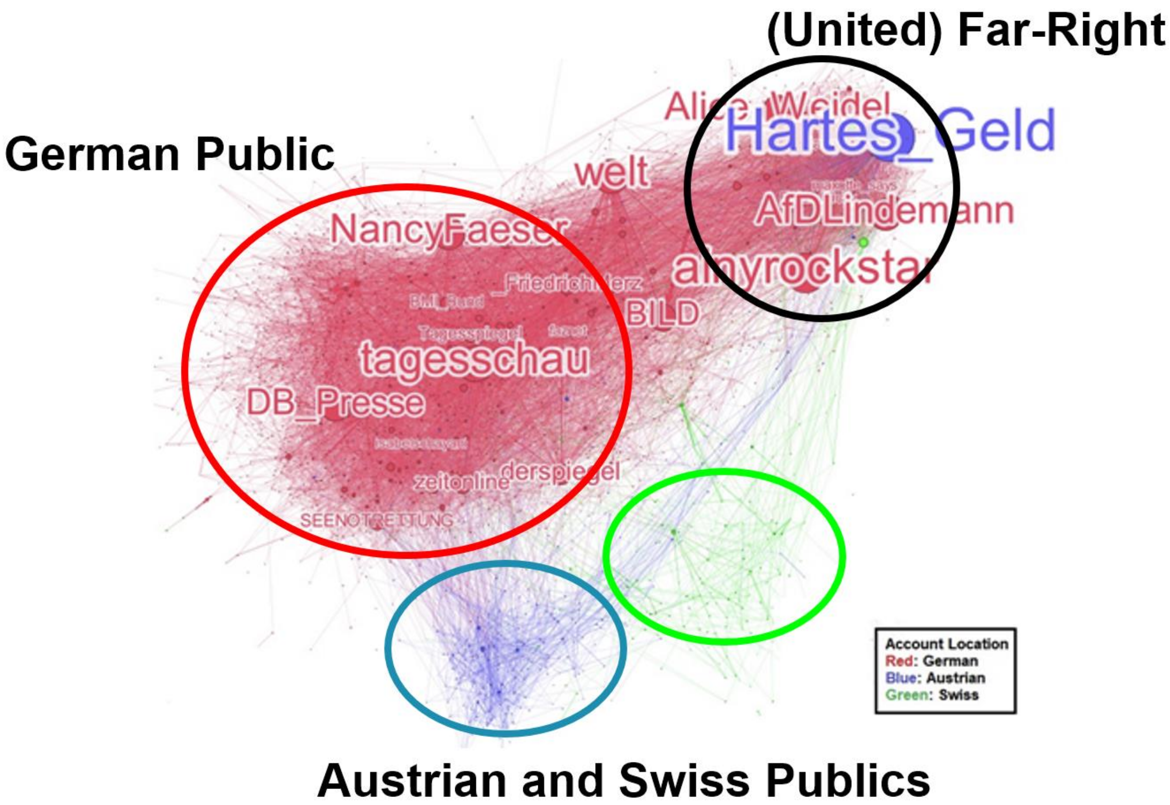
Table 5 provides insights into the composition of N2, revealing a substantial polarisation between two main opposing groups. The largest group, denoted as community 0, consists of influencers affiliated with AfD politicians, conservative opinion leaders, and their followers. In contrast, community 4 represents the largest pro-refugee group within this network. Community 2 is characterised by pro-Ukrainian accounts featuring CDU parliament members and journalists from conservative-leaning media outlets such as Welt. The fourth biggest community consists of influencer-activists who support Ukrainian refugees. The following smaller communities comprise government, mainstream media, and institutional accounts. Notably, we observe two smaller communities of pro-Ukrainian refugee accounts from Austrian (10) and Swiss users (15). However, we do not find anti-refugee Austrian or Swiss communities; we will explain why that might be the case below.



Graph 2. The community network structure of the top 10 communities in N2. See Graph 1 above for the explanations.

The analysis of Graph 2 reveals that the far-right community (0) is the most active one in N2. It is relatively consolidated and highly active in spreading its messages. On the other hand, the pro-refugee communities display smaller node sizes (internal activity) and weaker ties (external retweet connections) compared to N1. This shows sparse connections among the pro-refugee group, which is not helped by the weak connections of Austrian (10) and Swiss (15) to the main German pro-refugee community (4).

These observations answer RQ1 and RQ2. For the former, we found significant community-level retweeting behaviour in both networks and a polarised communication network as described above. Our analysis showed that while the pro-refugee communities are more sparsely connected when amalgamated, they constitute more than half of the users in the network. Conversely, we observed a notably higher level of activity and engagement from the anti-refugee clusters. This result holds particular significance since the anti-refugee communities do not consistently constitute the largest communities. We hypothesise that cross-national collaboration may be one contributing factor to this phenomenon of a highly active anti-refugee community.



Graph 3. A visualisation of N2 coloured by geolocation. Red indicates German, blue indicates Austrian and green indicates Swiss users and their retweets. The circle and labels were added manually to highlight the spatial differences. This graph is limited to users with location data.

	FAR-RIGHT (COM 0)	PRO-REFUGEE (COM 4)
GERMAN %	90	94.6
AUSTRIAN %	5.21	2.79
SWISS %	4.79	2.61

Table 6. Nationality Distribution of the top 2 communities in N2 in percentages.

Graph 3 shows the locations of far-right (0), German pro-refugee (4), Austrian pro-refugee (10) and Swiss pro-refugee (15) communities. Table 6 shows that compared to the main pro-refugee community (0), the anti-refugee community (5) exhibits a more transnational composition. This trend is also expressed in the analysis of its top nodes; while there were no non-German users in the top 50 central users (indegree) in community 0, there were five non-German users among the top 50 far-right users. Alongside their high indegree centrality within the graph, these users included the *hartes_geld*, the node with the highest indegree centrality in the graph, who is from Austria. Therefore, our results indicate that far-right groups engage and benefit from transnational communication and support more than the pro-refugee groups (RQ3).

4 DISCUSSION AND CONCLUSION

The present study has investigated the ongoing online communication networks on Twitter with regard to the Syrian and Ukrainian refugee crises (N1 and N2), focusing on retweets and community structure. The results indicate that the anti-refugee community displays higher activity levels despite not always having the largest numbers. Additionally, while constituting the majority on Twitter, the pro-refugee users are loosely connected with significantly fewer ties between themselves, suggesting less individual engagement and activity on social networks and a weaker community. While N1 showed two anti-refugee clusters (AfD and anti-Islam), in N2, the anti-refugee group is more consolidated, indicating more isolation and growing polarisation in recent years. Finally, in N2, the same community showed more transnational ties compared to the main pro-refugee community. These findings are consistent with previous research that is conducted in different national contexts regarding anti-migration communities being (what wefer to as) “a loud minority" phenomenon (Vilella et al. 2020; Dehghan and Bruns 2022).

Unfortunately, in this study, we had to focus on the explicit and strict criteria for our data, and we could not investigate the tweet contents. Moreover, we did not engage with the temporality of N1 and changes in the Twitter networks. Despite these weaknesses, our research contributes to the study of online communication about migrants by investigating the network structure and diffusion of information on Twitter. Furthermore, it highlights the importance of transnationality for analyzing virtual public discussions. It is a promising direction for future research, and it can help us avoid "methodological nationalism," whose critique highlights the challenges a researcher needs to navigate while studying nations and national public spheres (Wimmer & Schiller, 2003). The digital trace data and social networks of communication open new avenues to use this concept that came out of migration and transnationality studies. Regarding policy suggestions, our findings underscore the necessity of implementing measures to foster improved online discourse surrounding migration. Firstly, it is imperative to enhance moderation efforts aimed at curtailing the dissemination of hateful and misleading content, which could be effectively amplified by far-right factions. Secondly, pro-refugee civil society organisations and public institutions need to enhance their social media presence. In particular, the initiation of transnational campaigns promoting inclusivity and communication through social media channels hold the potential to counteract far-right activism and propaganda.

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