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FULL PAPER

From solidarity to blame game: A computational approach to comparing far-right and general public Twitter discourse in the aftermath of the Hanau terror attack

Zwischen Solidarität und Verantwortungszuschreibung: Eine vergleichende Analyse der allgemeinen und rechtsaußen Twitterdiskurse nach dem Terroranschlag in Hanau mittels automatisierter Textanalyse

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Abstract: Terror attacks are followed by public shock and disorientation. Previous research has found that people use social media to collectively negotiate responses, interpretations, and sense-making in the aftermath of terror attacks. However, the role of ideologically motivated discussions and their relevance to the overall discourse have not been studied. This paper addresses this gap and focuses specifically on the far-right discourse, comparing it to the general public Twitter discourse following the terror attack in Hanau in 2020. A multi-method approach combines network analysis and structural topic modelling to analyse 237,000 tweets. We find responsibility attribution to be one of the central themes: The general discourse primarily voiced sympathy with the victims and attributed responsibility for the attack to far-right terror or activism. In contrast, the far right – in an attempt to reshape the general narrative – raised a plethora of arguments to shift the attribution of responsibility from far-right activism towards the (political) elite and the personal circumstances of the shooter. In terms of information sharing and seeking, we demonstrate that new information was contextualised differentially depending on the ideological stance. The results are situated in the scientific discourse concerning differences in social media communication ensuing terrorist attacks.

Keywords: Far-right discourse, social media, Twitter, collective sense-making, #network analysis, topic modelling, terror attack.

Zusammenfassung: Aktuelle Forschung zeigt, dass Terroranschläge kollektive, öffentliche Schocks auslösen und so ein Gefühl der Orientierungslosigkeit erzeugen. Menschen nutzen soziale Medien, um ihre Gefühle nach Terroranschlägen auszudrücken und damit auch für eine Art kollektive Sinnfindung. Dabei bleibt bisher die Frage ungeklärt, wie die ideologischen Einstellungen von Nutzer:innen Sozialer Medien diese kollektive Sinnfindung beeinflussen. Die vorliegende Studie schließt diese Lücke und konzentriert sich speziell auf den rechtsaußen Twitter-Diskurs und vergleicht diesen mit dem allgemeinen öffentlichen Twitter-Diskurs nach dem Terroranschlag in Hanau im Februar 2020. Ein multimethodaler Ansatz kombiniert Netzwerkanalyse und Topic Modelling zur Analyse von 237.000 deutschen Tweets. Es wird deutlich, dass die Zuschreibung von Verantwortung das zentrale

Thema ist: Im allgemeinen Diskurs wird vor allem Mitgefühl mit den Opfern geäußert und die Verantwortung für den Anschlag dem rechtsradikalen und -extremen Aktivismus zugeschrieben. Im Gegensatz dazu bringen rechtsaußen Akteure – in dem Versuch, das allgemeine Narrativ zu beeinflussen – eine Fülle von Argumenten vor, um die Zuschreibung der Verantwortung vom Rechtsaußenaktivismus auf die (politische) Elite und die persönlichen Umstände des Schützen zu verschieben. In Bezug auf den Austausch und die Suche nach Informationen wird gezeigt, dass neue Informationen je nach ideologischer Einstellung unterschiedlich kontextualisiert wurden.

Stichwörter: Rechtsextremismus, Soziale Medien, Twitter, Terroranschlag, Anschlusskommunikation, Netzwerkanalyse, Topic Modeling.

1. Introduction

The far right is on the rise in Western countries, and the number of violent right-wing extremist terror attacks has surged by 320% in the past five years (Institute for Economics & Peace (IEP), 2019). One of many recent examples is the terror attack in Hanau. On 19 February 2020, a far-right extremist attacked two shisha bars in Hanau, Germany, and killed ten people. Nine of the victims had a migration background, one was the attacker's mother. At the end of his attack, he committed suicide. Against the backdrop of the attack's target locations and victims, it was quickly ruled a far-right motivated terrorist attack. Before the attack, the attacker had published documents and videos online that demonstrated far-right extremist sentiments, such as racist and Islamophobic themes as well as conspiratorial thinking (e.g., support for QAnon). However, in addition to his ideological stance, crime experts also attested to a mental illness (Gensing, 2020). This attestation incited a public debate about the controversial assessment of the attack. The Federal Criminal Police Office (BKA) investigation lasted longer than expected, and the final investigation report was not published until April. The leaking of an alleged version of this report by the end of March fuelled the public debate, and as a consequence, the public discussions lasted until nearly the end of April.

Terror attacks, like the one in Hanau, are followed by public shock and a sense of disorientation and cause feelings of fright, anger, and anxiety (Jin et al., 2016). People who are or feel affected by collective traumatic events have the urge to talk about them extensively as a coping mechanism (Garcia & Rimé, 2019). Previous research finds that people increasingly use social media in the aftermath of terror attacks for collective sense-making and to voice sympathy with the victims (Fischer-Preßler et al., 2019), to share information (Kessling et al., 2020), and to process emotions (Garcia & Rimé, 2019). In particular, Twitter appears to be a popular platform because of its technical architecture as a micro-blogging platform, which allows for the quick exchange of views and information (Schulze et al., 2022). Participating in public discourse – including via Twitter – allows individuals to form a common identity and fulfils a need for social belonging (Garcia & Rimé, 2019). However, these studies did not consider how ideologically motivated actors engage in these discussions and to what extent their opinions differ from mainstream points of view.

Simultaneously, we observe the rise of far-right online activism and strategically planted campaigns aimed at distorting online discourses and, thus, the perception of public opinion (Ahmed & Pisoiu, 2019). Little is known about to what extent far-right actors attempt to occupy, deviate from, or even disrupt these acts of collective processing. In this study, we compare the far-right discourse with the general public discourse on Twitter in the aftermath of the Hanau terror attack. The overarching research question asks:

> *Which themes distinguished the general and the far-right online discourse in the aftermath of the Hanau terror attack?*

To address the research question, we studied public reactions and analysed the Twitter discourse that followed the Hanau terrorist attack. We collected tweets containing the hashtag '#Hanau' (*N* = 237,000) over three months to account for longer-term discursive shifts and to include the time period until the final alleged report was published. The content of the tweets was analysed based on a multi-methodological design comprising network analysis and structural topic modelling.

The study results contribute to the overall scholarship of public negotiation processes in the aftermath of terror attacks by extending previous findings and further distinguishing different strands of public reasoning. In contrast to previous studies, we show how ideologically motivated actors communicate strategically to shape public debates and affect the process of collective sense-making to support their political goals. This analysis provides further evidence that social media content is skewed, can be strategically altered, and should thus not be considered a reflection of general public opinion.

2. Public reactions and discourses after terror attacks

Following a rising number of terror attacks over the past years, the concept of collective action has been increasingly addressed in empirical research (Garcia & Rimé, 2019). One main driving factor for collective action is rooted in individual responses to emotional sentiments like fright, anger, or anxiety (Jin et al., 2016). These emotions arise from the randomness of traumatic events and the threat to civil harmony that terror attacks cause (Lerner et al., 2003). Focusing on the public discussions ensuing a series of jihadist terror attacks from 2014 to 2017, several studies observed emotional responses to terror attacks, both on the individual and collective levels (Garcia & Rimé, 2019; Maitlis & Christianson, 2014). Social media are highly relevant for individuals looking to publicly share their emotional responses to terror attacks, especially Twitter, which is frequently used because of its discursive format (Schulze et al., 2022; Fischer-Preßler et al., 2019).

When individuals share their thoughts and emotions, a collective response can arise, clustering individuals and responses together in similar-minded statements (Cornelissen et al., 2014; Fischer-Preßler et al., 2019). Yum and Schenck-Hamlin (2005) categorised publicly voiced emotional reactions in the context of the 9/11 attacks to explain and distinguish emerging emotional sentiment and its processing. They created a category system of possible reactions, which included the search for meaning and value, rising nationalistic sentiment, counter-bigotry activism, altruistic behaviours, gratitude for helpers, and, in more general terms, information seeking and sharing (Yum & Schenck-Hamlin, 2005). Fischer-Preßler et al. (2019) revisited these categories and confirmed them in the context of an Islamist-motivated terrorist attack in Berlin in 2016. However, since this categorisation was found to be applicable to communication ensuing an Islamist terror attack, it is still an open question as to whether and how these categories occur in the context of a far-right motivated terror attack.

One main theme that appears to be of central relevance is *solidarity and the search for value and meaning*. The search for meaning can be considered a primary psychological response to emotions triggered by events, like terror attacks, to express grief and confirm own values. Concerning expressions of solidarity, in the aftermath of jihadist attacks in Europe, hashtags like '#JesuisCharlie' or '#PrayforParis' are just two examples of several collective public reactions of solidarity formations (Eriksson et al., 2018; Kiwan, 2016).

A further type of reaction is *increasing hostility towards different values or prejudice* (Yum & Schenck-Hamlin, 2005). In the event of public shock, sentiment towards individuals with similar beliefs increases, while sentiment towards those who differ in terms of beliefs or political attitudes decreases. This mechanism may increase cleavages and in- and outgroup polarisation (Cohen et al., 2005). Fischer-Preßler et al. (2019) found this category to be dominant in subsequent discussions ensuing jihadist attacks associated with an increase in nationalistic sentiment. Considering that the Hanau attack was a far-right hate crime, the same might not necessarily be the case, as an increase in nationalistic sentiment would have to be considered as support for the attacker. Instead, an increase in expressions of hostility towards nationalism appears more likely.

Twitter has been shown to play an increasing role in terror management information systems – even official state institutions have employed this platform to distribute new information (Eriksson, 2016; Morgan et al., 2013). The pace and the high interaction rate of Twitter allow for easy *information seeking and sharing and the exchange of ideas*. What information will be displayed depends on the algorithmic content filter that builds on each individual's preferences and who they follow. Hence, new information is therefore obtained from sources that rather correspond to the individual's ideological background. This biased display of receiving might be reinforced on social media platforms through recommender systems that support the development of like-minded information environments and echo chamber effects, specifically for more radical/extreme users (Mathew et al., 2019). A biased partisan information perception can lead to different contextualisation of new information in accordance with existing ideological attitudes (Neumann et al., 2018).

3. Far-right discourse and behaviour in digital environments

The term 'far-right' is increasingly employed to summarise all those heterogeneous movements and groups that – based on right-wing ideological values – consider people and the state as one unity and foreigners as an imminent threat to society (Pirro, 2022; Bjørgo & Ravndal, 2019). Basic principles and themes of the far-right include nationalism, racism, xenophobia, authoritarianism, and nativism, as well as, occasionally, anti-democratic attitudes or populism; though, themes vary from group to group (Mudde, 2002; Sterkenburg, 2019). Far-right groups started using the Internet in the early 1980s for strategic communication and planning, including propaganda, information exchange, and to recruit for these principles (Conway et al., 2019). Right-wing extremists "have been quick to adopt a variety of emerging online tools, not only to connect with the like-minded, but to radicalise some audiences while intimidating others" (Conway et al., 2019, p. 2).

As for most people today, social media platforms are part of far-right supporters' daily communication and information environment, or as Neumann (2019, p. 5) states, "extremists, whatever their political views, are products of their age. Or do we seriously expect extremists still to write letters, book their flights via travel agents and take their photos to be developed?". The far right has become proficient at adapting to the social media communication logic and has learned to use it to its advantage (Schmitt et al., 2018).

In recent years, the scholarship concerned with far-right online communication has been growing, and while it seemed to be always at least one step behind, a few strategic patterns have been exposed (Rothut et al., 2022; Guhl et al., 2020). Far-right activists aim to shift the (perceived) public discourse to fuel social conflicts, recruit new supporters, and mobilise groups. A further concept that has been discussed in this context is the shift of the 'Overton window', that is, the gradual shift in what is perceived as acceptable in public discourse and thus as supporting social cohesion (Reynolds, 2018). This concept was observed during the Charlie Hebdo Debate in Italy, as different far-right actors strategically employed the 'Overton window' to gain legitimacy in the mainstream public sphere (Castelli Gattinara, 2017). Terror attacks facilitate hostility against outgroups – even amongst non-radicalised, ordinary individuals – and thus render radicalised content more tolerable (Fischer-Preßler et al., 2019). Linked to ideological radicalism, this effect is also referred to as *mainstreaming* (Gallaher, 2020). The aim of mainstreaming is to silently shift the public discourse towards more radical positions without being perceived as doing so. Wright (2009) showed that far-right politicians strategically framed their response to terror attacks to mobilise for their policy goals as early as 1995. One strategy for mainstreaming far-right ideas is to soften the vocabulary and narratives on large social media platforms, such as Twitter, by "strategically mimicking conservative tropes" (Gallaher, 2020, p. 1). These activities may drive radicalisation processes through normalising extreme narratives (Miller-Idriss, 2020).

In addition to the general shift in discourses through mainstreaming, there are also indications that online discussions are deliberately disturbed by targeted actions and by exploiting technical possibilities. Thus, opponents can be attacked, and the assessment of the distribution of opinions can be distorted. German far-right groups have been shown to employ 'trolling' (i.e., the intentional disturbance of a person or a discussion using confusing, cynical, or even pejorative remarks) on Twitter as a strategy for disrupting discussions (Ahmed & Pisoiu, 2019). Through hashtag hijacking, a specific agenda can be strategically distributed or an online debate can be distorted by using other foreign hashtags (Knüpfer et al., 2019; Darius & Stephany, 2019). Thus, the perception of the overall debate may be altered.

Little is known about specific far-right strategic communicative actions in the aftermath of far-right terror attacks. However, it has been shown that, on Twitter, the German far-right has exploited "current events to motivate people into action" (Ahmed & Pisoiu, 2020, p. 13) and that it has linked its narratives to current topics to alter the perceptions and evaluations in favour of its ideological, extremist value system (Ahmed & Pisoiu, 2019; Kreißel et al., 2018). Studying the public debate after the 'Charlie Hebdo' attack in January 2015, Castelli Gattinara (2017, p. 1) examined far-right actors and concluded that "they collectively employed the Charlie Hebdo controversy to redefine their exclusionary discourse on liberal ground with the goal of gaining legitimacy in the mainstream public sphere."

Theory guided research questions

Based on existing findings concerning public discourse following terror attacks and studies on far-right discourse we presume a fundamental difference in collective sense-making between the two groups in the aftermath of the Hanau terror attack. We therefore ask:

> *RQ: Which themes distinguish the general and far-right online discourse in the aftermath of the Hanau terror attack?*

To further specify, we address the research question based on three aspects:

1) Since research has shown that more extreme accounts have a stronger coherence in the sense that their network is more closely connected (Mathew et al., 2019), we aim to inspect whether the far-right community discusses different topics than the general, unspecified discourse. Specifically, we focus on differences in information sharing behaviour and theme proportions, but also whether there are interactions in terms of counter-argumentation.
2) To investigate whether a right-wing extremist terrorist attack resulted in similar discourses, as was demonstrated for communication following Islamist terror attacks (Fischer-Preßler et al., 2019), we examine to what extent the topics of solidarity, search for meaning hostility, and responsibility attribution also appear in the Twitter communication after the Hanau attack.
3) As a relevant piece of information about the assessment of this attack entered the discourse only four weeks later, we seek to explore whether the discourse persists from a longer-term perspective and how the development of topics over time and between groups differ over time.

4. Methodology

To study the public discourse in reaction to a terror attack, we analysed the Twitter discourse occurring in the aftermath of the Hanau terror attack. We followed a multi-methodological approach and evaluated the results derived from hashtag co-occurrence network analyses in a structural topic modelling approach to extract topics from high-dimensional data. The topic models allow us to structure and categorize the vast amount of topics discussed and, more importantly, quantify their overall share within the data. Ultimately, quantifying and labelling topic proportions allow us to reveal differences between the general public and the far-right debate in the aftermath of the terror attack and to address parts 1) and 2) of our research questions. The labelling of derived containers was validated by conducting word embedding models of the most probable terms of each container and by qualitative inspection. Thus, the word embedding models and qualitative inspection were not used for the analyses, but instead for validating the topic modelling and can be viewed in the supplement material.

The data collection and analysis followed several – partly iterative – steps. First, two data sets were created by collecting tweets containing '#Hanau' via the premium Twitter Rest API, which allows for complete, unrestricted data fetching (~237,000 tweets). Data collection for the general data set (later used as DS1) started immediately after the attack, on 20 February 2020, and continued until 29 April 2020. The extended period of data collection allowed us to include possible long-term discursive shifts.

The next steps all served the purpose to find, extract and distinguish the far-right discourse about Hanau on Twitter. As a preliminary first step, a second data set (later used as DS2) was created based on a manually curated list of German-speaking, far-right Twitter accounts. The seed list of accounts for DS2 contains well-known, far-right actors such as radical-right politicians or influencers with at least 5,000 followers. We then inspected accounts that were a) either followed by the seed accounts or b) who followed these accounts and c) were mentioned in or commented on tweets. This resulted in a total of 366 seed accounts for the far-right data set (DS2). We then collected all tweets of these accounts containing mentions of 'Hanau', resulting in 670 tweets that served as the basis for the far-right data set. These accounts were collected separately from DS1 to ensure minimal data loss and were also eventually deleted from DS1 to avoid accounts being in both data sets.

4.1 Classifying far-right content

The next steps served the purpose to amplify the data set used for the far-right discourse and at the same time ensuring that the data set later used as the 'general discourse' entails less far-right accounts. In order to classify far-right content, we inspected accounts as well as the tweets in several steps:

1) In order to collect further possible far-right content as well as to detect and transfer possible far-right content from our main data set DS1 to DS2, we utilized the content that was collected within our far-right seed list. First, we analysed whether the 670 far-right tweets contained frequent terms used in the far-right community and valued to represent far-right narratives in the context of the Hanau terror attack. Secondly, we ran a first structural topic model based on the tweets of the seed accounts and extracted the most probable terms within prevalent containers. Words extracted this way were added to a dictionary.

2) This dictionary was used to extract tweets in the main data set (DS1) that contained one or more of these words[1], which resulted in ~117,000 posts. Following this simple dictionary approach, it is likely that only a small part of the extracted tweets contained far-right sentiment.
3) To extract more far-right tweets, we drew a 5% sample (= 5,875 tweets) of the tweets we found with this dictionary approach. Thereby, we aimed to have a higher chance of extracting possible far-right content than simply drawing a random sample from DS1. From this sample, 1,133 (= 19.3%) tweets originating from 195 accounts were manually classified as using the same context as found in our topic model of the far-right seed accounts. Thereby, indicating that an inspected tweet discusses similar topics that accounts in the far-right seed list are discussing.
4) To evaluate whether the accounts that had posted the tweets in our random sample were indeed far-right, they were then coded on the basis of each twitter feed (i.e., the account description, account's tweets, retweets, or comments in the last year). A specific account was evaluated as "far-right" by the coder based on whether far-right properties were present in parts of their Twitter profile. We chose to look for far-right properties that are well established in the literature on the far right (Carter, 2018) such as: nationalism, racism, xenophobia, authoritarianism, and anti-democratic sentiment (Mudde, 2004). We further added anti-elite sentiment (Mudde & Kaltwasser, 2017), hate speech (Adamczyk et al., 2014), and conspiracy narratives (Wood & Gray, 2019) as *weak factors*, which were seen as sufficient but not as necessary characteristics for a far-right classification. We included these *weak* factors as they are recently discussed to be important, but not exclusive, 'far-right' characteristic elements. Accounts that showed at least 3 of the above elements were added to our seed list of far-right accounts[2]. A detailed description of the elements we used can be viewed in the supplement material.

After this classification, 53 accounts displayed several far-right properties (= three or more properties are mentioned). Further, 83 were classified as accounts with few far-right properties (= at least one of the properties mentioned). We specifically chose to also shift tweets from DS1 into DS2 stemming from accounts with only one far-right property, if they showed racist, anti-democratic, or xenophobic properties. These elements state a strong extremist attitude compared to the weak factors mentioned above. Accounts entailing such elements can be seen as far-right actors even though, for example, they only showed one property such as anti-democratic attitudes. In addition, 26 accounts showed no affiliation to far-right characteristics, and 33 accounts had already been deleted. We then added the identified far-right accounts that either showed at least one property of the strong extremist properties or had at least three far-right properties overall to our seed list and shifted each of their posts or retweets from the main DS1 to the far-

1 The complete dictionary is available in an OSF repository: https://osf.io/p6h29/
2 A detailed description of all far-right properties can be viewed in the OSF repository. Accounts were not added if only three weak factors were present.

right DS2. Ultimately, our far-right data set contained 31,572 tweets, and the main data set included 191,510 tweets.

4.2 Pre-processing and exploratory approach

The data analysis followed an exploratory approach. First, we conducted network analyses based on hashtag co-occurrences. The derived networks showed which hashtags were used in combination with '#Hanau' and allowed for a first glimpse into the central aspects as well as the inspection of minor instances discussed in connection to the main hashtag '#Hanau'. We used R (Team, 2013) to process and analyse our textual data with the packages quanteda (Benoit et al., 2018), tidyverse (Wickham, 2016), and text2vec (Selivanov & Wang, 2016). The data cleaning comprised several steps: 1) we deleted all the tweets from DS1 that were moved to DS2 (see chapter 4.1); 2) for all descriptive analyses and topic models, tweets were split into single words and analysed as single units or features without their context (the bag-of-words approach; Grimmer & Stewart, 2013); and 3) to reduce the noise in the data, we deleted words without semantic meaning or analytical value, such as stop words, punctuation, links, emojis, and falsely encoded text (Benoit et al., 2018; Bolton & MacFarlane, 2001). Subsequently, all the remaining terms were stemmed. Words that occurred too often (i.e., words that appeared in 95% of all the tweets) were deleted. Additional manual extraction was performed iteratively to further clean the data regarding undetected noise.

4.3 Structural topic modelling

To further inspect the discourses, we applied structural topic modelling (STM) (Blei & Lafferty, 2007; Roberts et al., 2014). We specifically chose this type of modelling rather than other possible better fitting variants for short texts (e.g., tweets), like the biterm topic model, as it allows for calculating and quantifying prevalence effects over time (Jónsson & Stolee, 2015). We made this trade-off as we valued the gain of controlling for time effects higher than slightly less performing feature-to-topic allocation. Nevertheless, model diagnosis and the corresponding qualitative inspection of the resulting containers also revealed no apparent labelling issues. Most importantly, quantifying topic proportions across time also allows to address the third part of our research question (what topics were discussed in the long-term and whether there were thematic differences between the two data sets over time).

Although STM is good at extracting topics and reducing dimensionality, its efficiency and usefulness usually depend on the researchers' decisions regarding the number of containers. Validation measures were undertaken to ensure that the calculated containers referenced topics represented by the top words placed in each container. This process included the qualitative inspection of the words in their contexts, differentiating containers and their words from each other through perspective plots, and a series of model fit measures to define the optimal number of containers (= K). These model fits are displayed in Figure 1 for DS1 and in Figure 2 for DS2.

Figure 1. Model diagnostics by the number of topics – general public DS1: Comparing exclusivity and semantic coherence – general public DS1 model parameters of *K* = 25 perform best

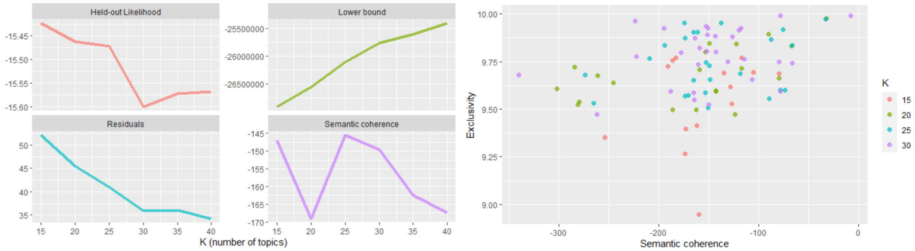
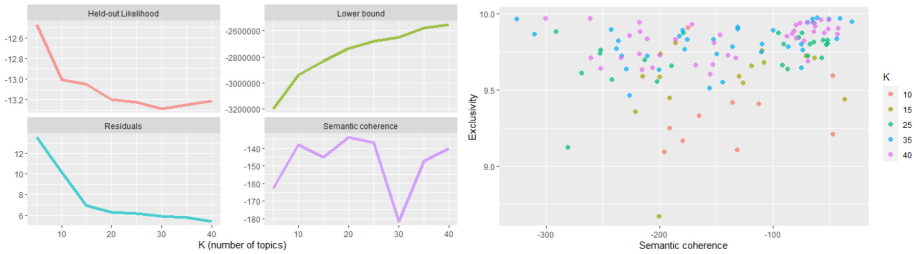


Figure 2. Model diagnostics by the number of topics – far-right DS2: Comparing exclusivity and semantic coherence – far-right DS2 fitted models seem to perform best at *K* = 10, 15, 25, and 40



Note. Held-out likelihood defines the likeliness of documents not being in a specific container. Accordingly, the value of *K* should be chosen when the likelihood is high and residuals of the containers low to extract distinguishable containers (Wallach et al., 2009). The value of K should be chosen when the lower bound approaches its peak (Grimmer, 2011). The best/ideal semantic coherence is achieved when the top words in a container co-occur together (Mimno et al., 2011), creating a more valid topic construct. Choosing the value of *K* when every model fit parameter is at its optimum is ideal. Fitted models seem to perform best around *K* = 25 and *K* = 30. After conducting topic models for both, we chose *K* = 25 and *K* = 15 for the far-right data set.

For DS1 as well as DS2, the model parameters indicated multiple options for the value of *K*. In the end, we chose *K* = 25 for DS1 and *K* = 15 for DS2, as they expressed the best compromise between all the parameters, and the interpretation of the containers yielded the best results. We further inspected the context and connotation of high influential container words via word embeddings (GloVe) to validate our labels for each container (Selivanov & Wang, 2016; Pennington et al., 2014)[3]. Hence, the evaluation of what is being discussed in each container could also be performed on a quantitative dimension in addition to the more qualitative approach via the inspection of single tweets. Previous

3 All word embeddings for the most probable terms within each container, syntax and model specification can be viewed in the OSF repository.

studies have used this before for Twitter data either to classify sentiments or as a method for evaluating topics and their coherence (Ren et al., 2016; Tang et al., 2014).

5. Results

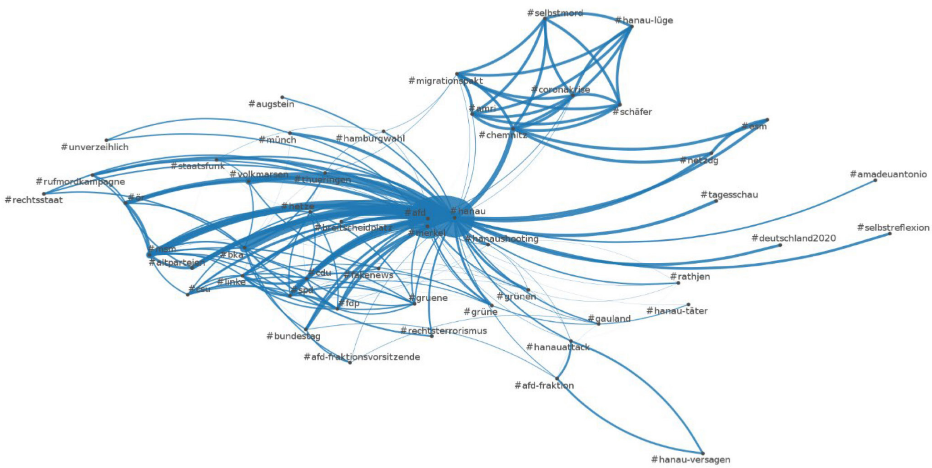
This section presents the analyses of the two data sets and explains the differences in topics and patterns between the general public discussion on Twitter and that of a far-right sub-group. Based on network analyses and structural topic modelling we show 1) how the hashtag '#Hanau' is used in different contexts, 2) what topics are mentioned following the terror attack in Hanau in comparison to already researched behavioural patterns, and 3) whether there are differences concerning topics and topic contextualisation over time.

5.1 Hashtag co-occurrence networks

We visualised two network analyses of co-occurring hashtags to display the most prominent themes discussed in connection to the main hashtag '#Hanau', split into a network for the general public in Figure 3 and one for the far-right in Figure 4. The more frequently a hashtag co-occurred with another one, the thicker the plotted ties are between them. For the general public discourse, the strongest ties concern references to previous terror attacks or right-wing extremist terrorists ('#halle', '#lübke') and references to racism, far-right terrorism, or Germany's radical right-wing party, the AfD (e.g., '#rechtsextremismus', '#rechterterror', '#noafd'). Further, several hashtag co-occurrences referred to solidarity with the victims, including hashtags such as '#Solidarität' (= solidarity), '#Hanausteht-zusammen' (= Hanau stands together), '#saytheirnames', or '#keinvergessen' (= no forgetting).

Figure 3. Co-occurrence network for the general public

Figure 4. Co-occurrence network for the far-right



Specifically, the radical right party was mentioned in several instances, but so were other German parties, like the Conservative Party (CDU) and the Social Democrats (SPD), in their role as the current parties of the coalition government. Besides, in relation to the AfD, '#noAfD' or '#AfDVerbotjetzt' indicated a negative sentiment towards the party. More generally, hashtags like '#nazis', '#fcknzs', or '#nonazis' depicted collective disapproval of right-wing extremist ideology.

Inspecting the hashtag network of the far-right data set, two clusters are apparent. First, placed on the left, the strongest co-occurrences concerned the German chancellor Merkel ('#merkel'), a word with negative connotations for the established democratic parties ('#altparteien'), the radical right party AfD ('#afd'), and names of cities/regions with similar right-wing movements or attacks ('#chemnitz') as well as upcoming elections ('#hamburgwahl', '#thueringen'). Several connections were made to news media, such as the most prominent German news broadcaster ('#tagesschau'), mass media in general ('#msm'), or public service broadcasting (PSB; '#ör').

On this descriptive level, in some instances, a far-right background became apparent, such as when Hanau was connected to a callous murder ('#rufmordkampagne'), a terror attack by an Islamist terrorist in Berlin ('#breitscheidplatz', '#amri'), a word with negative connotations for Germany's PSB ('#staatsfunk'), and several hashtags within the second cluster on the top right, that dealt with the issue of migration ('#migrationspakt'), claiming the reporting on Hanau to be a lie ('#hanau-lüge') and mentioning '#fakenews' and suicide ('#selbstmord') when referring to the attacker. The hashtags '#hanaushooting' and '#hanauattack' were the only frequently employed hashtags that could be found in both networks. It is also noteworthy that the density – measuring network density through dividing actual edges with all theoretical and possible edges – for the main data set is drastically higher (82.9%) than for the far-right data set (19.2%), indicating that the far-right discourse is more decentralised and less interconnected than the main discourse. To further contextualise hashtags in terms of their respective topics and see how popular topics appeared to be in comparison with each other, we employed STM.

5.2 Topic modelling results

5.2.1 Topics in general public discourse

Overall, the STM results in Tables 1 and 2 support the results of the hashtag co-occurrence networks. In DS1 (general public), 25 containers were extracted. The highest topic proportions are shared between a topic about remembering and naming the victims of the attack (19, 20) and a topic that mainly covers information and news sharing (13).

Table 1. Labelled topic model containers and discourse categories in the general public data set

Category	Label (topic proportion)	Most probable terms	Example post
Responsibility attribution (~38.3%)	**23:** Election boycott of AfD (6.7%)	afd, hamburg, wählt, morgen, rassistisch	On point. I hope that in Hamburg finally a sign is set against the AfD. Would be at least a step in the right direction. #HamburgWahl
	24: Blaming of AfD (3.7%)	afd, rechterterror, text, mord, noafd	The "AfD" is in every way a one to one copy of the NPD. AfD relativizes far-right extremism! #Hanau
	6: Racism in Germany (2.1%)	problem, rassismus, rechtsextrem, angst, deutschland	Despite #coronavirusdeutschland and the consequences: #Germany has a huge problem with #racism and #Nazis! Right down to the security organs. We must not forget the victims of #Hanau and #NSU!
	21: Previous attacks (2.7%)	deutschland, nsu, lübke, halle, afd	After the NSU, after Kassel, after Halle & after Hanau, we do not want to and cannot go back to business as usual. #racism #rechterterror
Information seeking & sharing (~34.7%)	**13:** Sharing news (7.4%)	attack, terrorist, opfer, germani, people	A German suspect was found dead in his apartment along with his mother's dead body. The terrorist attack took place in two different Shisha bars in German city #Hanau and has left 11 people dead and many others critically wounded.
	17: Alleged BKA statement (4.8%)	rassismus, bka, täter, mutter, rassistisch	"Not a right-wing extremist terrorist, but a mentally ill person who ran amok" – Alexander Gauland, AfD, on an alleged "final report" by the BKA on the terrorist attack in #Hanau. Good that the BKA is setting the record straight here.

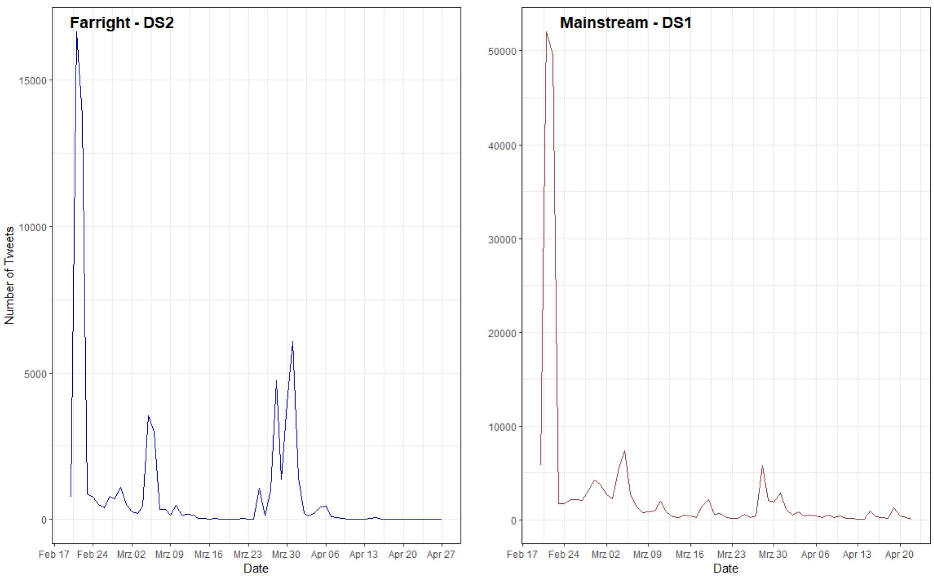
Category	Label (topic proportion)	Most probable terms	Example post
	2: New insights (3.8%)	polizei, täter, tobias, recht, tat	New findings on the night of the crime: The #Hanau murderer still had 350 cartridges in his backpack when the police found his body. This and other details from the night of the crime were reported by the Federal Prosecutor General in the Bundestag's Interior Committee.
Showing solidarity (~27%)	**20:** Memorial tweets (7.8%)	terror, anschlag, gedenken, heute, opfer	Our thoughts and deepest condolences are with the families and loved ones of the victims of yesterday's attack in #Hanau. We stand united in solidarity with the German people, and firm against such intolerance and hatred.
	19: #saytheirnames (6.5%)	opfer, namen, vergessen, gültekin, ferhat	#Hanau was nine weeks ago today. In memory of Ferhat Unvar, Gökhan Gültekin, Hamza Kurtovic, Said Nesar Hashemi, Mercedes Kierpacz, Sedat Gürbüz, Kalojan Velkov, Vili Viorel Paun, Fatih Saracoglu #saytheirnames
	12: Solidarity concert (2.0%)	verbreitet, nachricht, seid, gökce, hetze	In response to the racist attack in #Hanau, 18 rap artists have recorded a solidarity song in support of the bereaved. Spread the song! Stop the #RightTerror Together!

Note. The table only shows the most prevalent containers extracted from all 25 containers (see Figure 1 in the Appendix for a complete overview). The numbers in parentheses express the overall proportion of one container or the overall category in the complete data set. The original number of the container is placed in front of every label. Example posts were translated into English.

Among the most frequently mentioned topics (in terms of the total proportions spread over all the containers), we labelled a series of topics that referred to the radical right party. With approximately 38.3 percent, these responsibility attributions after the attack show the public call for immediate action to punish those perceived as responsible for attacks like the one in Hanau. For example, in one frequent theme, people called for an immediate boycott of the AfD in the upcoming regional elections in Hamburg (23). Further topics were labelled as a form of responsibility blame towards the AfD (i.e., container 24). In a similar stance, the general public data set included many containers labelled as a form of discussion about increasing terrorism, referring to racism and far-right extremism in Germany (6). Also, we found several connections to similar attacks in the past in containers displayed in Figure 1 in the Appendix (i.e., 1, 21, 10).

As an additional large proportion within the general public discourse, several containers included seeking and sharing new information (approx. 34.7%). While the second-largest container (13) provided more general information, the next container referred to statements from the Federal Criminal Police Office (BKA) and investigation reports (17). Other containers (2, but also 14, 18, 5, 3, 4, and 25 in the Appendix) presented insights not published immediately after the attack but one or a few days later. These topics mainly discussed a second crime scene, police activities in Hanau, and information about the far-right motives of the attacker, and they peaked in the days following the attack (see Figure 5). With regard to this, tweet coverage massively declined for both data sets after just a few days. After approximately March 5, a second, far smaller peak is visible for both communities. This resurgence might be attributed to the memorial for the victims held in the federal parliament, during which Members of Parliament harshly attacked the AfD. A third peak, especially in the far-right data set, arose in late March, referring to news reports about the alleged police report.

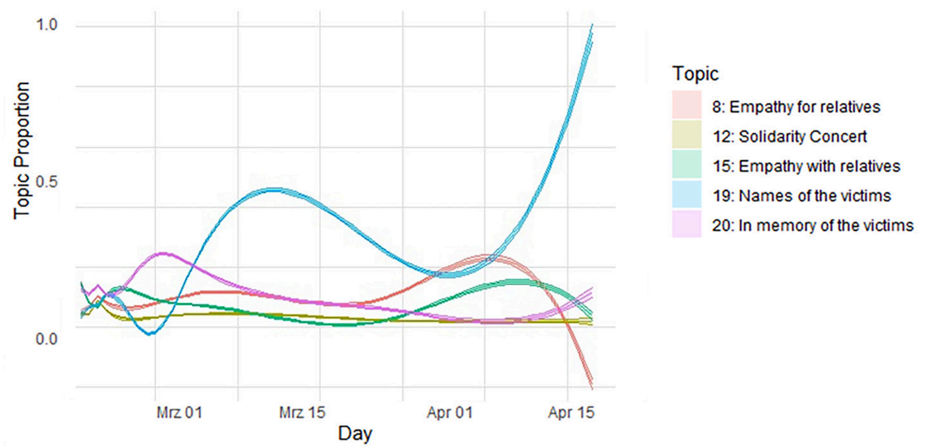
Figure 5. Comparison of tweets per day between the far-right and general public



Note. Displayed are tweets differentiated between the far-right and general pubic per day (y-axis) and over time (x-axis).

Lastly, several containers could be categorised into several instances of showing solidarity (approx. 27%). Hence, amongst the most frequent containers, people referenced the victims and showed empathy with the bereaved families (20). In a similar stance, a very popular type of tweet presented a collection of all the victims' names with a call to not forget them (19). This was also included in container 12, which peaked in the days after the attack, as the names were incorporated into the solidarity concert organised for the victims (12). In opposition to studies of similar attacks, we also find that this reaction was not only prevalent in the hours and days after the terror attack, but occurred regularly throughout the whole observation period (see Figure 6). In comparison to all other containers derived from the general public topic model, showing solidarity is the only category that remains prevalent even several weeks after the attack.

Figure 6. Searching for meaning and value through solidarity and memorials



Note. Displayed are the containers and their overall proportions in all the documents (y-axis) over the whole observation time on the x-axis for the general public data set regarding some form of solidarity. Topic Containers 8 and 15 are not displayed in Table 1 and deal with showing empathy for the victims' relatives.

5.2.2 Topics in far-right discourse

The results of the topic model for the far-right discourse presented a different picture. Fifteen containers were extracted. The overall discourse and labelled topics shared almost no similarities with the general public discourse. Contrary to the themes picked up by the general public, the top topics in the far-right data set dealt with the mental illness of the attacker, either directly (8) or indirectly in the form of criticism of the initial investigation by the BKA, only days after the attack (12). As the second-largest overall category (approx. 30.3%), the attacker's psychological condition was determined as the main motive of the attack (7).

Table 2. Labelled topic model container and overall discourse categories in the far-right data set

Category	Label	Most probable terms	Example post
Responsibility attribution (~32.8%)	12: Critique towards the BKA (9.6%)	bundesan-waltschaft, eingang, attentäterbrief, teilen, angriff	The Federal Public Prosecutor's Office admitted that they had already been in contact with the suspected perpetrator in 9/2019. On this @HuberMdB: "#Federal Government considers misjudgement of the Federal Prosecutor's Office in the Hanau case is justified." https://t.co/jBmmSBZeIz
	5: Gun licence provided by the SPD (7.5%)	hanau, waffen, kannte, polizei, politisch	Hanau in a nutshell: the crazy son of a green politician kills 10 people. The police already knew him, the SPD city council allowed him to have weapons and the AfD is to blame for everything. Germany2020, or also: there is a method to madness.
	1: Main-stream blam-ing (2.4%)	hanau, altparteien, gesellschaft. hass, afd	The BKA did not allow itself to be pressured by the media and politics and has now announced the results of its investigations. Blaming the AfD for Hanau was shabby from the start. It's time for self-reflection dear mainstream media and old parties.
Mental illness of the attacker (~30.3%)	8: Mental ill-ness (9.7%)	psychisch, gewalt, krank, problem, terror	Martin Sellner proves in his video that the murderer of Hanau was not a politically motivated perpetrator, but a severely mentally disturbed killer who lived in a paranoid delusional world. Most mainstream media are not interested in this.
	7: Counter-arguing re-sponsibility (9.0%)	rechter, psychsich, afd, opfer, täter	When a child is pushed in front of a train in Frankfurt, the perpetrator is said to have been mentally ill. When a mentally ill person shoots people in Hanau, it becomes right-wing terrorism. Hysterical shrieking of the old parties!
	2: Status of mental illness investigation (6.0%)	täter, eigentlich, ermittlungen, mann, hanau	Is the perpetrator from Volkmarsen still not fit for questioning? There is also no news from Hanau about the investigation and the alleged perpetrator, except that the police are now taking massive action against so-called hate comments.

Category	Label	Most probable terms	Example post
Politicising & instrumentalisation (~25.1%)	13: Political instrumentalisation (7.1%)	politisch, verantwortlich, benefizsong, hanau, rückgängig	The madness takes its course: no idea, no information, but a cowardly judgement driven by the effort to politically instrumentalise the Hanau assassin. We have read his manifesto, the manifesto of a psychopath.
	6: Anti-elite sentiment (6.3%)	altparteien, bundestag, instrumentalisierung, hetz, afd	Today's discussion in the Bundestag shows once again where the agitators, hate preachers, populists and social dividers are. In the ranks of the Left, CDU, CSU, @spdbt and The Greens. Hanau was not right-wing terrorism.
	3: Biased news reporting (4.3%)	afd, amokläufer, staatsfunk, afd, hanau	Even the left-wing state media is slowly allowed to publicly doubt that the attack in Hanau had a right-wing background. How about an apology from Merkel, Steinmeier and Co towards the AfD?

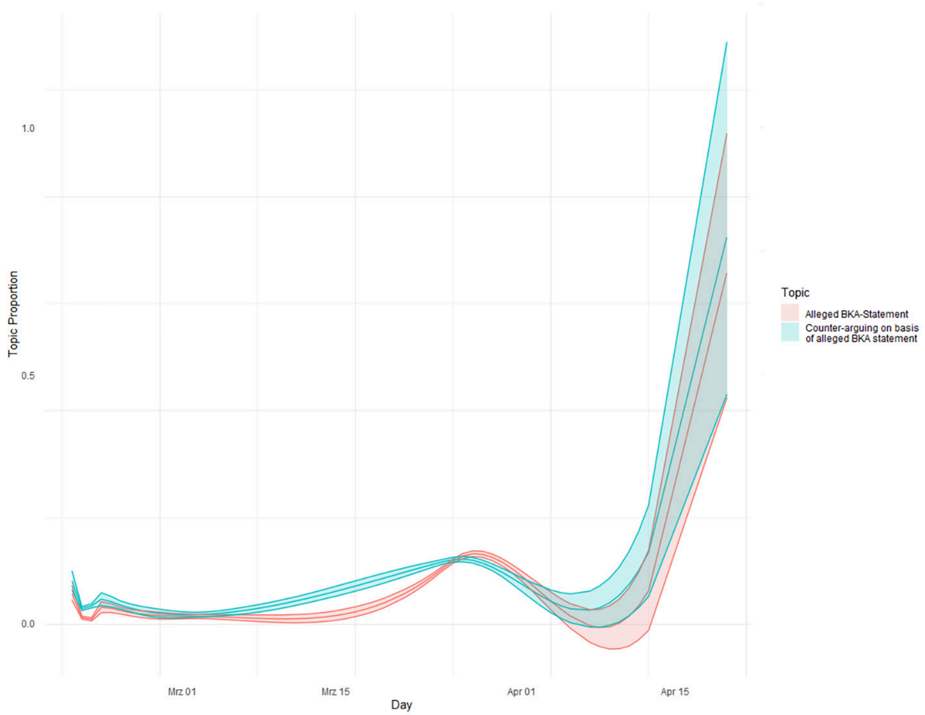
Note. The table only shows the most prevalent containers extracted from all 25 containers (see Figure 1 in the Appendix for a complete overview). The numbers in parentheses express the overall proportion of one container or the overall category in the complete data set. Example posts were translated into English.

The mental illness was also represented in larger topics that could be extracted in container 2, pressuring the media and politics to invest more resources in the investigation into the psychological condition of the attacker. Further containers referred to the politicising and instrumentalisation of the attack through centrist parties and the alleged state-controlled media (13 and 3), and in an adjacent topic, container 6 rather echoed a general anti-elite sentiment. Overall, the criticism of such politicising and instrumentalisation aimed at the general public by the far-right made up one-quarter of the total far-right discourse.

Lastly, the largest proportion in terms of content variation could be labelled as counter-arguing and responsibility attribution (~32.8%). While the first container discussed the perceived biased ongoing police investigation into the attack (12), the regional parliamentary party group of the Social Democrats was criticised for providing the attacker with a gun license. The remaining topics referred to a statement of the BKA in late March (1). Newspapers published an alleged BKA report that refuted far-right motives of the attacker as the main drivers of his attack. Even though the BKA denied this finding and instead stressed the importance of far-right motives for the attack, it favoured far-right narratives, resulting in a drastic increase in topic proportion that deals with the alleged BKA statement starting at the end of march (Figure 7). The point estimates of probable topic proportion ultimately reach around 75 percent, meaning that approximately three quarters of text in all tweets deal with the alleged BKA report at its peak. Inspecting the number of tweets generated in this time period, approximately 44.5 percent of all tweets in the far-right data set have a high probability of dealing with this topic – highlighting the importance of the report for far-right narratives. Such an increase is not identifiable in the general public data set.

It has to be noted that we only summarised the most prevalent categories into overall discourse topics. Several other containers matched the overall categories and, in some instances, referred to other, less salient discussions. An overview of all the identified and labelled containers can be found in the Figures 1 and 2 in the Appendix.

Figure 7. Topic proportions of far-right discourse based on the alleged BKA report



Note. Displayed are the labelled containers and their overall proportions in all the documents (y-axis) over the whole observation time (in terms of the day-count) on the x-axis for the far-right data set regarding the alleged BKA statement in late March (day 90 onwards). The transparent lines represent the 95 percent confidence intervals.

6. Discussion

The present study aimed to investigate the themes occurring in Twitter communication ensuing the terror attack in Hanau, Germany, in February 2020. As discussed in aspects one and two of our research question, we compared the general public discourse with the discourse extracted from far-right accounts. Based on network analyses, we found that the general public discourse contained many hashtag co-occurrences referring to solidarity with the victims. This result is in line with the findings of Yum and Schenck-Hamlin (2005) and Eriksson Krutrök and Lindgren (2018) concerning collective reactions, such as showing solidarity. It appears this specific reaction is universal and independent of the ideological origin of an attack. For aspect three of our research question and focusing on temporal patterns in topic proportions, we were also able to demonstrate that showing solidarity is the only category that persists over long periods of time. In contrast, we were unable to find a similar reaction discourse in the far-right community.

Another big part of the general public discourse dealt with negatively connoted sentiments towards the far right. In particular, the radical right party AfD was negatively mentioned in several instances. Comparing these findings with behaviour observed by Fischer-Preßler et al. (2019), we find rising hostility towards far-right ideology instead of a nationalistic uprising, as might be the case for attacks originating from jihadism.

As Eriksson Krutrök and Lindgren (2018) indicate, people seem to place a specific event in the context of similar, previous instances. The Hanau attack was associated with the far-right motivated assassination of a German politician (Walter Lübcke), an anti-Semitic attack in Halle in 2019, far-right risings in Döbeln and Chemnitz, or in more general terms, '#hanauwarkeineinzelfall' (= Hanau was not an isolated case). The Hanau attack is evaluated as being part of a more significant development and not as a singularity.

Concerning the far-right discourse, we find more negatively connoted hashtags. There are multiple instances in which the political parties in the German parliament are discussed negatively. The way that Chancellor Merkel was referenced indicates anti-elite sentiment. News media and newspapers were also identified, stating a negative connoted tone towards biased news reports. This finding can be interpreted as an attempt to shift the responsibility attribution of the attack to the perceived political and media elite.

6.1 Information sharing and news seeking

As for news reports, information seeking and sharing made up a great portion of the hashtag networks displayed, also in the topic models. The topics that dealt with information about the attack peaked in the hours after the attack, a result that was previously found by other scholars in similar contexts (Eriksson, 2016; Fischer-Preßler et al., 2019). Even though not that prevalent, this is also true for far-right discourse topics referring to information sharing. However, both data sets differed regarding their understanding of what was perceived as new information.

While the general public discourse mainly referred to rather informational topics, like new insights into how the attack happened, the far-right focused on new information about the attacker's psychological condition, indicating a clear pattern of different forms of information sharing. As we explored long-term information sharing, both communities showed new and increasing topic proportions when referring to the news reports about alleged findings in the BKA report in late March (see Figure 7).

When specifying the different contextualisations of this news report, topic proportion in the end of March indicate that the far right mainly referred to the report itself and argued that federal agencies supported its argument of mental illness rather than ideological motives. In contrast, the general public discourse criticised the news report's publication when the BKA's president officially declared that the news report was disinformation. This discrepancy demonstrates how such communities differently contextualise new information and how different discourses evolve, even though the specific discourse is based on the same information input.

6.2 Shifts in responsibility attribution

The topic models further illustrate how the overall evaluation of the attack and the responsibility attribution differed: A large part of the general public discourse deals with either the problem of increasing racism and nationalism in Germany, or directly confronts the radical right party. Considering the far-right topic model, we observed a debate about the different possible motives of the attacker. While in the general public discourse, the topic of the attacker's mental illness accounted for only the smallest share, it encompassed nearly one-third of the overall discourse in the far-right data set, including attempts to distract from, downplay, and depoliticise the attacker's far-right motives. These results point toward the far-right strategy of providing alternative interpretations of the attack to affect the opinion climate and mainstream their radical views (Neubaum & Krämer, 2017).

In addition, we find several attempts of the far-right to blame political enemies, trying to create a cleavage between 'the people' and 'the elite', while incidentally serving the purpose of counter-arguing the responsibility shift with regard to the AfD by the general public and redirecting it towards political enemies to portray the party as the protector of the 'the people' against 'the elites' (Mudde & Kaltwasser, 2017). In this context, the BKA was criticised for withholding investigative reports on the attacker's mental illness, which was subsequently discredited as an elitist and primarily politically motivated proceeding. Similarly, the media environment was deemed state-controlled and biased towards the general public (topic 3). Other targets were parties or politicians (topic 6), in particular Angela Merkel. Merkel was accused of favouring left-wing orientated communities and of establishing a so-called *Opferhierarchi*e (= hierarchy salience regarding victims of different ideology-minded terror attacks) by putting greater value on victims of far-right attacks and victims with migration backgrounds than on victims of jihadist terror attacks. The main argument was that jihadist and left-wing extremist attacks and attacks by mentally ill individuals increased due to her unwillingness to act (topics 1 and 6). In contrast, we find no presence of these issues in the general public discourse. This shows that collective sense-making differs fundamentally with respect to the political background and ideology of the people involved in the discourse. (New) Information, like the alleged BKA report, is picked up by both communities, but it is evaluated and contextualised in entirely different ways by each group in favour of its own respective arguments.

As a last central point regarding responsibility attributions, we also find a discrepancy regarding the display of solidarity and empathy for the victims. In line with the findings of Fischer-Preßler et al. (2019), solidarity and empathy made up a large proportion of the general public discourse. In contrast, the victims were nearly absent in the far-right discourse. The far-right referenced the victims of the attack only in terms of critique towards the elites.

Overall, our analyses show that the far-right reaction to a far-right terrorist attack differs immensely from the general public's sense-making of such an attack. The main differences concern the (lack of) solidarity with the victims, the responsibility attribution concerning the possible explanations for the attack, and the existence of an ideological motive for the attack. While these differences in responsibility attributions are not problematic per se, they can be strategically used by far-right actors to distribute their interpretations, thereby shaping discourse and the opinion climate surrounding the attack (Ahmed & Pisoiu, 2019). While our study cannot confirm whether such parallel far-right discourses can support the development of echo chambers, it can be used as a starting point to further investigate the importance, effects, and consequences of (hyper-)partisan discussions.

6.3 Limitations

Several limitations have to be noted when considering the results and their generalisability. First, the far-right data set's content can only be considered an approximation of the overall far-right discourse. We cannot estimate the potential of other discussions in the far-right sphere that took place outside of the tweets we extracted through the seed accounts. However, our approach (using known far-right accounts as seeds) provides external validity as it uses known far-right actors as seed accounts. We cannot estimate the true percentage of far-right discourse following the Hanau terror attack and, thus, acknowledge the non-representativity of the far-right sample. We also have no indication of the number of tweets that had already been deleted or of the speed at which this takes place, though we tried to tackle this by scraping far-right tweets in small intervals right after the attack. Our primary goal was to populate the far-right data set, while at the same time reducing the amount of far-right content in the general public data. As a result of our approach, we only detected a margin of all possible far-right accounts in DS1. Because of this, there is a high probability that far-right sentiment is still undetected and remains in DS1 – displaying a limitation of this study.

Second, although we termed one data set 'general public', we cannot infer who precisely this 'general public' is on Twitter. We are aware that only a small percentage of the German population uses Twitter as a means of communication, so our data set is not representative of the general public (Newman et al., 2019). For instance, the US Twitter-sphere is known to be left-skewed (Alexander, 2020). However, we only use this term to indicate that we did not filter our scraped data.

Third, the question arises as to whether our findings hold true when inspecting the far-right and general public discourse in the context of similar terrorist attacks. In the face of recent terror attacks, like those in Paris or Vienna, it is noteworthy to also take co-radicalisation effects into account, as both jihadist and far-right terror attacks seem to become more frequent (Lee & Knott, 2020).

We extracted several attempts of the far-right to shift or counter-argue the responsibility attribution of the general public discourse. However, co-occurring hashtags in terms of hashjacking or similarly contextualised topics occurred only rarely. A possible reason – though our methods cannot measure this – might be that there is no communicative exchange between them and that the communities discuss the topics within their echo chambers without interacting with different groups.

6.4 Conclusion

In this study, we investigated how the Twitter discussions in the aftermath of a far-right terrorist attack differed between the discourse found in sub-samples of the general public and of far-right actors. We find *responsibility attribution* to be one of the central themes in both discourses. The general discourse primarily voiced sympathy with the victims and attributed the responsibility for the attack to far-right (terrorist) activism. Categories described by Fischer-Preßler et al. (2019), such as meaning and value-seeking as well as message sharing and searching, were also found in this study. However, this only holds true for the general public discourse. In contrast, the far-right mostly attempted to reshape the public narrative by raising several arguments to shift responsibility attributions towards the (political) elite and the shooter's personal circumstances.

We show how ideology-based reasoning might a) motivate actors to strategically intervene in the public and collective processing of an event and b) influence the contextualisation and perception of novel information, and thereby support polarisation dynamics and influence the opinion climate. Regarding discourse shaping, the specific focus of our analysis on far-right communities aids our understanding of how and why the far-right operates in digital environments, specifically on social media. This is essential for scientific research and for governmental actors like security agencies and counter-radicalisation institutions. Our results indicate a strategic behaviour of the far right and highlight attempts to use terror attacks as a means to nurture extremist thinking and radicalisation.

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Appendix

All Figures, including the Figure 1 and 2 of the appendix, can be downloaded and inspected in higher resolution via https://osf.io/p6h29/.

Figure 1. Complete Topic model containers in general public discourse

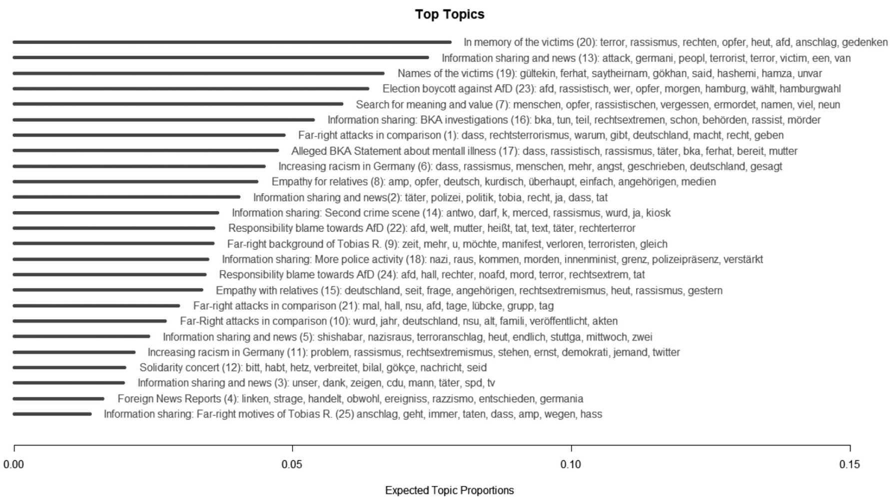

Figure 2. Complete Topic model containers in far-right discourse