Rage against the machine: exploring violence and emotion in conspiracy narratives on Parler

Darja Wischerath[a*], Lukasz Piwek[a], Jonathan F. Roscoe[b] and Brittany I. Davidson[a]

[a]School of Management, University of Bath, Bath, UK; [b]BT Applied Research, Ipswich, UK

*corresponding author, dw942@bath.ac.uk

The mainstreaming of conspiracy narratives has been associated with a rise in violent offline harms, from harassment, vandalism of communications infrastructure, assault, and in it's most extreme form, terrorist attacks. Group-level emotions of anger, contempt, and disgust have been proposed as a pathway to legitimizing violence. Here, we examine expressions of anger, contempt, and disgust as well as violence, threat, hate, planning, grievance, and paranoia within various conspiracy narratives on Parler. We found significant differences between conspiracy narratives for all measures and narratives associated with higher levels of offline violence showing greater levels of expression.

Keywords: conspiracy theories, conspiracy narratives, ANCODI, emotion, violence, Parler

Introduction

Conspiracy theories are narratives that attempt "to explain the ultimate causes of significant social and political events and circumstances with claims of secret plots by two or more powerful actors" (Douglas et al., 2019). Although real conspiracies can happen (such as the Tuskegee syphilis study where black men in Tuskegee, Alabama were deliberately not treated for syphilis; Heller, 2017), they are rare. Generally, conspiracy theories lack plausible accounts of events given the available facts and are often unfalsifiable or believed despite available contrary evidence (Bartlett & Miller, 2010).

The mass proliferation and mainstreaming of conspiracy narratives in recent years poses a new threat for harms to both individuals and society (Bruns, Harrington, & Hurcombe, 2020). Whilst the majority of those who consume conspiracy narratives remain peaceful, there have been an increasing number of documented instances of violence. For example, acts range from attacks on vaccine clinic workers (Seidman, 2022) and 5G infrastructure (Parveen & Waterson, 2020), to homicides of family members believed to be part of the lizard race (Southern District of California, 2021), as well as large-scale events such as the 2021 Capitol Insurrection (BBC, 2021) or terrorist attacks such as the Christchurch (Davey & Ebner, 2019) or the Utoya shooting (van Buuren, 2013).

Therefore, we explore the prevalence of anger, contempt, and disgust emotion expressions in posts on the free-speech social media platform Parler across multiple conspiracy narratives associated with a range of violent and non-violent offline behaviors.

Conspiracy narratives in online communities

The participatory affordances of online forums form a unique place for collective sensemaking and community formation (Brown, Smith, Davidson, & Ellis, 2022), allowing people to collectively question, share, and discuss complex information (Dailey & Starbird, 2015; Kou, Gui, Chen, & Pine, 2017), with some evidence that social validation from online communities can aid participation in offline collective action (Smith, Piwek, Hinds, Brown, & Joinson, 2023).

Conspiracy communities are fundamentally social. In online forums and social media platforms, users can gather and share evidence for their chosen conspiracy, thereby collectively shaping conspiracy narratives through their discoveries and creating a perceived abundance of information that needs to be consumed (Sunstein & Vermeule, 2009; Xiao, Cheshire, & Bruckman, 2021; Zeng & Schäfer, 2021). These social networks can further foster a sense of social belonging that extends beyond the confines of conspiracy narratives (Xiao et al., 2021). Participation in these communities' feeds users' innate curiosity, push them further down the rabbit hole and, combined with a strong sense of social commitment, can keep users engaged in communities even when they experience frustrations over an answer that is never found (Sutton & Douglas, 2022; Xiao et al., 2021).

Alternative platforms, such as Gab, Parler, or Odyssee, play an important role in pushing extreme narratives due to their free speech policies and minimal content moderation, attracting organizations and users banned from mainstream sites like Facebook and Twitter (de Keulenaar, 2023; Rogers, 2020; Zeng & Schäfer, 2021). The combination of familiar affordances of social media platforms, explicit lack of content moderation, and a grievance-based identity of oppression by "Big Tech censors" create ideal conditions for conspiracy narratives to thrive and turn to more extreme, and even violence legitimating ideas (Cinelli et al., 2022; Jasser, McSwiney, Pertwee, & Zannettou, 2021; Nouri, Lorenzo-Dus, & Watkin, 2021).

Conspiracy narratives, emotion, and sensemaking

Conspiracy narratives provide easy, seemingly logical and causal answers to questions about blameworthiness, intentionality, and factors that explain how a specific threat emerged (van Prooijen, 2011), making them ideal to aid in making sense of complex or distressing societal events (Franks, Bangerter, Bauer, Hall, & Noort, 2017). That is, blaming identifiable groups and institutions is more effective in reducing distress than admitting the role of uncontrollable factors and randomness as actions of agents can be understood and anticipated (Sullivan, Landau, & Rothschild, 2010). For example, people may find the loss of a loved-one from COVID-19 easier to process if they can blame the government or pharmaceutical companies, rather than face the randomness of such a grave event.

Appraisal theory posits that emotion and emotional appraisal of situations is a known route for people to cope with distressing events (Lazarus, 1991, 2001). The emotional response of the subjective situation appraisal leads to emotion expression, for example, someone may feel angry that their social life was impacted by COVID-19 lockdowns. This appraisal leads to action tendencies, such as figh-or-flight responses, which are unique to different emotions (Lazarus, 1991). For example, if someone perceives a situation as a threat, the emotional response might be fear, leading to actions such as avoidance or seeking help. Conversely, if the situation is appraised as unjust, it may elicit anger, resulting in actions like confrontation or advocacy.

Conspiracy narratives tend to make heavy use of emotional appraisal of grievance laden situations, and as polysemic narratives, thus leaving room for individuals to decode the conspiracy narrative to fit with their pre-existing beliefs and social identity (Harambam & Aupers, 2021). The uncertainty around the rapid spread of COVID-19 led some people to appraise the situation as threatening and, in an attempt to reduce uncertainty, believe conspiracy theories that 5G technology causes the virus, feeling fear and anxiety that drove them to destroy 5G towers near hospitals as a protective action against the perceived danger (Sweney & Waterson, 2020).

Through shared sensemaking, online communities can transform feelings of despair and confusion into a shared identity and purpose, and even incite group members to engage in violent political action as a last resort (Törnberg & Törnberg, 2023). For example, protesters of the Anti-Extradition Law Amendment Bill Movement in Hong Kong were found to be more supportive of violent action when they experienced higher emotions of anger, disgust, or fear, or identified more strongly with the group (Zhu, Cheng, Shen, & Walker, 2022). Here, we expand on this work by examining the pathway from emotions of anger, contempt, and disgust, as a pathway to legitimating discourse around violence in conspiracy narratives on Parler.

Emotions as a pathway to violence and collective action

Group-based emotions, and in particular perceived inequality and injustice, are powerful motivators of collective action (Iyer, Schmader, & Lickel, 2007; van Zomeren, Postmes, & Spears, 2008). The ANCODI model proposes that historical narratives and reactions to events result in emotions of anger, contempt, and disgust that work together to motivate action, devalue the other group and legitimate violence against outgroup members (Matsumoto, Frank, & Hwang, 2015). Anger, contempt, and disgust comprise three components of hate that contribute to aggression and violence (Sternberg, 2003). These emotions become integral to the group's narratives, thus providing guidelines for making appraisals about the outgroup and accelerating action (Matsumoto et al., 2015). For example, initial anger around mask-mandates turned to narratives invoking disgust for those wearing masks and encouraging harassment of those wearing masks, even after mask-mandates were lifted (Smith, 2022).

Anger, contempt, and disgust are each associated with distinct action tendencies. Anger is typically directed at a situational grievance that the ingroup experiences that they blame the outgroup for (Matsumoto, Hwang, & Frank, 2013), thus driving action against those deemed responsible (van Zomeren, Spears, Fischer, & Leach, 2004). Contempt and disgust on the other hand focus on the disposition of the outgroup members (Matsumoto & Hwang, 2012). Contempt deems the target as inferior and unworthy of esteem and is marked by exclusion tendencies that intend to punish the excluded. Disgust on the other hand deems the target to be 'contaminated' (e.g. through comparisons to animals or implications of disease; (Rozin, Haidt, & McCauley, 2008), instilling a contamination avoidance response rooted in existential threat and excluding the target to the point of elimination (Miceli & Castelfranchi, 2018).

Violence legitimating narratives

As a non-normative action, violence can only become a viable path of action when it is encouraged and legitimized by narratives in a network (Kruglanski, Molinario, Ellenberg, & Di Cicco, 2022). Grievance-based narratives and terrorism-justifying ideologies accomplish this by identifying a specific outgroup as the culprit responsible for hardship, making violence against them seem justified (Webber & Kruglanski, 2017). When no out-group is directly responsible for the grievance, uninvolved outgroups can get scapegoated and assigned blame to reduce uncertainty and increase perceptions of control for the ingroup (Glick, 2005; Webber & Kruglanski, 2017). For example, great replacement conspiracy narratives utilize grievances about socio-economic hardship and blame immigrants and the UN for them. Consequently, the narratives propose that elimination of the scapegoated out-group will relieve the experienced hardship, for example by freeing up jobs and reducing pressures on the housing market.

Additionally, narratives can legitimate violence by delegitimizing the outgroup itself, that is through excluding the outgroup from the group to which norms and values apply (Bar-Tal, 1990; Webber & Kruglanski, 2017). Dehumanization of the outgroup, for example through comparisons to animals and implications of disease, are key strategies for delegitimization as it degrades the outgroup. This can consist of stripping member so their human characteristics or invoking a contamination avoidance response, for example, by calling a group "dirty", "diseased", or implying that they are animals, thus making violence an acceptable course of action (Ebner, Kavanagh, & Whitehouse, 2023; Miceli & Castelfranchi, 2019).

While conspiracy narratives on their own may not necessarily lead to violent extremism, they can contribute to the radicalization process in two ways: First, conspiracy narratives perpetuate vanguardist ideas of being part of the enlightened group, justifying (if necessary extreme) acts as a necessity in order to awaken people from their slumber (Bartlett & Miller, 2010; Basit, 2021). Second, conspiracy narratives can create a picture where violence is a necessary and only option available because the group is under attack (Bartlett & Miller, 2010). Individual predispositions may also moderate susceptibility to engaging in violence: traits such as low self-control, low law-relevant morality and high-self-efficacy have been associated with increased extremist intentions (Rottweiler & Gill, 2020) and state anger has been shown to mediate intent to engage in violence and conspiracy belief (Jolley & Paterson, 2020). Further, the 3N model (Kruglanski et al., 2022; Webber & Kruglanski, 2017) poses that the need for significance can, when networks and narratives encourage and justify it, incite an individual to violence.

The present research: Emotion expression in violent and non-violent conspiracy narratives

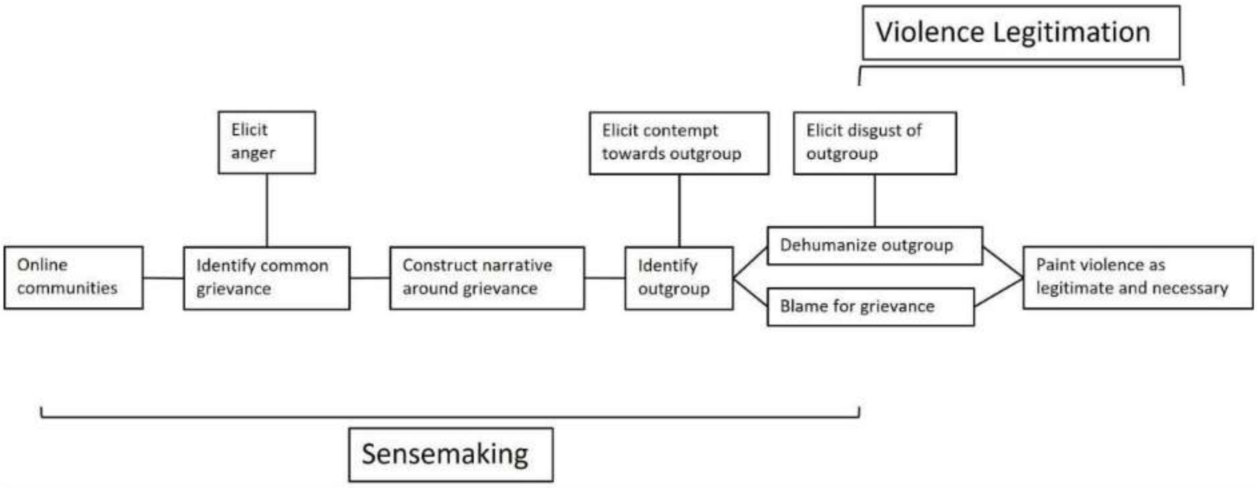
The aim of this paper is to explore the expression of anger, contempt, and disgust and narrative violence legitimation across multiple conspiracy narratives on Parler. Little research (e.g. Hartman et al., 2021; Wood et al., 2012) has compared conspiracy narratives to each other, hence, we aim to compare prevalence of emotions and violent expressions across violent and non-violent narratives.

Our second aim explores the prevalence of anger, contempt, and disgust, alongside expressions of hate, violence, threat, planning, and grievances. Drawing on the ANCODI theory (Matsumoto et al., 2015), we expect that disgust and contempt will be more prominent in narratives that have stronger violent rhetoric and are associated with more offline violence. Figure 1 shows a diagrammatic overview of our interests, showcasing the role of emotions in sensemaking and violence legitimating narratives.

Hence, our research questions are:

- RQ1: Do expressions of anger, contempt, and disgust differ between conspiracy narratives?
- RQ2: Do expressions of hate, grievance, threat, planning, and violence differ between conspiracy narratives?
- RQ3: Is the expression of anger, contempt, and disgust emotions correlated to expressions of violence, grievance, threat, planning, and hate within conspiracy narratives?

Figure 1. Framework showing narrative evolutions towards violence legitimation and associated emotions.



Ethics Statement

Ethical approval has been granted by the University of Bath's Social Sciences Research Ethics committee (SSREC), REF: SS22-104.

Materials and Methods

We compare five conspiracy narratives prevalent in social media discourse: flat earth, anti-5G, false flag, anti-vaccine, and great replacement narratives. These narratives were notably popular in 2020, often in response to current events of that period, such as, the COVID-19 pandemic, and social movements like the Black Lives Matter protests. Further, these narratives exhibit a range of violent and non-violent outcomes associated with their respective communities, and showcase a variety of beliefs and outgroups, which range from general distrust of "the global elite" to identifying governmental bodies and ethnic minorities (see Table 1).

Table 1. Selected conspiracy narratives, main beliefs, and associated outcomes

Conspiracy Narrative	Main belief	Outgroup	Outcomes
Flat earth	The earth is not a sphere. Evidence is hidden by NASA and the global elites	NASA, the global elite	Not violent; frequent offline conferences
Anti-5G	Microwaves radiated through 5G cause bodily harm and are used as population control	Bill Gates, the government	Arson of 5G masts Harassment of engineers
False flag	Mass shootings are staged events from the government to increase gun control measures	The government	Harassment of bereaved families Association with QAnon and US Capitol insurrection
Anti-vaccine	The pharma industry intentionally hides harms of vaccines and uses vaccines as population control	Pharma industry, the government	Harassment and attacks of vaccine clinic staff; reduced uptake of vaccines

The great replacement	Alleges that white populations are being replaced by non-white immigrants	Immigrants, Jews, the government, the UN	Key component of mass shooter manifestos such as the Christchurch attack or the Buffalo shooting

The Parler social network

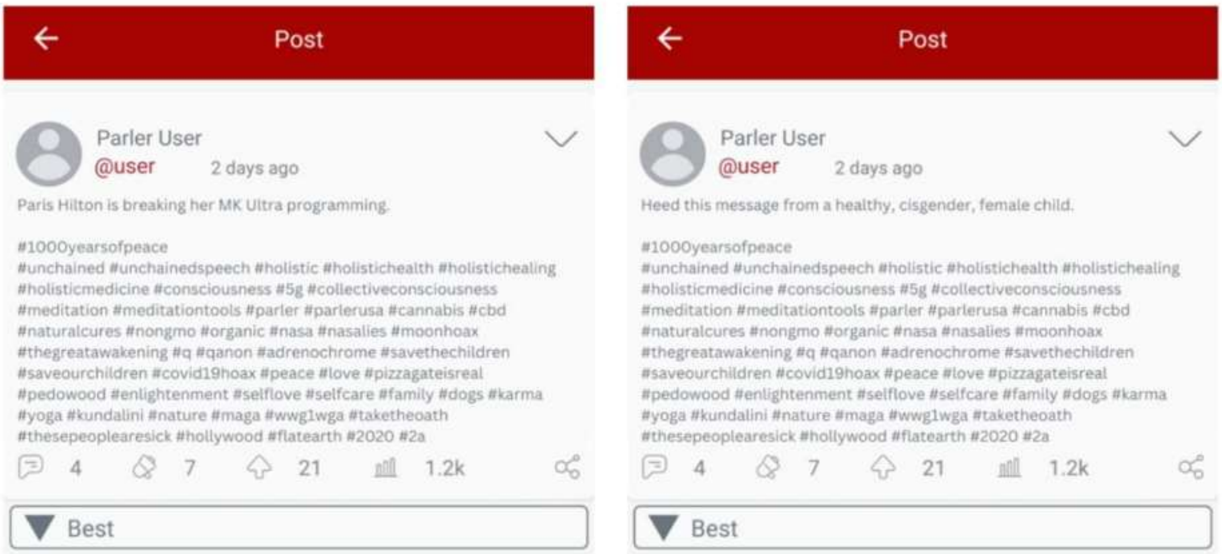
Until 2022, Parler was a self-proclaimed "premier global free speech platform" (Parler, 2022) - launched in 2018, the social network had minimal rules and content guidelines, allowing fighting words and NSFW content, yet banning "unlawful acts" and spambots (Parler, 2021). The lax content moderation rules made it a safe haven for users banned from and those who thought their speech to be censored by mainstream platforms. Registered users were able to write short posts (Parleys) up to 1000 characters long, share images and links, and engage with other users' posts through comments and votes. Posts were displayed in individual feeds from followed users and were not algorithmically curated. We selected Parler due to its popularity amongst those who had been banned on mainstream platforms, like QAnon affiliates and Trump supporters. By January 2021, 13.25 million users had joined Parler, making it the most popular app on the Apple store for a short period of time.

Data and data collection

We used a subset of the open Parler dataset published by Aliapoulios et al. (2021). The dataset comprises 183 million Parler posts made between August 2018 and January 2021 as well as metadata from 13.25 million user profiles. Our dataset consists of the post content, the date created, an anonymous creator ID, and a post ID. For our dataset, we pulled posts from January 2020 until January 2021 that contained specific hashtags associated with each of the five conspiracy narratives. In doing this, we created separate datasets for each conspiracy theory, thus the same posts could occur in more than one dataset. We retained these duplicates as it is common for posts to be applicable to more than one conspiracy theory, and thus we wanted to ensure each dataset of each conspiracy theory was "complete".

During data cleaning and processing, we discovered that the dataset contained posts that were solely used for self-promotion purposes, as well as posts that contained only hashtags, emojis, or text that made no sense on its own (e.g., "This is so good!"), because they contained links or images that were not included in the dataset. Further, some users used a large number of hashtags, emojis, and short phrases after every post as a signature-esque part of their content to signal their beliefs regardless of the post's content (see Figure 2). This resulted in a lot of posts being falsely pulled or mistagged due to the hashtags used.

Figure 2. Two example posts of not explicitly conspiratorial texts with signature-esque uses of hashtags. Text is paraphrased from the data



These posts were retagged after temporary removal of the hashtag signatures. Further, posts were filtered for English language. In total, the final dataset comprised of n=30,478 text only posts. The flat earth dataset contained 1,097 posts, the anti-5G dataset contained 1,546 posts, the anti-vaccine dataset contained 21,116 posts, the false flag dataset contained 1,852 posts, and the great replacement dataset contained 4,867 posts. Furthermore, we found that not every post is explicitly conspiratorial, however, we elected to keep these posts in the dataset as they contribute to the overall narrative of distrust and alternative reasoning and our data thus mirrors the experience of the user most closely.

Dictionary analysis

The present research examines the proportion of text in a post that corresponds to a given dictionary category. To calculate this, we divided the raw count of word matches by the number of words in a post after it had been tokenized and had stop words removed. We then calculated the mean of each dictionary measure for every conspiracy narrative. The analysis was conducted in R and full documentation and code can be found on the OSF.

We measured emotions of anger, contempt, and disgust using the moral justification dictionary (Wheeler & Laham, 2016). The dictionary comprises 12, 20, and 27 words for contempt, anger, and disgust respectively. We selected the Grievance Dictionary (van der Vegt, Mozes, Kleinberg, & Gill, 2021) as a measure for overt expressions of violence (269 words), threat (151 words), hate (175 words), and planning (183 words), as well as grievance (64 words) and paranoia (133 words). The grievance dictionary dimensions were chosen to (1) measure overt expressions and discussions of violence via dimensions of violence, threat, hate, and planning, (2) underlying general grievances and (3) paranoid thinking which has been associated with conspiratorial belief

(Hafez & Mullins, 2015; McCauley & Moskalenko, 2009; Oliver & Wood, 2014). The full list of words contained in each dictionary can be found on the OSF.

Dictionary calibration

Due to the highly specific nature of our data and context, we conducted a manual check of dictionary word accuracies against two raters. This is because we are acutely aware that the language used in these communities may be nuanced in their use of words, and thus we wanted to ensure the dictionaries had the best chance to provide accurate results, given the limitations dictionaries often have. In order to do this, we selected the top 10 most used words of each dictionary category from Study 1, as well as 5 random words that were found in the corpus, resulting in 114 words in total for a manual calibration exercise (noting that contempt only contained 9 words in the corpus). Taking these 114 words, each rater separately and blindly manually labeled words with TRUE or FALSE against the selected category (e.g., hate, disgust). The two raters demonstrated moderate concordance in their assessment (Cohen's kappa = 0.433) across all examined dictionary words. In contrast, the alignment between the coders and the dictionary's assigned scores was merely slight (Light's kappa = 0.144). The coders discussed their assessment of the codes and came to an agreement that three words were disproportionately represented in the data that did not fit with the concept of the dictionary. These words were "sick" (disgust category), "fight" (hate) and "agenda" (planning). Sick and agenda have different meaning in our datasets; "sick" can refer to sickness rather than disgust, which is highly probable within our dataset given that it was selected for peak COVID-19 period; "agenda" is commonly used in Agenda21 Agenda2030 discussions and particularly in hashtags rather than discussion of one's own agenda. Hence, for all results reported in the paper, we used our calibrated dictionaries where we excluded "fight" from hate as we found it to be more representative of categories like "violence" and "threat" which it was also a part of. Furthermore, these terms were disproportionately represented within our dataset ("sick" was detected a total of 2,164 times but the next highest term was only detected 88 times; agenda was detected 1160 times and the next highest term was detected 975 times; fight was detected 1,116 times and the next highest term was detected 316 times).

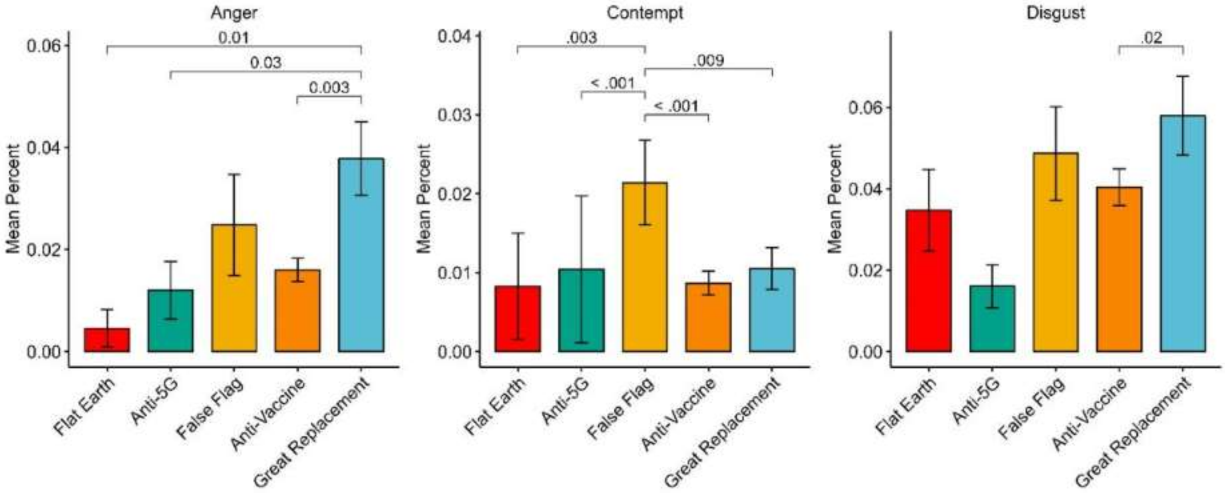
Results

In the interest of space, we only report significant interactions. Full results including non-significant findings can be found on the OSF.

RQ1: How do expressions of anger, contempt, and disgust differ between conspiracy narratives?

We examined the proportion of post texts that expressed anger, contempt, or disgust across different conspiracy theory narratives using Kruskal-Wallis tests and Dunn post-hoc comparisons with Benjamini Hochberg corrections. We expect that proportions of anger, contempt, and disgust will be higher for narratives associated with more offline violence.

Figure 3. Mean percent of anger, contempt, and disgust words per post and significant differences between narratives. Bars left-to-right are in order of increasing associated violence. Error bars show standard error of the mean.



Anger

There were significant differences between conspiracy narratives for anger words, H(4) 7.8, p = .001. Great replacement narrative posts contained a higher proportion of anger words than anti-5G narratives (Z = 2.61, p = .03), anti-vaccine narratives (Z = -3.66, p = .003) and flat earth narratives (Z = 3.1, p = .01).

Contempt

There were significant differences in contempt word usage between conspiracy narratives, H(4) = 23.9, p < .001. Post-hoc Dunn tests with Benjamini-Hochberg adjustments revealed that false flag narratives contained a higher proportion of contempt words than anti-5G narratives (Z = 3.91, p <.001), flat earth narratives (Z = 3.29, p = .003), great replacement narratives (Z = -2.92, p = .009), and anti-vaccine narratives (Z = -4.4, p <.001).

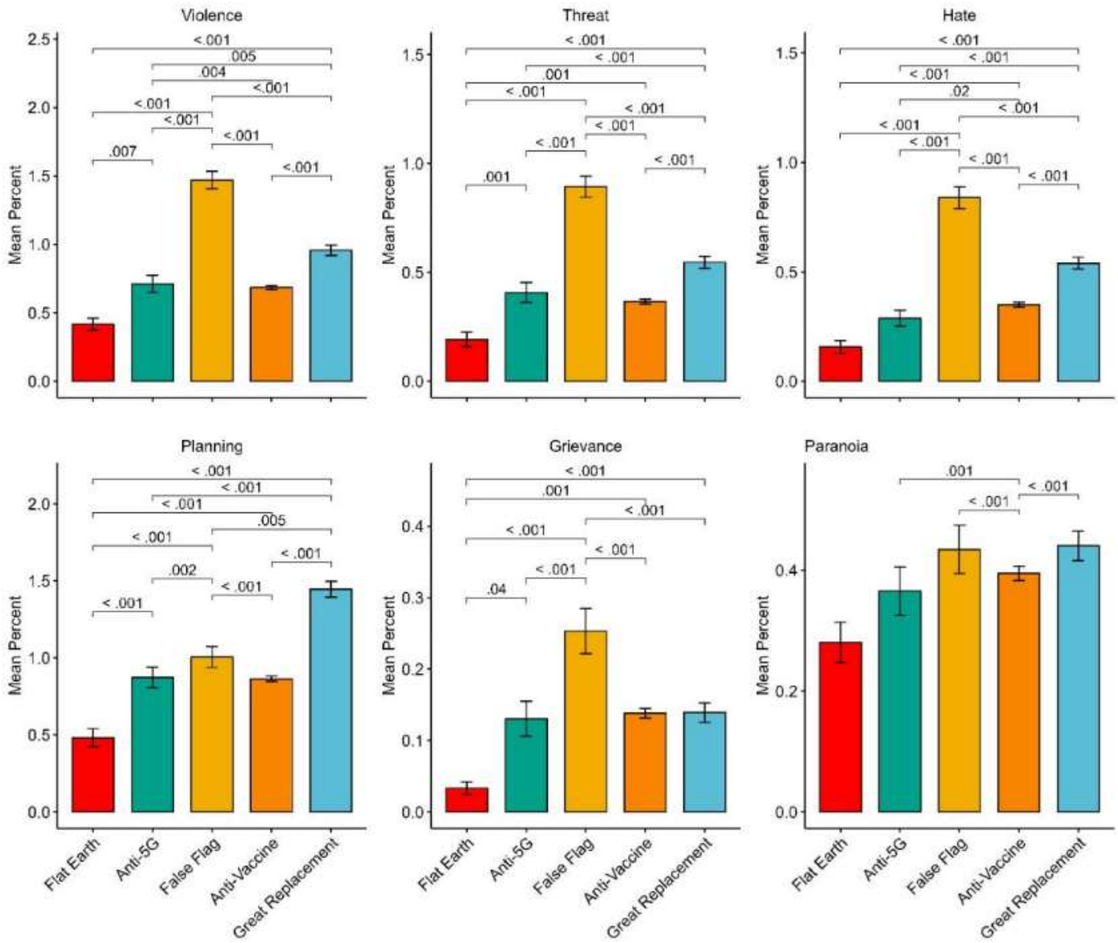
Disgust

There were significant differences in disgust between conspiracy narratives, $H(4) = 16.2$, $p = .003$. Dunn post-hoc tests with Benjamini-Hochberg corrections revealed significant differences between great replacement narratives and anti-vaccine narratives ($Z = -3.05$, $p = .02$).

RQ2: Do expressions of violence, threat, hate, planning, grievance, and paranoia differ between conspiracy narratives?

We examined the proportion of post texts that expressed violence, threat, hate, grievance, or paranoia across different conspiracy theory narratives using Kruskal-Wallis tests and Dunn post-hoc comparisons with Benjamini Hochberg corrections. We expect that proportions of violence, threat, hate, grievance, and paranoia will be higher for narratives associated with more offline violence.

Figure 4. Mean percent of violence, threat, hate, grievance, and paranoia words per post and significant differences between narratives. Bars left-to-right are in order of increasing associated violence. Error bars show standard error of the mean.



Violence

There were significant differences in violence expressions between conspiracy narratives, $H(4) = 521$, $p<.001$. Expressions of violence were higher for false flag narratives compared to anti-5G narratives ($Z = 12.6$, $p < .001$), flat earth narratives ($Z = 14.3$, $p <.001$), great replacement narratives ($Z = -12.8$, $p <.001$), and anti-vaccine narratives ($Z = -21.3$, $p <.001$). Great replacement narratives contained a higher proportion of violence words than anti-5G narratives ($Z = 2.90$, $p = .005$), flat earth narratives ($Z = 5.79$, $p <.001$), and anti-vaccine narratives ($Z = -10.3$, $p <.001$). Lastly, anti-5G narratives contained a higher proportion of violence words compared to flat earth narratives ($Z = -2.76$, $p = 0.007$) and anti-vaccine narratives ($Z = -3.02$, $p = .004$).

Threat

There were significant differences in threat word use between conspiracy narratives, $H(4) = 668$, $p <.001$. False flag narratives contained a higher proportion of threat words than anti-5G narratives ($Z = 16.3$, $p <.001$), flat earth narratives ($Z = 18.3$ $p < .001$), great replacement narratives ($Z = -16.1$, $p <.001$), and anti-vaccine narratives ($Z = -24.4$, $p <.001$). Great replacement narratives contained a higher proportion of threat words than anti-5G narratives ($Z = 4.17$, $p <.001$), flat earth narratives ($Z = 7.66$, $p <.001$), and anti-vaccine narratives ($Z = -9.42$, $p <.001$). Vaccine narratives exhibited a higher proportion of threat words than flat earth narratives ($Z = 3.34$, $p = .001$). Anti-5G narratives contained a higher proportion of threat words than flat earth narratives ($Z = -3.39$, $p = .001$).

Hate

There were significant differences between conspiracy narratives in the proportion of hate words, $H(4) = 485$, $p < .001$. False flag narratives contained significantly higher proportion of hate words than anti-5G narratives ($Z = 15.4$, $p < .001$), flat earth narratives ($Z = 15.7$, $p < .001$), great replacement narratives ($Z = -11.4$, $p < .001$), and anti-vaccine narratives ($Z = -19.3$, $p < .001$). Great replacement narratives had a higher proportion of hate words than anti-5G narratives ($Z = 7.49$, $p < .001$), flat earth narratives ($Z = 8.51$, $p < .001$), and anti-vaccine narratives ($Z = -9.77$, $p < .001$). Anti-vaccine narratives had a higher proportion of hate words than anti-5G narratives ($Z = 2.40$, $p = .018$) and flat earth narratives ($Z = 4.17$, $p < .001$).

Planning

There were significant differences between conspiracy narratives in the proportion of planning words, $H(4) = 207$, $p < .001$. False flag narratives used a higher percentage of planning words than anti-5G narratives ($Z = 3.19$, $p = .002$), flat earth narratives ($Z = 7.67$, $p < .001$), and anti-vaccine narratives ($Z = -4.77$, $p < .001$). Further, great replacement narratives had a significantly higher proportion of planning words than anti-5G narratives ($Z = 6.46$, $p < .001$), flat earth narratives ($Z = 10.8$, $p < .001$), and anti-vaccine narratives ($Z = - 12.2$, $p < .001$). Anti-vaccine narratives used more planning words than flat earth narratives ($Z = 5.39$, $p < .001$). Anti-5G narratives used more planning words than flat earth narratives ($Z= -4.37$, $p <.001$).

Grievance

There were significant differences in use of grievance words between conspiracy narratives, $H(4) = 132$, $p <.001$. False flag narratives contained a higher proportion of grievance words than anti-5G narratives ($Z = 8.09$, $p < .001$), flat earth narratives ($Z = 9.56$, $p < .001$), great replacement narratives ($Z = -8.61$, $p <.001$), and anti-vaccine narratives ($Z = -10.6$, $p < .0001$). Great replacement narratives contained a higher proportion of grievance words than flat earth narratives ($Z = 3.86$, $p < .001$). Anti-vaccine narratives contained a higher proportion of grievance words than flat earth narratives ($Z = 3.45$, $p < .001$). Anti-5G narratives contained a higher proportion of grievance words than flat earth narratives ($Z = -2.16$, $p = .04$).

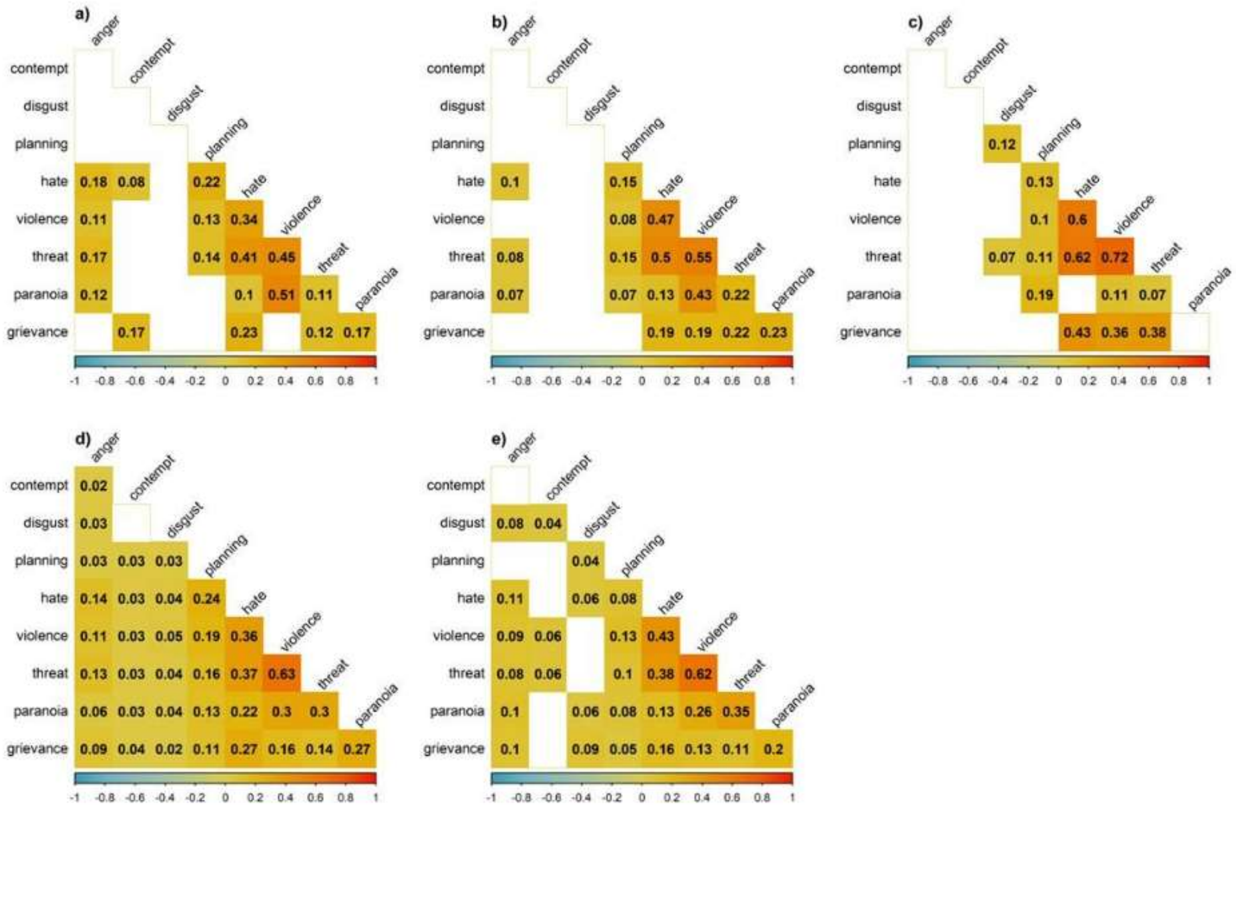
Paranoia

There were significant differences in paranoia words between conspiracy narratives, $H(4) = 44.2$, $p < .001$. Anti-5G narratives contained a higher proportion of paranoia words than anti-vaccine narratives ($Z = -3.57$, $p = .001$). False flag narratives contained a higher proportion of paranoia words than anti-vaccine narratives (Z = -4.34, p <.001). Great replacement narratives contained a higher proportion of paranoia words than anti-vaccine narratives (Z = -4.56, p <.001).

RQ3: Is the expression of anger, contempt, and disgust emotions correlated to expressions of violence, grievance, and hate within conspiracy narratives?

We examined whether expressions of anger, contempt and disgust emotions were correlated to expressions of violence, threat, hate, planning, grievance, and paranoia within conspiracy narratives. We expected correlations to be positive and significant regardless of association of the narrative with violence. As the data was non-parametric, we used Spearman's correlations.

Figure 5. Correlation heatmaps for each conspiracy narrative. A) Flat Earth, b) Anti-5G, c) False Flag, d) Anti-Vaccine, e) Great Replacement. Alpha = .01



Flat Earth

Anger was not significantly correlated to contempt and disgust were ($p > .01$). Anger was weakly correlated to hate ($\rho = 0.18$, $p < .001$), violence ($\rho = 0.11$, $p < .001$), threat ($\rho = 0.17$, $p < .001$), and paranoia ($\rho = 0.12$, $p < .001$). Contempt was weakly correlated to grievance ($\rho = 0.17$, $p < .001$) and hate ($\rho = 0.08$, $p = .005$). Hate, violence, and threat were moderately correlated ($\rho = 0.434 - 0.51$, $p < .001$). Violence was moderately correlated to paranoia ($\rho = 0.51$, $p < .001$).

Anti-5G

Anger, contempt, and disgust were not significantly correlated ($p > .01$). Anger was positively correlated to hate ($\rho = 0.1$, $p < .001$), threat ($\rho = 0.08$, $p < .001$), and paranoia ($\rho = 0.07$, $p = .009$). Hate, threat, and violence were moderately positively correlated to each other ($\rho = 0.47$- 0.55, $p < .001$). Violence was moderately correlated to paranoia ($\rho = 0.43$, $p < .001$) and grievance ($\rho = 0.19$, $p < .001$).

False Flag

Anger, contempt, and disgust were not significantly correlated ($p > .01$). Disgust showed a significant weak positive correlation to planning ($\rho = 0.12$, $p < .001$) and threat ($\rho = 0.07$, $p = .002$). Further, hate, threat, and violence showed moderate to high positive correlations ($\rho = 0.6 - 0.72$, $p < .001$). Violence was positively correlated to paranoia ($\rho = 0.11$, $p < .001$) and grievance ($\rho = 0.36$, $p < .001$).

Anti-Vaccine

Anger showed a weak positive correlation with contempt ($\rho = 0.02$, $p = .004$) and disgust ($\rho =0.03$, $p < .001$). Contempt was not significantly correlated to disgust ($p > .01$). Anger showed a positive weak significant correlation to planning ($\rho = 0.03$, $p = .001$), hate ($\rho =$

0.13, $p < .001$), violence ($\rho = 0.11$, $p < .001$), threat ($\rho = 0.13$, $p < .001$), paranoia ($\rho = 0.06$, $p < .001$), and grievance ($\rho = 0.09$, $p < .001$). Contempt was positively correlated with planning ($\rho = 0.03$, $p < .001$), hate ($\rho = 0.03$, $p < .001$), violence ($\rho = 0.03$, $p < .001$), threat ($\rho = 0.03$, $p < .001$), paranoia ($\rho = 0.03$, $p < .001$), and grievance ($\rho = 0.04$, $p < .001$). Disgust showed a weak positive correlation with planning ($\rho = 0.03$, $p < .001$), hate ($\rho = 0.04$, $p < .001$), violence ($\rho = 0.05$, $p < .001$), threat ($\rho = 0.04$, $p < .001$), paranoia ($\rho = 0.04$, $p < .001$), and grievance ($\rho = 0.02$, $p < .001$). Further, hate, violence, and threat were moderately positively correlated ($\rho = 0.36 - 0.63$, $p < .001$). Violence was positively correlated to paranoia ($\rho = 0.3$, $p < .001$) and grievance ($\rho = 0.16$, $p < .001$).

The Great Replacement

Anger showed a weak positive correlation with disgust ($\rho = 0.08$, $p < .001$). Contempt showed a weak correlation with disgust ($\rho = 0.04$, $p < .001$). Anger was not correlated to contempt ($p > .01$). Anger showed a weak positive correlation with hate ($\rho = 0.11$, $p <.001$), violence ($\rho = 0.09$, $p < .001$), threat ($\rho = 0.08$, $p < .001$), paranoia ($\rho = 0.1$, $p < .001$), and grievance ($\rho = 0.1$, $p < .001$). Contempt showed a weak positive correlation with violence ($\rho = 0.06$, $p < .001$) and threat ($\rho = 0.06$, $p < .001$). Disgust was positively correlated with planning ($\rho = 0.04$, $p < .001$), hate ($\rho = 0.06$, $p < .001$), paranoia ($\rho = 0.06$, $p < .001$), and grievance ($\rho = 0.09$, $p < .001$). Hate, violence and threat were moderately correlated ($\rho = 0.38 - 0.62$, $p < .001$). Violence was correlated to paranoia ($\rho = 0.26$, $p < .001$) and grievance ($\rho = 0.13$).

Discussion

The aim of this paper was to investigate whether there were differences in expressions of anger, contempt, and disgust emotions between different conspiracy narratives, as well as overt expressions of grievances, hate, threat, violence, and paranoia. We also explored how these expressions were correlated within each narrative. Overall, we found significant differences between conspiracy narratives for all measures. As expected, proportions of post texts containing anger and contempt were highest for narratives that were associated with more violent events (e.g. false flag and the great replacement narratives) and lowest for flat earth narratives. For disgust expressions, we found that great replacement narratives contained the highest proportion of disgust words and showed a significant difference to anti-vaccine narratives. Similarly, grievance expressions, hate, planning, and threat expressions were all highest for the narratives associated with the most violent offline events. Interestingly, paranoia showed few differences between narratives. Within narratives, we found weak correlations of anger, contempt, and disgust with expressions of grievance, paranoia, hate, threat, and violence and moderate correlations between violence, threat, and hate, as well as violence, paranoia, and grievance.

Emotions as violence legitimators

Considering our two main research questions regarding whether there are differences in levels of selected emotions across conspiracy narratives, we find support for our hypotheses with the exception of disgust. We further observed significant correlations of disgust with hate, threat or violence for narratives that had a clear outgroup and were associated with violence in the offline world. Our findings support the ANCODI model as a model of violence legitimation in conspiracy narratives (Matsumoto & Hwang, 2012) and highlight the role of anger and disgust as sensemaking emotions that open pathways to legitimating and encouraging violence. Our findings further highlighted the relationship between grievances and discussion of violence, particularly in conspiracy narratives associated with more offline violence.

Thus, examining antecedents and attitudes to violence within conspiracy communities in a naturalistic setting is incredibly important for conspiracy narratives as there has been a range of violent protest, attacks, and even mass shootings. For effective prevention and countermeasures, an understanding of the motivating forces behind collective and individual action is therefore key. Hence, our study contributes novel insights through utilizing social media data, exploring narratives and emotion expression in a naturalistic setting.

Interestingly, it can be difficult to fully differentiate conspiracy narratives: Superconspiracy narratives such as QAnon tie together conspiracy theories and use singular event conspiracy theories such as those in the False Flag category as proof of a wider sinister plot (Harambam & Aupers, 2021). This was evident in our data where hashtags from other conspiracy theories were used to corroborate arguments, or simply state one's beliefs, leading to narratives mixing and expanding to other seemingly less conspiratorial themes. Particularly in the age of algorithmic feeds, this highlights the connected nature of all conspiracy narratives (Cinelli et al., 2022). This means that a user will likely encounter a variety of narratives on their feed, even if they are originally only interested in one narrative, which may inadvertently expose them to further grievances and violence legitimating narratives and aid their journey 'down the rabbit hole'. Given the wide adaptation of conspiracy narratives by extremist actors (Bartlett & Miller, 2010), this can also lead to users getting exposed to extreme ideological viewpoints and further aid radicalization journeys.

Methodological issues

Given the constraints of dictionary analyses as a methodology for detecting complex emotional constructs such as disgust, we therefore elected to have two raters calibrate the dictionaries to see if they were fit for the context they are being used in. We believe this is a critically important element often missing from the social sciences, where the idea of calibrating measurement tools is less common than in STEM subjects. For example, when conducting natural language processing, it is common to tune various models for the specific application (e.g., one could tune BERT or other machine learning approaches for more specific usages such as hate speech to help improve model performance). While these measurements are much more complex than word counting / dictionary approaches, we believe it is critical to evaluate how we are actually measuring constructs – especially when they are complex emotions, such as disgust or contempt. While we can consider the usual limitations of dictionaries (e.g., spelling errors, the lack of context taken into consideration), the key problem we focused on was how the words in the dictionaries are regularly used in our community.

In our analysis, notably, three specific words were not contextually relevant ("sick" in disgust, "agenda" in planning and "fight" in hate) and were thus removed to yield more accurate results. Interestingly, after refining the dictionary, we observed a decrease in the occurrence of disgust-related words within anti-5G narratives, great replacement, and false flag narratives, while flat earth narratives became the narrative with the highest proportion of words associated with disgust. This shift was presumably due to the inclusion of COVID-19 related content within these narratives. We found that, whilst correlations between anger, contempt, and disgust did not change very much, there were some changes in correlations between disgust and grievance, hate, threat, planning, and paranoia words. Particularly, for anti-vaccine narratives the weak negative correlations we observed initially were now changed to weak positive correlations, mirroring results from other narratives. We also observed that correlations of threat, hate, and violence got weaker, as "fight" was a word within all three categories.

Our findings illustrate the difficulties of using dictionary methods for detection of emotion and complex linguistic rhetoric, such as expressions of grievances, violence or hate. Text mining approaches like dictionaries are becoming increasingly popular within fields of political and social sciences (e.g. Ebner et al., 2023; Kennedy et al., 2022; van der Vegt et al., 2021), due to their ability to deal with large datasets and low computational intensity, as well as their accessibility to non-technical researchers. However, one large drawback of dictionaries is that they do not take context information into account. Whilst some context-sensitive dictionaries have been developed (e.g. Kennedy et al., 2022), as well as created through qualitative coding of comparable datasets (e.g. Ebner et al., 2023), it is important to note that these dictionaries still face limitations in distinguishing multiple meanings of words. Thus, including or excluding words from the dictionary can introduce both type 1 and type 2 errors, hence we only report the findings from our calibrated dictionaries. Combining qualitative insights with quantitative text mining methods, for example through a computational grounded theory approach (Nelson, 2020), can thus provide further insights into the data and supplement the shortcomings of text mining methods.

Limitations

Social media environments include information beyond post text, such as username, profile photo, added links or media, or emojis which we did not analyze. Emojis and attached media can include crucial information about the text that convey emotions or context (Kaye et al., 2021; Kaye & Schweiger, 2023; Wiseman & Gould, 2018). Usernames and profile photos also can convey an account's group identity, and sometimes even posting intent. Matsumoto and Hwang (2015) stress that the communication of anger, contempt, and disgust occurs not only through the use of emotion-laden words, but also through non-verbal means such as gestures, facial expressions, and images. H Here, we analyzed only text and excluded special characters, which means we potentially overlooked additional context that could have provided further insights into the emotions conveyed beyond the text of the post.

Conclusion and future directions

In two studies we explored the expression of emotions associated with violence legitimation, as well as overt expressions of violence, threat, planning, grievance, and paranoia across multiple conspiracy narratives on Parler. We found significant differences in expressions of anger, contempt, and disgust across conspiracy narratives, with narratives that were associated with more offline violence using more emotion words. Our work highlights the important role of emotion in legitimizing violence, and poses implications for early-stage prevention efforts, which can utilise grievance-focused counternarratives to divert those interested in more harmful narratives (see also Reed, Ingram, & Whittaker, 2017).

Additionally, we note the importance of validating the methods, and specifically here, dictionaries through qualitative checks, as some frequently occurring words like "sick" and "agenda" were found to have different meanings when considered in their specific context. Removing these words had a substantial impact on our results, showcasing the difficulties of relying solely on text mining for complex rhetorical analysis. Hence, we strongly note that researchers must consider calibrating and evaluating their measurement tools, especially when looking at specific communities, whose use of words may be highly specific and thus cause inaccurate and inflated results when using dictionaries/word counting techniques in particular. Combining computational approaches with qualitative insights is therefore key for future work aiming to explore complex psychological and rhetorical mechanisms in large textual datasets. We therefore encourage future work to utilize a mixed methods approach to strengthen computational findings.

Acknowledgements

We would like to thank Michael Becker, Julietta Stoencheva, Nicola Mathieson, and Audrey Gagnon for their support and comments on the manuscript.

Declaration of Interest Statement

This work was part-funded by the Engineering and Physical Sciences Research Council (EPSRC Grant Ref: EP/W522090/1) as a PhD studentship to Darja Wischerath as an EPSRC iCASE with Brittany Davidson and Jonathan Roscoe.

Authorship Contributions

Conceptualization: DW, BID, LP, JFR; Methodology: DW, BID, LP; Validation: DW, BID; Analysis: DW; Data Visualization: DW, BID; Supervision: BID, LP, JFR; Writing Original Draft: DW, BID, LP, JFR; Writing, Editing & Reviewing: DW, BID, LP, JFR

References

Aliapoulios, M., Bevensee, E., Blackburn, J., Bradlyn, B., Cristofaro, E. D., Stringhini, G., & Zannettou, S. (2021). A Large Open Dataset from the Parler Social Network. *Proceedings of the International AAAI Conference on Web and Social Media*, *15*, 943–951.

Bar-Tal, D. (1990). Causes and consequences of delegitimization: Models of conflict and ethnocentrism. *Journal of Social Issues*, *46*(1), 65–81.

Bartlett, J., & Miller, C. (2010). The Power of Unreason: Conspiracy theories, Extremism and Counter-terrorism. *Demos*.

Basit, A. (2021). Conspiracy Theories and Violent Extremism: Similarities, Differences and the Implications. *Counter Terrorist Trends and Analyses*, *13*(3), 1–9.

Berger, J., & Milkman, K. L. (2012). What Makes Online Content Viral? *Journal of Marketing Research*, *49*(2), 192–205.

Brown, O., Smith, L. G. E., Davidson, B. I., & Ellis, D. A. (2022). The problem with the internet: An affordance-based approach for psychological research on networked technologies. *Acta Psychologica*, *228*, 103650.

Bruns, A., Harrington, S., & Hurcombe, E. (2020). 'Corona? 5G? or both?': the dynamics of COVID-19/5G conspiracy theories on Facebook. *Media International Australia*, *177*(1), 12–29.

Capitol riots timeline: What happened on 6 January 2021? (2021, February 10). *BBC News*. Retrieved from https://www.bbc.com/news/world-us-canada-56004916

Cinelli, M., Etta, G., Avalle, M., Quattrociocchi, A., Di Marco, N., Valensise, C., … Quattrociocchi, W. (2022). Conspiracy theories and social media platforms. *Current Opinion in Psychology*, *47*, 101407.

Dailey, D., & Starbird, K. (2015). "It's Raining Dispersants": Collective Sensemaking of Complex Information in Crisis Contexts. *Proceedings of the 18th ACM Conference Companion on Computer Supported Cooperative Work & Social Computing*, 155–158. Vancouver BC Canada: ACM.

Davey, J., & Ebner, J. (2019). The 'Great Replacement': The violent consequences of mainstreamed extremism. *ISD*, 36.

de Keulenaar, E. (2023). The affordances of extreme speech. *Big Data & Society*, *10*(2), 20539517231206810.

Douglas, K. M., Uscinski, J. E., Sutton, R. M., Cichocka, A., Nefes, T., Ang, C. S., & Deravi, F. (2019). Understanding Conspiracy Theories. *Political Psychology*, *40*(S1), 3–35.

Ebner, J., Kavanagh, C., & Whitehouse, H. (2023). Assessing Violence Risk among Far-Right Extremists: A New Role for Natural Language Processing. *Terrorism and Political Violence*, *0*(0), 1–18.

Franks, B., Bangerter, A., Bauer, M. W., Hall, M., & Noort, M. C. (2017). Beyond "Monologicality"? Exploring Conspiracist Worldviews. *Frontiers in Psychology*, *8*.

Glick, P. (2005). Choice of Scapegoats. In *On the nature of prejudice: Fifty years after Allport* (pp. 244–261). Malden: Blackwell Publishing.

Hafez, M., & Mullins, C. (2015). The Radicalization Puzzle: A Theoretical Synthesis of Empirical Approaches to Homegrown Extremism. *Studies in Conflict & Terrorism*, *38*(11), 958–975.

Harambam, J., & Aupers, S. (2021). From the unbelievable to the undeniable: Epistemological pluralism, or how conspiracy theorists legitimate their extraordinary truth claims. *European Journal of Cultural Studies*, *24*(4), 990–1008.

Hartman, T. K., Marshall, M., Stocks, T. V. A., McKay, R., Bennett, K., Butter, S., … Bentall, R. P. (2021). Different Conspiracy Theories Have Different Psychological and Social Determinants: Comparison of Three Theories About the Origins of the COVID-19 Virus in a Representative Sample of the UK Population. *Frontiers in Political Science*, *3*.

Heller, J. (2017, May 10). AP WAS THERE: Black men untreated in Tuskegee Syphilis Study. *AP News*. Retrieved from https://apnews.com/article/business-science-health-race-and-ethnicity-syphilis-e9dd07eaa4e74052878a68132cd3803a

Iyer, A., Schmader, T., & Lickel, B. (2007). Why Individuals Protest the Perceived Transgressions of Their Country: The Role of Anger, Shame, and Guilt. *Personality and Social Psychology Bulletin*, *33*(4), 572–587.

Jasser, G., McSwiney, J., Pertwee, E., & Zannettou, S. (2021). 'Welcome to #GabFam': Far-right virtual community on Gab. *New Media & Society*.

Jolley, D., & Paterson, J. L. (2020). Pylons ablaze: Examining the role of 5G COVID-19 conspiracy beliefs and support for violence. *British Journal of Social Psychology*, *59*(3), 628–640.

Kaye, L. K., Rodriguez-Cuadrado, S., Malone, S. A., Wall, H. J., Gaunt, E., Mulvey, A. L., & Graham, C. (2021). How emotional are emoji?: Exploring the effect of emotional valence on the processing of emoji stimuli. *Computers in Human Behavior*, *116*.

Kaye, L. K., & Schweiger, C. R. (2023). Are emoji valid indicators of in-the-moment mood? *Computers in Human Behavior*, *148*, 107916.

Kennedy, B., Atari, M., Davani, A. M., Yeh, L., Omrani, A., Kim, Y., … Dehghani, M. (2022). Introducing the Gab Hate Corpus: Defining and applying hate-based rhetoric to social media posts at scale. *Language Resources and Evaluation*, *56*(1), 79–108.

Kou, Y., Gui, X., Chen, Y., & Pine, K. (2017). Conspiracy Talk on Social Media: Collective Sensemaking during a Public Health Crisis. *Proceedings of the ACM on Human-Computer Interaction*, *1*(CSCW), 1–21.

Kruglanski, A. W., Molinario, E., Ellenberg, M., & Di Cicco, G. (2022). Terrorism and conspiracy theories: A view from the 3N model of radicalization. *Current Opinion in Psychology*, *47*.

Lazarus, R. S. (1991). Progress on a cognitive-motivational-relational theory of emotion. *American Psychologist*, *46*(8), 819–834.

Lazarus, R. S. (2001). Relational meaning and discrete emotions. In *Series in Affective Science. Appraisal processes in emotion: Theory, methods, research* (pp. 37–67). New York, NY, US: Oxford University Press.

Matsumoto, D., Frank, M. G., & Hwang, H. C. (2015). The Role of Intergroup Emotions in Political Violence. *Current Directions in Psychological Science*, *24*(5), 369–373.

Matsumoto, D., Hwang, H. C., & Frank, M. G. (2013). Emotional Language and Political Aggression. *Journal of Language and Social Psychology*, *32*(4), 452–468.

Matsumoto, D., & Hwang, S. (2012). The Role of Emotion in Predicting Violence. *FBI Law Enforcement Bulletin*, *81*(1).

McCauley, C., & Moskalenko, S. (2008). Mechanisms of Political Radicalization: Pathways Toward Terrorism. *Terrorism and Political Violence*, *20*(3), 415–433.

Miceli, M., & Castelfranchi, C. (2018). Contempt and disgust: The emotions of disrespect. *Journal for the Theory of Social Behaviour*, *48*(2), 205–229.

Nelson, L. K. (2020). Computational Grounded Theory: A Methodological Framework. *Sociological Methods & Research*, *49*(1), 3–42.

Nouri, L., Lorenzo-Dus, N., & Watkin, A.-L. (2021). Impacts of Radical Right Groups' Movements across Social Media Platforms – A Case Study of Changes to Britain First's Visual Strategy in Its Removal from Facebook to Gab. *Studies in Conflict & Terrorism*, 1–27.

Oliver, J. E., & Wood, T. J. (2014). Conspiracy Theories and the Paranoid Style(s) of Mass Opinion. *American Journal of Political Science*, *58*(4), 952–966.

Parler. (2021). *Parler Community Guidelines*. Retrieved from https://legal.parler.com/documents/guidelines.pdf

Parler. (2022). Parler—Where Free Speech Thrives. Retrieved June 27, 2022, from Parler website: https://company.parler.com/

Parveen, N., & Waterson, J. (2020, April 4). UK phone masts attacked amid 5G-coronavirus conspiracy theory. *The Guardian*. Retrieved from https://www.theguardian.com/uk-news/2020/apr/04/uk-phone-masts-attacked-amid-5g-coronavirus-conspiracy-theory

Reed, D. A., Ingram, D. H. J., & Whittaker, J. (2017). Countering Terrorist Narratives. European Policy Department for Citizens' Rights and Constitutional Affairs.

Rogers, R. (2020). Deplatforming: Following extreme Internet celebrities to Telegram and alternative social media. *European Journal of Communication*, *35*(3), 213–229.

Rottweiler, B., & Gill, P. (2020). Conspiracy Beliefs and Violent Extremist Intentions: The Contingent Effects of Self-efficacy, Self-control and Law-related Morality. *Terrorism and Political Violence*, 1–20.

Rozin, P., Haidt, J., & McCauley, C. R. (2008). Disgust. In *Handbook of emotions, 3rd ed* (pp. 757–776). New York, NY, US: The Guilford Press.

Schwartz, H. A., Eichstaedt, J., Blanco, E., Dziurzynski, L., Kern, M. L., Ramones, S., … Ungar, L. (2013). Choosing the Right Words: Characterizing and Reducing Error of the Word Count Approach. In M. Diab, T. Baldwin, & M. Baroni (Eds.), *Second Joint Conference on Lexical and Computational Semantics (*SEM), Volume 1: Proceedings of the Main Conference and the Shared Task: Semantic Textual Similarity* (pp. 296–305). Atlanta, Georgia, USA: Association for Computational Linguistics.

Seidman, L. (2022, January 5). Man attacks workers at Calif. COVID-19 vaccine clinic, calling them 'murderers.' *The Seattle Times*. Retrieved from https://www.seattletimes.com/nation-world/nation/man-attacks-workers-at-calif-covid-19-vaccine-clinic-calling-them-murderers/

Smith, A. (2022, April 4). Stop Employees from 'Mask Shaming' Colleagues. Retrieved November 22, 2023, from SHRM website: https://www.shrm.org/resourcesandtools/legal-and-compliance/employment-law/pages/stop-mask-shaming.aspx

Smith, L. G. E., Piwek, L., Hinds, J., Brown, O., & Joinson, A. (2023). Digital traces of offline mobilization. *Journal of Personality and Social Psychology*, *125*(3), 496–518.

Southern District of California. (2021, September 8). Santa Barbara Man Indicted in San Diego for Killing his Children in Mexico [Press release]. Retrieved November 22, 2023, from https://www.justice.gov/usao-sdca/pr/santa-barbara-man-indicted-san-diego-killing-his-children-mexico

Spiegel, S., Nitzke, S., Anton, A., Amlinger, C., & Pause, J. (2020). Verschwörungstheorien als narratives Phänomen. *Zeitschrift für Fantastikforschung*, (1).

Sternberg, R. J. (2003). A Duplex Theory of Hate: Development and Application to Terrorism, Massacres, and Genocide. *Review of General Psychology*, *7*(3), 299–328.

Sullivan, D., Landau, M. J., & Rothschild, Z. K. (2010). An existential function of enemyship: Evidence that people attribute influence to personal and political enemies to compensate for threats to control. *Journal of Personality and Social Psychology*, *98*(3), 434–449.

Sunstein, C. R., & Vermeule, A. (2009). Conspiracy Theories: Causes and Cures*. *Journal of Political Philosophy*, *17*(2), 202–227. https://doi.org/10.1111/j.1467-9760.2008.00325.x

Sutton, R. M., & Douglas, K. M. (2022). Rabbit Hole Syndrome: Inadvertent, accelerating, and entrenched commitment to conspiracy beliefs. *Current Opinion in Psychology*, 101462.

Sweney, M., & Waterson, J. (2020, April 14). Arsonists attack phone mast serving NHS Nightingale hospital. *The Guardian*. https://www.theguardian.com/technology/2020/apr/14/arsonists-attack-phone-mast-serving-nhs-nightingale-hospital

Törnberg, A., & Törnberg, P. (2023). White supremacists anonymous: How digital media emotionally energize far-right movements. *Journal of Information Technology & Politics*, *0*(0), 1–18.

van Buuren, J. (2013). Spur to Violence?: *Anders Behring Breivik and the Eurabia conspiracy. Nordic Journal of Migration Research, 3*

van der Vegt, I., Mozes, M., Kleinberg, B., & Gill, P. (2021). The Grievance Dictionary: Understanding threatening language use. *Behavior Research Methods*, *53*(5), 2105–2119.

van Prooijen, J.-W. (2011). Suspicions of Injustice: The Sense-Making Function of Belief in Conspiracy Theories. In E. Kals & J. Maes (Eds.), *Justice and Conflicts* (pp. 121–132). Berlin, Heidelberg: Springer Berlin Heidelberg. *Psychological Bulletin*, *134*(4), 504–535.

van Zomeren, M., Spears, R., Fischer, A. H., & Leach, C. W. (2004). Put Your Money Where Your Mouth Is! Explaining Collective Action Tendencies Through Group-Based Anger and Group Efficacy. *Journal of Personality and Social Psychology*, *87*(5), 649–664.

Webber, D., & Kruglanski, A. W. (2017). Psychological Factors in Radicalization: A "3 N" Approach. In G. LaFree & J. D. Freilich (Eds.), *The Handbook of the Criminology of Terrorism* (pp. 33–46). Hoboken, NJ, USA: John Wiley & Sons, Inc.

Wheeler, M. A., & Laham, S. M. (2016). What We Talk About When We Talk About Morality: Deontological, Consequentialist, and Emotive Language Use in Justifications Across Foundation-Specific Moral Violations. *Personality and Social Psychology Bulletin*, *42*(9), 1206–1216.

Wiseman, S., & Gould, S. J. J. (2018). Repurposing Emoji for Personalised Communication: Why 🍕 means "I love you." *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–10. New York, NY, USA: Association for Computing Machinery.

Wood, M. J., Douglas, K. M., & Sutton, R. M. (2012). Dead and Alive: Beliefs in Contradictory Conspiracy Theories. *Social Psychological and Personality Science*, *3*(6), 767–773.

Xiao, S., Cheshire, C., & Bruckman, A. (2021). Sensemaking and the Chemtrail Conspiracy on the Internet: Insights from Believers and Ex-believers. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW2), 1–28.

Zeng, J., & Schäfer, M. S. (2021). Conceptualizing "Dark Platforms". Covid-19-Related Conspiracy Theories on 8kun and Gab. *Digital Journalism*, *9*(9), 1321–1343.

Zhu, Y., Cheng, E. W., Shen, F., & Walker, R. M. (2022). An Eye for an Eye? An Integrated Model of Attitude Change Toward Protest Violence. *Political Communication*, *39*(4), 539–563.