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How Elites Invigorate Emotionality and Extremity in Digital Networks

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Abstract

The October 2017 Las Vegas shooting was the deadliest shooting in modern American history, but little scholarship has examined the public uproar in its wake, particularly in digital networks. Drawing on a corpus of 100,000 public Tweets and 1,119,638 unique words written in reaction to the shooting, this article addresses this lacuna by investigating the topics of reactions and their linkages with elites. This article theorizes that elites invigorate the emotionality of public reactions and broker the connection between discursive and affective content in digital networks. The results show that Tweets engaging with elites expressed statistically greater emotionality and extremity in emotional valences compared to Tweets written independent of elites. Additionally, this article identifies variations in the discursive themes invoked based on the types of elites. Mentions of non-political elites drew on themes about expressive support and depictions of the immediate environment with little emotional extremity. By contrast, mentions of political elites drew on themes about broader policy debates on gun ownership laws and adherent policy reforms. Unlike with non-political elites, mentions of political elites also exhibited greater extremity in negative emotional valences, reflective of increasing polarization in American politics.

Keywords: digital networks, elites, emotions, extremity, Las Vegas shooting, public debate

Introduction

On October 2, 2017, 64-year-old Stephen Craig Paddock opened fire from the thirty-second floor of the Mandalay Bay resort upon an unsuspecting crowd attending the Route 91 Harvest music concert on the Las Vegas Strip below. Before police officers arrived to arrest him, he turned his gun on himself – and ended his own life. The shooting killed 60 people and injured over 800, making the event one of the worst shootings and the deadliest mass shooting by any one individual in the country's history (Wolfe & Murphy-Teixidor, 2022). In the days after, tributes, grief, and fevered discussion poured out from all parts of the country.

Despite the historical scale of the shooting and observations of intense public reactions in its wake (Dolliver & Kearns, 2022; Kantack & Paschall, 2019), little work has been done to examine grassroots responses to the shooting. This dearth is especially apparent in the context of digital networks, where the multilateralism of public reactions was most observable as governmental, organizational, media, communal, and individual actors stepped forward to voice concerns (Houston et al, 2015).

Social media research has investigated the contributions of digital platforms for various forms and functions of collective organization, including facilitating the exchange of information pertinent to preparing relief (Houston et al, 2015), coordinating response efforts (Sutton, Palen, & Shklovski, 2008), informing the public (Yin et al, 2015), recruiting informants and volunteers (Boulianne, Koc-Michalska, & Bimber, 2020; Breuer, Landman, & Farquhar, 2015), crowdsourcing (Gao et al, 2011), and exchanging support across geographical boundaries (Li & Fung, 2022).

In conversation with this literature, this article investigates the public reaction to the Las Vegas shooting. By text mining a corpus of Tweets in the wake of the Las Vegas shooting in

2017, this article traces the development of core themes in reactions and their escalating emotional extremity with particular attention to one class of actors: elites. The staggering human toll of disasters like the Las Vegas shooting offers a rare field where discourses from political and non-political sources are brought into the same public sphere. By examining public reactions to the Las Vegas shooting across political and non-political sources in digital networks, I offer a sociological account of the role that elites play in invigorating the emotionality of reactions and bridge the connection between their discursive and affective content.

Discourse and Attitude Formation on Digital Networks

Discourses and attitudes are consisted of cognitive, but also emotional content. Emotions are defined as appraisals of a situational stimulus and expressive gestures with special attention to feelings (Mercer, 2014, p.516), particularly positive and negative feelings, such as happiness, sadness, and fear. Accordingly, emotions have been theorized to prefigure cognition as a roadmap for attitudes and action. That is, individuals develop affective associations toward objects and actors, such as firearms and political parties, that inadvertently influence convictions and identifications (Brader & Marcus, 2013). These convictions and identifications, in turn, percolate into behaviours like voting.

Emotions are thus said to prefigure, not supersede, cognition by creating preconscious affective responses that have the effect of shaping conscious responses (Wollebæk et al, 2019). A partisan Republican voter, for instance, who reads a news article on Hillary Clinton may first experience anger, which then comes to shape the cognitive thoughts and attitudes they choose to express – before even reading the article. It was on this basis that Max Weber referred to emotions as the intersection of social structure and habitual decision-making (Weber, 1978, p.903), which sociologists and psychologists have remarked as cognitive core of political communication (Barbalet, 2006; Demertzis, 2020).

Digital networks on Twitter manifest the social context for emotion by indicating rules about how to feel and rules about how one ought to feel, wherein desires, morality, and expectations are relationally shaped vis-à-vis other users (Au, 2020, 2021; Hochschild, 2012; Pugh, 2013; Tian & Guo, 2021). As Jones et al (2016) found in the wake of three incidents of college violence, negative emotions were overwhelmingly present in Twitter discourses, coalesced into broad themes about surprise and dismay at the shooting happening so close to home.

Digital networks are distinct from physical networks for their superior imputation of structural embeddedness, particularly on Twitter, where the boundaries of public and private spheres of behaviour blur (Au, 2020, 2022; Ellison & boyd, 2008; Wellman & Rainie, 2012). Much research has examined how these properties facilitate the formation of interlinked personal communities and sense of community (Gruzd, Wellman, & Takhteyev, 2011; Ostertag, 2021).

Examining the "geography of Twitter networks," Takhteyev, Gruzd, and Wellman (2012) find that Twitter is particularly apt at creating communities. This has since been credited to the porousness of national boundaries online, more recent functions to translate Tweets from foreign languages, the frequency with which Tweets are posted and exchanged, the presence of opinion leaders, and digital etiquettes of emotional discharge where users are normatively encouraged to share their thoughts and feelings (Au, 2022; boyd, 2014; Tian & Guo, 2021; Warner, McGowen, & Hawthorne, 2012). These properties energize the diffusion of discourses and emotional valences – that is, both information and emotions spread quickly on Twitter (Goldenberg & Gross, 2020).

Interactions on Twitter are highly expressive, especially around disasters and collective organizations like the Las Vegas shooting. Scholars have identified that Twitter facilitates emotional support on a transnational level (Duncombe, 2019; Snow et al, 2014; Stieglitz & Dang-Xuan, 2013). As Jasper (2008, p. 127) asserts, emotions "give ideas, ideologies, identities and even interests their power to motivate." Li and Fung (2022), for instance, qualitatively show that diasporic Hong Kong and Taiwanese protesters rely on social media to exchange emotional support for fellow protesters back home even after their migration abroad. In an evocative case study of the Gezi park protests, Eslen-Ziya et al (2019) demonstrate that its collective organization was buttressed by the gradual synchronization of individual participants' emotions into similar emotional states, namely, shared anger.

In a similar vein, the Las Vegas shooting serves as a stimulating event for shared frustration as its sheer loss of life gives added moral weighting to the discourses that arise and strengthens emotional responses as people struggle to reconcile, cope with, and recover their human, economic, and social costs – especially in digital networks where such individual frustrations are made communal (O'Connell, Abbott, & White, 2017; Ott, 2017; Whittle et al, 2012).

The Role of Elites in Interlinking Emotions and Public Opinion

This article theorizes that elites galvanize emotionality in public debate as both purveyors and sites of discourse themselves. I theorize that elites invigorate the emotionality and extremity of valences in reactions to disasters like the Las Vegas shooting, which I test by comparing Tweets engaging with elites and Tweets written independent of them.

Analogs of this argument can be found in empirical research on the influence that elites exert on public opinion toward policy reforms. In a large choice experiment of public support for climate policies, Rinscheid, Pianta, and Weber (2020) find that endorsements by political parties shape support, where individuals are more likely to support a policy if proposed by a party of the same political orientation. Replicated in comparable studies on the effect of political figure on public trust (Van Boven & Sherman, 2021), this phenomenon captures the influence that elites wield over their audiences, resulting in times where individuals place greater emphasis on loyalty to an elite than to a given policy issue. So powerful is the pull of elites that typically anti-climate action Republican respondents, for instance, are even found to be supportive of climate policies when proposed by Republican politicians, and vice versa for Democratic respondents (Van Boven, Ehret, & Sherman, 2018).

In conversation with this literature, I theorize that Tweets engaging with elites exhibit different emotional valences and extremity of these valences, compared to Tweets that I call independently written or written without reference to any elite. I adopt a broader theorization of elites beyond class-based criteria. In digital networks, elites are nodal gatekeepers of information flow that not only include conventional elites like politicians, but also social and cultural elites. Artists, for instance, have increasingly turned to digital networks to build their consumer followings, market their products, and directly generate revenue by producing content in collaboration with advertisers (Leaver, Highfield, & Abidin, 2020; Saboo, Kumar, & Ramani, 2016; Salo, Lankinen, & Mäntymäki, 2013).

Aware of their influence, elites may seek to guide public debate during times of uncertainty, such as by inviting popular scrutiny of extant policy paradigms laid down by the regime in power (Munger et al, 2019). In a survey of social media users, Winter and Neubaum

(2016) observe that opinion leaders are motivated to present themselves positively and convince others to do the same. Such elites essentially "[pass] along information that is already available elsewhere and [make] it personally relevant to their social network" (Oeldorf-Hirsch & Sundar, 2015, p.241), effectively brokering and re-contextualizing information to influence public debates.

Emotions constitute the crux of elite influence over public opinion. Marcus, Neuman, and MacKuen (2000) theorize that individuals respond to stimuli based on whether it is consistent with their goals or beliefs, which results in positive and negative moods of enthusiasm. Empirical research in the context of disasters further corroborate the linkages between elites and emotions. Many such studies have fleshed out the conditions under which negative emotions (e.g. anger) or positive emotions (e.g. hope) possess greater staying power in shaping audience cognition, such as when opinion leaders elicit anger by being uncivil, share negative imagery of a war, or stoke exclusionist fears (Aday, 2010; Gervais, 2019; Wollebæk et al, 2019).

Rather than prescribing which types of emotions belong to which stimuli, I return to the underlying thrust of this body of work, namely, that emotional responses among the public change when elites are involved because feelings toward elites are conflated with feelings toward the event itself. I build on this to theorize that differences exist in the extremity in emotional valences for Tweets engaging with elites compared to those that do not. I further explore how emotional responses among the public differ with respect to different types of elites.

My argument gains credence from evidence of affective polarization on digital platforms, where, contrary to popular initial expectations, the public sphere is qualified by antideliberative tendencies such as echo chambers and partisanship (Gervais, 2019). Recent studies on echo chambers show that policy debates on gun control, led by digital elites, has given rise to a general tendency to network only with like-minded peers (Au, 2022; Cinelli et al, 2021; Dubois et al, 2020; Guo, Rohde, & Wu, 2020). Individuals exhibit greater extremity in their emotional responses when elites are involved, because elites escalate the stimuli that generates feelings of anxiety and anger (Valentino et al, 2011). Stapleton and Dawkins (2022) observe, for instance, that political elites "create angrier citizens" by expressing anger that is then adopted as anger, disgust, and outrage by partisans. This affective link is not necessarily intentional, such as when elites wilfully stoke anxiety among their audiences (Wollebæk et al, 2019).

Rather, by enhancing the visibility of an issue, the presence of elites creates a preconscious affective reaction among individuals. Emotions are contagious, especially so from opinion leaders who serve as reference groups for audiences to mimic and draw inspiration from (Au, 2023; Duncombe, 2019, p.415; Smith & Anderson, 2018). Individuals are then motivated to participate in antideliberative behaviour, namely, to polarize their emotional reactions because of an elite-induced escalation of perceived threat (Gervais, 2019). Widmann (2022) finds that during the COVID-19 pandemic, incumbent politicians were more likely to evoke fear while challenger politicians were conversely likely to increase hope. Irrespective of party affiliation, however, diffusion of party messages "precede[d] changes in emotional expressions among citizens" (p.829). Put differently, reactions to the pandemic only grew emotionally charged once information had become affiliated with a political party or elite.

For similar reasons, I theorize that political elites generate more extremity in their emotional valences. This also reflects a rising level of partisanship and polarization in the electorate who increasingly mistrust those on the "other side," ideological differences that spillover into social networking sites (Engesser et al, 2017; Iyengar & Westwood, 2015). Deeply involved in policymaking, political elites like incumbent politicians and challenger politicians evoke emotional extremity among partisans across the political spectrum. Politicians embody and thus come to be associated with policy positions that call upon deeply affective appraisals, such as gun reform or abortion, for which reason audiences instinctively react to politicians with preconscious affective reactions (Valentino et al, 2011). These reactions then percolate into protective behaviours that are recursively linked to political convictions and identifications (Brader & Marcus, 2013). In Widmann's (2022) study of the pandemic, for instance, incumbent politicians invoked fear to render constituents more alert and curb the effects of the pandemic, a theme that resonated with incumbent voters who respected establishment values. Simultaneously, challenger politicians invoked hope to discredit the severity of the pandemic and cast doubt on the legitimacy of the party in power, a theme that conversely resonated with opposition voters holding anti-establishment values.

Conversely, I theorize that cultural elites generate less extremity. Since artists are not involved in policymaking, cultural elites largely refer to disasters with messages of support, rather than polemical statements with the ability to polarize audiences as with political elites. Unlike politicians, artists are additionally absolved of the responsibility to devise policy platforms and instead focused on the production of creative objects. Preliminary studies of artistic opinion leaders, for instance, unsurprisingly find that artists concentrate their audience engagement on self-promotion exercises (Verboord & Noord, 2016). As a result, the preconscious emotional appraisals that audiences make of artists do not refer to mnemonic repertoires of policy issues that invoke extremely volatile emotions, but from repertoires of cultural objects that invoke less volatile emotions in the wake of disasters (Childress, Rawlings, & Moeran, 2017; Griswold, 2012).

Data and Methods

The sample was created using Tweets that met three criteria: (i) they included the hashtag #LasVegas. Given how hashtags are used to signal user participation in a social phenomenon or trend (Tsur & Rappoport, 2012), it provided the ideal measure with which to broadly record and examine user involvement in the issue on the days of and after the shooting, particularly as the appearance of #LasVegas surged in the stream as it became associated with the shooting. As such, the gravity and the singularity of the shooting within Las Vegas ensured that no competing trends were confounded within this hashtag. (ii) They were made from October 2, 2017 (the day of the shooting) to October 3, 2017 (the day after the shooting), in order to capture the most relevant uses of the hashtag #LasVegas and, as such, immediate response and participation by users in the discussions on the Las Vegas shooting online. Tweets after this date would have a significantly higher chance that Tweets using these the hashtag were about experiences unrelated to the shooting, particularly given how "topics that make it to the top… last for a short time" and more and more Tweets simply become retweets and only recycle existing information (ibid). (iii) They were made on Twitter, given its prominence for publicly coordinating the exchange of information and resources (Eltantawy & Wiest, 2011). The resultant sample was a collection of 100,000 Tweets.

As Mathioudakis and Koudas (2010) assert, efficient trend detection on Twitter should not depend on quantity – trend detection does not require analysis of all the Tweets related to a given trend. The architecture of efficient trend detection can rely on other analytic techniques that "make as few passes over the data as possible" (ibid, p.1155). To this effect, real-time Tweet collection and collection of "bursty" keywords (encountered at an unusually high rate on Twitter, signalling the occurrence of an event and its subsequent discussion) are important techniques for building a manageable, yet representative sample of a trend (ibid). To complement this analytical approach, Tweets were collected every hour until 100,000 Tweets were captured.

This was done for two interrelated reasons. First, this approach kept the sample at a manageable size in order to conduct the subsequent content analysis. Second, it benefited the study by capturing a representative scope of the trend as it progressed over a very critical period. That is, trends can vary a significant deal in user participation within the first twenty-four hours, particularly in this case as users from multiple time zones saw and reacted to the news at different times (Aral et al, 2011). As the content analysis reveals, 100,000 Tweets were also a sufficient sample to produce data saturation – consistent themes began appearing in the Tweets. Furthermore, mentions comprised 62.70% of Tweets and retweets consisted 91.29%. These strong retweeting patterns indicate what Asur et al (2011) take to be the propagation of existing information and essentially data saturation. Thus, attempting to capture all the Tweets related to the shooting would have been an inefficient way of analyzing the trend, as the analysis already reveals a growing proportion of retweets and so, saturation.

Using QDAMiner and WordStat, the full corpus of 100,000 Tweets was systematically text mined unstructured information by identifying cases of user-defined concepts based on categorization dictionaries and extracting them to build and visualize themes. First, frequency analysis inductively captured trends in the usage of the most popular words and calculated the terms taken to represent the most relevant themes in the full corpus. Afterward, topic modelling with Latent Dirichlet Association (LDA) was conducted to generate thematic clusters and assessed their appearance in the full corpus. LDA is a probabilistic model that assumes each Tweet is a random distribution of underlying topics. Capturing a latent topic structure, LDA assumes that these topics consist the major themes that organize the Tweets (Sievert & Shirley, 2014). The LDA was supplemented with qualitative content analysis to investigate the contexts of each topic. To identify the optimal number of topics for the corpus, standard diagnostic perplexity analysis was conducted and ascertained that six was the ideal number of topics for the most parsimonious model that explained the greatest amount of variation, past which the variation explained declined drastically (ibid).

To trace the evolution of emotions, this article additionally used the Evaluative Lexicon to identify the Tweets that expressed emotional content and to determine their emotional valences over time. Using the Evaluative Lexicon, 67,500 Tweets out of the initial 100,000 were identified to express emotional content and used for sentiment analysis. The Lexicon is an algorithm developed using multiple levels of training, starting from millions of product reviews on Amazon, which were then analyzed using regressions to determine the probability of a word's association with positive versus negative reviews (Rocklage, Rucker, & Nordgren, 2017). The final Lexicon is based on 1,541 words which were tested for reliability using bootstrapped samples repeated 100 times. Quantifying emotional reactions based on word use and semantic positions, the Evaluative Lexicon sifts out emotional attitudes toward things.

This model of sentiment analysis finds similarity with a form of keyword in context (KWIC) or positioning text analysis that rationalizes words in their natural context. Conceiving the Tweet as a semantic space and a word as a position in this space, it (a) reduces words to their lemmas and (b) analyzes words with a sufficient level of frequency (Bogren, 2010). These two rules enable a co-occurrence analysis that identifies "how words appear together in a section of text and benchmarks this against other parts of text" (Ilia, Sonpar, & Bauer, 2014, p.354). The present article takes this sentiment analysis further by associating specific actors with the context of word co-occurrence.

This article focuses on two measures of emotions in particular: the valence of emotional responses, which captures the degree to which emotions are positive or negative (Rocklage & Fazio, 2015) from 0 (most negative) to 9 (most positive), and the extremity of positive and negative emotional responses, which measures the deviation from the midpoint of the valence scale from 0 (least extreme) to 4.5 (most extreme). I also statistically compare differences between Tweets that engaged with elites and those written independently using unequal variance t-tests. Also known as Welch's t-tests (Ruxton, 2006), unequal variance t-tests are ideal for groups of different sizes, as is the case in the sample of elite-related and independent Tweets.

To capture the connections between the LDA topics and the Evaluative Lexicon results, I additionally conducted manual content analysis. This involved cross-comparatively coding emergent themes from the Tweets identified in the Evaluative Lexicon and identifying the context within which the LDA topics emerged. This coding further captured the ways in which themes differed between Tweets that engaged with elites compared to Tweets written independently.

Frequency Analysis and Topic Modelling: Emergent Themes in the Corpus

1,119,638 unique words were identified from the corpus. They were then filtered by deleting words that met one or more of five criteria: (i) "leftover" words or punctuation marks irrelevant to substantial or topical issues in the articles; (ii) words in other languages; (iii) words with very small frequencies (fewer than ten appearances); (iv) the hashtag #lasvegas itself. Keeping the hashtags #lasvegas and even #lasvegasshooting as a result in the frequency analysis would skew the rest of the results, as #lasvegas was itself a criterion for sampling and as a result, redundant. Other references to Las Vegas were kept, however, in case it was discussed in terms of other themes. (v) Words that contained account handles of users.

Following this initial sweep, 2,600 keywords remained that were directly pertinent to the substantive content of posts. Term Frequency-Inverse Document Frequency (TF-IDF) values were then automatically calculated for all words, which evaluates frequency by weighing it in terms of how relevant a keyword is to the discursive themes in a given corpus (Salton & Buckley, 1988). A higher TF-IDF value imputes greater importance to a word.

Table 1 compares the frequencies of the top thirty-one, most relevant words that represented key themes according to their TF-IDF value. Given the short duration of the data collection time, there was no temporal axis with which to measure their frequencies over time. TF-IDF values were not always aligned with raw frequencies, as words with high frequencies sometimes produced a low TF-IDF value. "LasVegas," for instance, had a high frequency (9.91%), but only had a TF-IDF value of 92.3, indicating it was not relevant to the overarching themes appearing in the text. Thus, words with high frequencies were not always the most relevant words to deciphering themes in the corpus. Most of the other characteristics in Table 1 followed the descending value of TF-IDF in the graph, with the exception of "RT" (indicating retweets) whose frequency spiked up to 9.25% of the keywords and 91.29% of the corpus.

Table 1. The frequencies of the thirty-one most used words in posts as a proportion of total key words and of total cases in the total corpus, ranked according to their TF-IDF value. Thirty-one terms were kept, rather than an even thirty, to account for how "BTS" and "TWT" both are part of the same group's name. Frequencies as a proportion of the corpus did not add up to one hundred, as the use of words often co-occurred in the same posts.

WORD	% KEYWORDS	% CORPUS	TF • IDF
BTS	11.41%	56.72%	2783.5
Justice	5.68%	56.31%	1404.5
Loves	5.68%	56.32%	1404.3
Words	5.69%	56.41%	1402.6
TWT	5.70%	56.46%	1401.7
Family	5.70%	56.52%	1400.6
Today	5.74%	56.93%	1392.8
USA	5.78%	57.22%	1387.6
Hearts	5.77%	57.21%	1387.5
Tragedy	5.90%	58.42%	1364.7
Shooting	0.69%	6.81%	798.1
Victims	0.50%	4.91%	642.7
Gun	0.36%	3.44%	516.6
Shooter	0.29%	2.17%	477.4
Vegas	0.27%	2.51%	420.9
RealJamesWoods	0.26%	2.60%	412.1
People	0.24%	2.31%	391.1
GunControlNow	0.24%	2.42%	391.1
LasVegasShooting	0.23%	2.29%	375.6
RT	9.25%	91.29%	362.6
Prayers	0.22%	2.17%	361.0

FoxNews	0.18%	1.80%	314.1
Free	0.17%	1.71%	302.2
Talk	0.14%	0.79%	300.6
Country	0.16%	1.60%	287.3
Life	0.16%	1.54%	284.6
PrayforVegas	0.16%	1.57%	283.2
Blood	0.15%	1.39%	280.4
Families	0.15%	1.45%	272.1
Attack	0.14%	1.27%	265.5
VegasStrong	0.14%	1.38%	256.7

Single words not only represented different themes, but different themes that were actually represented within a single post. Four thematic words referred to the location of the event itself: “VegasStrong,” “LasVegasShooting,” “Vegas,” and “PrayforVegas.” Eight thematic words depicted the actual incident: “attack,” “blood,” “shooter,” “gun,” “victims,” “shooting,” “tragedy,” “today.”

Ten thematic words expressed supportive sentiments and rallied solidarity for those affected by the shooting: “families,” “prayers,” “free,” “life,” “victims,” “people,” “tragedy,” “hearts,” “today,” “loves,” “justice.” Users predominantly offered emotional support, demonstrating solidarity, advising locals not to despair or give up, and sending “love and prayers.” Only one word showed instrumental support: “blood,” which was used to disseminate information about where and how people could donate blood in the area.

Five thematic words focused on framing the incident as a springboard for policy recommendations: “talk,” “guncontrolnow,” “people,” “country,” “USA.” For instance, users often emphasized the need to talk about instituting better gun control in the USA, one of the most advanced nations in the world, against the backdrop of the Las Vegas shooting being ranked one of the worst shootings in history.

To triangulate the construction of relevant themes and how they relate to one another with a deductive angle, topic modelling was conducted to uncover topics generated from co-occurrences of the most common words or phrases, within which were sub-topics taken to be topics or themes in the data. Topics within this analysis were deductively created first, populated with keywords that would most likely capture key themes in the corpus.

Table 2. Six largest topics from the LDA. Words in each topic are arranged in the order of most to least frequent appearances, and bolded are the top five words in each category. Under General Negative Feelings, “grieving” and “bad” had the same number of appearances. Under Time, “late” and “fast” had the same number of appearances.

Environment (12)	**Policy (7)**
Gun	**Trump**
Blood	**NRA**
Quiet	**Violence**
Police	**Change**
Shot	**White House**
Shoot	#gunviolence
Light	Future

Low Dark Long Fire Loud	
General Positive Feelings (14)	**General Negative Feelings (12)**
Good **Kind** **Great** **Thankful** **Proud** Happy Funny Lucky Perfect Lively Brave Smiling Comfortable Helpful	**Why** **Evil** **Terrible** **Awful** **Grieving** **Bad** Heavy Hurt Disturbed Cruel Upset Dangerous
Support (8)	**Time (9)**
One **Many**	**Modern** **Long**

Together	**Old**
Stay	**Young**
Community	**Late**
Support	**Fast**
Care	Early
Strong	Short
	Quick

A categorization dictionary was constructed from the topics that emerged, detailing the individual themes within each topic and their occurrences (Table 2). Themes were individually analyzed to further filter irrelevant ones detected or framed incorrectly by the LDA topic modelling. Ten topics were generated, but three were removed as a result of low word counts and irrelevance (words pertaining to "quantity," "size," and "touch" were removed). Furthermore, themes from one topic (originally "sound") were collapsed into another more relevant one ("environment").

Table 2 also shows the resultant topics from the LDA topic modelling, where the size of the topic indicates its prevalence as a proportion of the total. "Environment" constituted the largest category, wherein the most prominent themes were about guns in the scene, scenes of blood, updated information released by police, people being shot, and other descriptors that gravitated toward depictions of the immediate scene and of the dark atmosphere that surrounded the shooting.

Themes within this topic branched into subtopics that crossed into other topics. Discussion about guns, for instance, also ventured into criticisms about gun violence as a systemic problem in the United States and the backwardness of its gun laws compared to other countries. Moreover, blood was not only a descriptor for the environment, but also the core of the dissemination of information links about how and where to donate blood in Las Vegas.

The second-largest topic dealt with “policy” (reform), within which the most popular themes consisted of targeted actors seen as responsible for policies that enabled the tragedy itself, including Donald Trump, the National Rifle Association (NRA), and the White House. Violence and gun violence emerged in this category, rather than the “environment” category, as they were more consistently framed as a policy issue, rather than as a depiction of the immediate environment. Amidst news and pictures of Donald Trump responding to the shooting, posts largely criticized him for a lax approach to gun regulation. Posts about the NRA were much more explicit, (i) accusing the association of corruption by citing evidence of donations from the NRA to current members of Congress in the White House, and (ii) framing the NRA as the “largest terror organization in the world” for endorsing gun sales. Thus, subtopics within the topics of “environment” and “policy” were also comprised of broader calls for bans on gun violence.

The next largest topic was “support,” as users emphasized messages of solidarity. Individuals, largely based outside of Las Vegas, expressed support for those in the vicinity of the shooting. They stressed how important it was for everyone to come together to form a shared community within Las Vegas itself and among those outside Las Vegas to express support and solidarity for it, painting a picture of a common humanity. Posts cited memorials being set up around Las Vegas and encouraged the community to “stay strong.”

Closely following were two topics of “general positive feelings” and “general negative feelings.” General positive feelings included gratitude for survivors, resisting the negativity the shooting brought to the online atmosphere, believing in the good of humanity, particularly those in the area who helped the crisis by donating blood, and the need to do good in face of the shooting. On the other hand, general negative feelings were more consistent, producing assessments of how terrible and awful the shooting was, grievances for the lives lost, expressions about the pain it caused, and how the shooter was a man of pure evil.

Finally, "time" was a topic where the event was framed in a sense of historical progression – how the shooting was "[one of] the worst mass shootings in modern American history" and how the time to act upon gun violence was too late or had long passed. "Time" also captured subtopics about age. Posts commemorated victims and heroes who were young, and highlighted ideological rifts between the old and the young. Specifically, posts showed resentment toward "old white men" who not only decided gun laws, but whom the shooter was taken to represent.

Evaluative Lexicon: Emotional Valences and Extremity over time

Using the Evaluative Lexicon, I trace the evolution of emotions over time in connection to prospective elites in the corpus. Tweets were coded based on the key opinion leader or elite that they responded to or mentioned and communicated with. I identified five major elites in the corpus that users engaged with: Donald Trump, the British Broadcasting Centre (BBC) News, Hillary Clinton, Bangtan Boys (BTS), and Fox News. Those who did not engage with any elite were coded as Independent.

Figure 1 captures the general valence of emotional responses over the day (in EST) in the entire corpus.

[Insert Figure 1]

The overall valence rose drastically from a neutral rating of 4.5 at 1:00AM to close to a strongly positive rating of 8 by 4:00AM, after which it declined toward 7.8 throughout the day. Why were valences so volatile? I conducted a manual content analysis based on randomly selected Tweets during the greatest leap in sentiment to examine the change in connection to the themes identified prior.

Tweets around 1:00AM focused on describing the event as it unfolded on the ground. According to one user, @she_smith70, for instance, “relatives of victims in need of accommodations in the midst of the #LasVegas tragedy have free rooms offered.” Similarly, the most widely shared Tweets contained telephone numbers with which users and readers could discover if their contacts were among the victims. Information about ways to liaise and coordinate resources to help survivors was commonly shared, including contact information for blood donation centers in the region. These myriad attempts to coordinate disaster relief were accordingly assessed as a negative valence, one that was compounded by an outpouring of grief, confusion, and anger at the event. According to a well-circulated Tweet by @JaviraSseb, “bad is bad no matter who does it. Saddened to hear about the #LasVegas killings. May God comfort families of the bereaved.” Another user, @SethDawson20, remarked, “why would I wanna kill our own kind... Why is violence the easy way to solve problems. Bleeding, Pain, Gunfire, Death..is not ok.”

Toward 3:00AM, the valence had shifted in large part because the official BTS account had released a Tweet about the shooting, stating "there are no words that can do justice to this tragedy. BTS loves #LasVegas and our #USA family who are in our hearts today. #prayforvegas.” Users began discovering and sharing the Tweet, which sharply elevated the corpus’ emotional responses toward a positive valence.

To further assess whether the change was due to elites, I compared the average emotional valence and average extremity evoked by Tweets that engaged with elites versus Tweets that were independent of them (Table 3). The Evaluative Lexicon focused on analyzing Tweets that expressed notable emotionally-based attitudes focusing on feelings about the shooting and cognitively-based attitudes focusing on beliefs about the shooting, but excluded those that did not express either of such attitudes (Rocklage, Rucker, & Nordgren, 2017). The results find that elite Tweets report greater emotionality compared to independent Tweets by 0.36 and greater extremity by 0.05, differences that are statistically significant difference at the 0.1% level. These results tentatively corroborate my theorization that elites play a role in invigorating the emotionality of public discourses in the wake of disasters.

Table 3. Valence and extremity of emotional reactions among Tweets engaging with elites and independent Tweets. Standard errors are in parentheses. P-values were determined using unequal variance t-tests.

	Elite	**Independent**	***t***	**p-value**
Valence	7.49	7.13	7.67	0.001
	(0.023)	(0.041)		
Extremity	3.35	3.30	4.99	0.001
	(0.005)	(0.009)		
N	44,260	23,240		

We further assess differences in the *extremity* of documented emotional responses, which I parse out by positive and negative valences. Extremity measures the extent of positivity or negativity based on the deviation of their valence from the midpoint of the valence scale. It thus offers a barometer for capturing extremity of beliefs, which I stratify across the specific actor associations.

[Insert Figure 2]

Figure 2 visualizes the extremity of positive valences across actors. Tweets engaging with all elites appear to be in line with one another, largely holding constant around an extremity value of 3.3. Tweets engaging with Clinton appear to be lower in extremity around a value of 3.2, but their extremity nonetheless holds constant as do the rest. Here, I observe few differences between Tweets engaging with elites compared to independent Tweets.

[Insert Figure 3]

Figure 3 focuses on the extremity of negative valences. Unlike with positive valences, I observe greater heterogeneity and significant differences between Tweets engaging with elites compared to independent Tweets. Independent Tweets hold constant in their extremity around a value of 2.8, as do those engaging with BTS. Other elites, however, exhibit significant volatility, consistent with my theorization that elites galvanize extremity in beliefs. Among Tweets engaging with Trump, those expressing negative emotions report a steep decline in their extremity over time from a value of 3 to just 2. By contrast, Tweets engaging with Clinton and Fox News who express negative emotions overlap in their extremity, both of which rise from a value of 2.3 to 3.4.

Why the dissonance between BTS and the others? Combining the LDA results with manual content analysis shed light on the present dynamics. Cultural elites like BTS are cognitively disassociated from the complexities of policy reforms and political campaigning that enshrouded the other elites. Many of the themes of justice, love, and family identified in the "positive feelings" and "support" topics encircled BTS.

By contrast, political elites like Trump and Clinton captured greater volatility in negative emotions. Here, "policy" and "environment" were prominent LDA topics that oriented emotional responses to the two actors. For Donald Trump, the most prominent comments used were about the police, the shock of the event, the gunman, and the president. On a technical level, the decrease in the extremity score means that negative valences in Tweets drew closer and closer to the midpoint of valence values. Theoretically, this convergence toward the midpoint suggests conformity in emotionally-based attitudes over time. Corroborating the topic modelling, Tweets used immediate depictions of the shooting as context for accusing Trump of insufficient commitment to tackling the systemic roots of gun violence through reforms. Tweets about Trump also heavily criticized the NRA for sponsoring and endorsing the open, unregulated distribution of guns responsible for the loss of life witnessed in the Las Vegas shooting as part of a long history of gun violence in the nation.

For similar reasons, negative sentiment surrounding Clinton shifted toward more volatile and extreme valences on account of her policy statements. Clinton wrote, "The crowd fled at the sound of gunshots. Imagine the deaths if the shooter had a silencer, which the NRA wants to make easier to get… Our grief isn't enough. I can and must put politics aside, stand up to the NRA, and work together to try to stop this from happening again." By 5PM, the Tweet had garnered criticism from a Fox News commentary that remarked that silencers were not effective nor relevant to the shooting. The news report (Fox News, 2017), shared on Twitter, moved to criticize Clinton for ignorance on the operation of firearms. Quoting then-White House Press Secretary Sarah Sanders, Fox News further accused Clinton of politicizing a moment of mourning by advancing a policy discussion, a sentiment that was echoed by users who retweeted the Fox report. As such, the extremity of the negative valences expressed toward Clinton moved along the same trajectory as that of Fox News toward the more extreme polarity.

Conclusion

Consistent with my theorization of the role that elites play in public discourse, I observe that mentions of elites galvanized the emotionality and the extremity of this emotionality in public responses to the Las Vegas shooting (O'Connell, Abbott, & White, 2017; Whittle et al, 2012). I trace a general rise in the emotionality in the entire corpus to engagements with elites like BTS and Trump. Indeed, the tightly packed clusters and high proportion of retweets indicate a striking level of rigidity in the boundaries between these groups as well as their conformity to ideological agendas laid forth by their respective elites, much like echo chambers (Cinelli et al, 2021).

Contributing to a more fine-grained understanding of elites in digital networks, I further observe important differences in extremity between Tweets engaging with elites and independent Tweets, as well as between different types of elites. Sentiment analyses using the Evaluative Lexicon, in combination with unequal variance t-tests, also corroborate significant differences in the emotionality and extremity between elite-related and independent Tweets. Elite-related Tweets invigorate both greater emotionality and extremity compared to independent Tweets.

Topics in the corpus were identified using LDA topic modelling and observed variations in their invocation across different types of elites using manual content analysis. I observed that that cultural elites, like BTS, were tied to topics about expressive support, which are insulated from the other themes and topics, particularly political ones. By contrast, Tweets engaging with political elites prominently bifurcated discourses into contentious values, agendas, and extremity.

Themes associated with political elites, most notably Donald Trump and Hillary Clinton who had just participated in the 2016 U.S. Presidential election, were framed as a form of political endorsement or criticism against them, their parties, and their policy agendas. Accusations against Trump focused on his complicity in lax gun ownership laws directly responsible for arming the shooter and his associations with the NRA, which had the effect of creating consensus in negative valences associated with him over time. Accusations by Fox News aimed at Clinton, whose topics focused on progressive licensing reforms for gun ownership, led to their coincident rise in extremity for negative valences.

The analysis builds upon, yet extends literature on attitude and discourse formation as well as affective polarization. I demonstrate the role that elites play in exacerbating emotionality and bridging connections between the cognitive and emotional content of public reactions. I illuminate the variations in this effect by the type of elite, and in so doing draw attention to the preconscious emotional appraisals that explain the extremity in responses toward different elites.

That said, LDA topic modelling and sentiment analysis have important, well-known limitations. They require troves of data that, even if sampled comprehensively, can be prone to generating significant noise, especially so in the context of Twitter. The outcome – a set of topics and sentiments – carries a certain imprecision. Topics and sentiments rely upon dictionaries that are trained using experiments, but as we know from much behavioural research, the biographical qualities of the experimental sample matter tremendously. Just as the qualities of one sample may not lend well for another experiment, a dictionary developed from one experimental sample might not be applicable to another study attempting to use the same dictionary. For this reason, we observe additional noise when researchers produce different results of analysis using different dictionaries.

Furthermore, topic modelling and sentiment analysis effectively reduce a universe of text into a lower-dimensional space and suggest that reason can stand separate from emotion. However, as this article has argued, social phenomena are at times better explained by a narrative with more dimensions, rather than fewer, and one equally rooted in emotion and discourse. Researchers using these tools thus arrive at a number of topics and sentiments that might do well to summarize implicit themes in a corpus of text, but which struggle to peer beyond into the motivations for the themes to begin with.

This study has attempted to address these concerns by adding analytical safeguards such as perplexity analysis. More importantly, this study grounds the topic selection in theories of elite influence and networks, which help fill in the gaps between topics and sentiments by drawing connections between them. In so doing, this article raises several implications for future research on affective polarization. I demonstrate that in an age of digitalization, attitude formation cannot be understood outside of the influence of elites. These elites are especially ubiquitous given the proliferation of a number of political and non-political elites in digital networks, such as artists and political figures alike. Relatedly, previous research on disaster response and public opinion formation has been preoccupied with the role of political elites (Widmann, 2022). While I corroborate the salience of political elites on emotionality and extremity in public reactions, I additionally draw attention to the importance of non-political elites as well. Indeed, the process(es) of preconscious affective appraisals and the linkages it shares with attitude and discourse formation remains fertile ground for future empirical research, but which I tentatively demonstrate is as true of non-political elites as much as political elites.

References

Aday, S. (2010). Leading the charge: Media, elites, and the use of emotion in stimulating rally effects in wartime. *Journal of Communication, 60*(3), 440-465.Asur, S., Huberman, B., Szabo, G., & Wang, C. (2011). Trends in social media: Persistence and decay. *5th Proceedings of the International AAAI Conference on Web and Social Media*, *5*(1), 434-437.

Au, A. (2020). Reconceptualizing the generation in a digital (izing) modernity: Digital media, social networking sites, and the flattening of generations. *Journal for the Theory of Social Behaviour*, *50*(2), 163-183.

Au, A. (2021). Guanxi 2.0: The exchange of likes in social networking sites. *Information, Communication & Society*, *24*(13), 1891-1906.

Au, A. (2022). Guanxi in an age of digitalization: Toward assortation and value homophily in new tie-formation. *The Journal of Chinese Sociology*, *9*(1), 1-19.

Au, A. (2023). *Chinese social networks in an age of digitalization: Liquid guanxi*. London: Routledge.

Barbalet, J. (2006). Emotion. *Contexts, 5*(2), 51-53.

Bogren, A. (2010). Studying social power in textual data: Combining tools for analyzing meaning and positioning. Critical Discourse Studies, 7(1), 73-84.

Boulianne, S., Koc-Michalska, K., & Bimber, B. (2020). Mobilizing media: Comparing TV and social media effects on protest mobilization. *Information, Communication & Society, 23*(5), 642-664.

boyd, d. (2014). *It's Complicated: The Social Lives of Networked Teens*. New Haven, CT: Yale University Press.

Brader T., Marcus G. E. (2013). Emotions and political psychology. In Huddy L., Sears D. O., Levy J. S. (Eds.), *The Oxford handbook of political psychology* (pp. 384–401). Oxford, UK: Oxford University Press.

Breuer, A., Landman, T., & Farquhar, D. (2015). Social media and protest mobilization: Evidence from the Tunisian revolution. *Democratization, 22*(4), 764-792.

Childress, C., Rawlings, C. M., & Moeran, B. (2017). Publishers, authors, and texts: The process of cultural consecration in prize evaluation. *Poetics*, *60*, 48-61.

Cinelli, M., De Francisci Morales, G., Galeazzi, A., Quattrociocchi, W., & Starnini, M. (2021). The echo chamber effect on social media. *Proceedings of the National Academy of Sciences*, *118*(9), Article e2023301118.

Demertzis, N. (2020). *The political sociology of emotions: Essays on trauma and ressentiment*. London: Routledge.

Dolliver, M. J., & Kearns, E. M. (2022). Is it terrorism?: Public perceptions, media, and labeling the Las Vegas shooting. *Studies in Conflict & Terrorism, 45*(1), 1-19.

Dubois, E., Minaeian, S., Paquet-Labelle, A., & Beaudry, S. (2020). Who to trust on social media: How opinion leaders and seekers avoid disinformation and echo chambers. *Social media+ society*, *6*(2), Article 2056305120913993.

Duncombe, C. (2019). The Politics of Twitter: Emotions and the Power of Social Media. *International Political Sociology, 13*(4), 409–429.

Eisingerich, A., Bell, S., & Tracey, P. (2010). How can clusters sustain performance? The role of network strength, network openness, and environmental uncertainty. *Research policy*, *39*(2), 239-253.

Ellison, N., & boyd, d. (2008). Social Network Sites: Definition, History, and Scholarship. *Journal of Computer-Mediated Communication 13*, 210-230.

Eltantawy, N., & Wiest J. (2011). Social Media in the Egyptian Uprising: Reconsidering Resource Mobilization Theory. *International Journal of Communication 5*, 1207–24.

Engesser, S., Ernst, N., Esser, F., & Büchel, F. (2017). Populism and social media: How politicians spread a fragmented ideology. *Information, communication & society*, *20*(8), 1109-1126.

Eslen-Ziya, H., McGarry, A., Jenzen, O., Erhart, I., & Korkut, U. (2019). From anger to solidarity: The emotional echo-chamber of Gezi park protests. *Emotion, Space and Society, 33,* 100632.

Gao, H., Barbier, G., & Goolsby, R. (2011). Harnessing the crowdsourcing power of social media for disaster relief." *IEEE Intelligent Systems 26*(3), 10-14.

Gervais, B. T. (2019). Rousing the partisan combatant: Elite incivility, anger, and antideliberative attitudes. *Political Psychology*, *40*(3), 637-655.

Goldenberg, A., & Gross, J. J. (2020). Digital emotion contagion. *Trends in Cognitive Sciences, 24*(4), 316-328.

Griswold, W. (2012). *Cultures and societies in a changing world* (4th edition). London: Sage.

Gruzd, A., Wellman, B., & Takhteyev, Y. (2011). Imagining Twitter as an imagined community. *American Behavioural Scientist 55*(10), 1294-1318.

Guo, L., A. Rohde, J., & Wu, H. D. (2020). Who is responsible for Twitter's echo chamber problem? Evidence from 2016 US election networks. *Information, Communication & Society*, *23*(2), 234-251.

Himelboim, I., McCreery, S., & Smith, M. (2013). Birds of a feather tweet together: Integrating network and content analyses to examine cross-ideology exposure on Twitter. *Journal of computer-mediated communication*, *18*(2), 154-174.

Hochschild, A. (2012). *The outsourced self: Intimate life in market times*. New York: Metropolitan Books.

Houston, J. B., Hawthorne, J., Perreault, M. F., Park, E. H., Goldstein Hode, M., Halliwell, M. R., Turner, S., Davis, R., Vaid, S., McElderry, J., & Griffith, S. A. (2015). Social media and disasters: a functional framework for social media use in disaster planning, response, and research. *Disasters*, *39*(1), 1-22.

Hutchinson, E. & Bleiker, R. (2014). Theorizing Emotions in World Politics. *International Theory 6*(3), 491–514.

Illia, L., Sonpar, K., & Bauer, M. W. (2014). Applying co-occurrence text analysis with ALCESTE to studies of impression management. *British Journal of Management, 25*(2), 352-372.

Iyengar, S., & Westwood, S. J. (2015). Fear and loathing across party lines: New evidence on group polarization. *American Journal of Political Science, 59*(3), 690–707.

Jagers, J., & Walgrave, S. (2007). Populism as political communication style: An empirical study of political parties' discourse in Belgium. *European Journal of Political Research, 46*(3), 319–345.

Jasper, J. (2008). *The art of moral protest: Culture, biography, and creativity in social movements*. Chicago, IL: University of Chicago Press.

Jones, N. M., Wojcik, S. P., Sweeting, J., & Silver, R. C. (2016). Tweeting negative emotion: An investigation of Twitter data in the aftermath of violence on college campuses. *Psychological methods, 21*(4), 526-541.

Kantack, B. R., & Paschall, C. E. (2020). Does "politicizing" gun violence increase support for gun control? Experimental evidence from the Las Vegas shooting. *Social Science Quarterly, 101*(2), 893-908.

Leaver, T., Highfield, T., & Abidin, C. (2020). *Instagram: Visual social media cultures*. John Wiley & Sons.

Li, Y. T., & Fung, K. Y. (2022). Donating to the fight for democracy: The connective activism of overseas Hong Kongers and Taiwanese in the 2019 Anti-extradition bill movement. *Global Networks, 22*(2), 292-307.

Marcus, G. E., Neuman, W. R., & MacKuen, M. (2000). *Affective intelligence and political judgment*. Chicago, IL: University of Chicago Press.

Mathioudakis, M., & Koudas, N. (2010). Twittermonitor: Trend detection over the twitter stream. *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*, 1155-1158. New York, NY.

McDonald, S., Lin, N., & Ao, D. (2009). Networks of Opportunity: Gender, Race, and Job Leads. *Social Problems 56*, 385-402.

Morgan, J. (2010). Twitter and Facebook Users Respond to Haiti Crisis. *BBC News,* Jan 15, 2010.

Munger, K., Bonneau, R., Nagler, J., & Tucker, J. A. (2019). Elites tweet to get feet off the streets: Measuring regime social media strategies during protest. *Political Science Research and Methods*, *7*(4), 815-834.

Narayan, D. & Cassidy, M. (2001). A Dimensional Approach to Measuring Social Capital: Development and Validation of a Social Capital Inventory. *Current Sociology 49*(2), 59–102.

O'Connell, E., Abbott, R. P., & White, R. S. (2017). Emotions and beliefs after a disaster: A comparative analysis of Haiti and Indonesia. *Disasters, 41*(4), 803-827.

Oeldorf-Hirsch, A., & Sundar, S. S. (2015). Posting, commenting, and tagging: Effects of sharing news stories on Facebook. *Computers in Human Behavior, 44*, 240–249

Ostertag, S. F. (2021). A cultural sociology of social media: Social drama, cultural affordances and blogging in the wake of Hurricane Katrina. *Cultural Sociology, 15*(1), 113-133.

Ott, B. L. (2017). The Age of Twitter: Donald J. Trump and the Politics of Debasement. *Critical Studies in Media Communication 34*(1), 59–68.

Pugh, A. J. (2013). What good are interviews for thinking about culture? Demystifying interpretive analysis. *American Journal of Cultural Sociology, 1*, 42-68.

Rinscheid, A., Pianta, S., & Weber, E. U. (2021). What shapes public support for climate change mitigation policies? The role of descriptive social norms and elite cues. *Behavioural Public Policy*, *5*(4), 503-527.

Rocklage, M. D., & Fazio, R. H. (2015). The Evaluative Lexicon: Adjective use as a means of assessing and distinguishing attitude valence, extremity, and emotionality. *Journal of Experimental Social Psychology, 56,* 214-227.

Rocklage, M. D., Rucker, D. D., & Nordgren, L. F. (2018). The Evaluative Lexicon 2.0: The measurement of emotionality, extremity, and valence in language. *Behavior Research Methods, 50,* 1327-1344.

Ruxton, G. D. (2006). The unequal variance t-test is an underused alternative to Student's t-test and the Mann–Whitney U test. *Behavioral Ecology*, *17*(4), 688-690.

Saboo, A. R., Kumar, V., & Ramani, G. (2016). Evaluating the impact of social media activities on human brand sales. *International Journal of Research in Marketing*, *33*(3), 524-541.

Salo, J., Lankinen, M., & Mäntymäki, M. (2013). The use of social media for artist marketing: Music industry perspectives and consumer motivations. *International Journal on Media Management*, *15*(1), 23-41.

Salton, G., & Buckley, C. (1988). Text-weighting Approaches in Automatic Text Retrieval. *Information Processing & Management 24*(5), 513-523.

Sasley, B. (2011). Theorizing States' Emotions. *International Studies Review 13*(3), 452–76.

Sievert, C., & Shirley, K. (2014). LDAvis: A method for visualizing and interpreting topics. *Proceedings of the workshop on interactive language learning, visualization, and interfaces*, 63-70. Baltimore, MD.

Smith, A., & Anderson, M. (2018). Social Media Use in 2018. *Pew Research Center – Internet & Technology*. Retrieved from: https://www.pewinternet.org/2018/03/01/social-media-use-in-2018/

Snow, D., Benford, R., McCammon, H., Hewitt, L., & Fitzgerald, S. (2014). The emergence, development, and future of the framing perspective: 25+ years since "frame alignment. *Mobilization: An International Quarterly, 19*(1), 23–46.

Stapleton, C. E., & Dawkins, R. (2022). Catching my anger: How political elites create angrier citizens. *Political Research Quarterly*, *75*(3), 754-765.

Stieglitz, S., & Dang-Xuan, L. (2013). Emotions and information diffusion in social media—sentiment of microblogs and sharing behavior. *Journal of management information systems*, *29*(4), 217-248.

Sutton, J, Palen, L., & Shklovski, I. (2008). Backchannels on the front lines: Emergency uses of social media in the 2007 Southern California Wildfires. *Proceedings of the 5th International ISCRAM Conference,* 624-632. Washington, DC.

Takhteyev, Y., Gruzd, A., & Wellman, B. (2012). Geography of Twitter networks. *Social networks, 34*(1), 73-81.

Tian, X., & Guo, Y. (2021). An online acquaintance community: the emergence of Chinese virtual civility. *Symbolic Interaction, 44*(4), 771-797.

Tsur, O & Rappoport, A. (2012). What's in a hashtag?: content based prediction of the spread of ideas in microblogging communities. *Proceedings of the fifth ACM international conference on Web search and data mining*, 643-652. Seattle, WA.

Valentino N. A., Brader T., Groenendyk E. W., Gregorowicz K., Hutchings V. L. (2011). Election night's alright for fighting: The role of emotions in political participation. *The Journal of Politics*, 73, 156–170.

Van Boven, L., Ehret, P. J., & Sherman, D. K. (2018). Psychological barriers to bipartisan public support for climate policy. *Perspectives on Psychological Science*, *13*(4), 492-507.

Van Boven, L., & Sherman, D. K. (2021). Elite influence on public attitudes about climate policy. *Current Opinion in Behavioral Sciences*, *42*, 83-88.

Verboord, M., & Noord, S. V. (2016). The online place of popular music: Exploring the impact of geography and social media on pop artists' mainstream media attention. *Popular Communication, 14*(2), 59-72.

Warner, B. R., McGowen, S. T., & Hawthorne, J. (2012). Limbaugh's social media nightmare: Facebook and Twitter as spaces for political action. *Journal of Radio & Audio Media, 19*(2), 257-275.

Weber, M. (1978). *Economy and society: An outline of interpretive sociology* (Vol. 2). Thousand Oaks, CA: University of California Press.

Wellman, B. & Rainie, L. (2012). *Networked: The New Social Operating System*. Cambridge, MA: Massachusetts Institute of Technology Press.

Whittle, R., Walker, M., Medd, W., & Mort, M. (2012). Flood of emotions: Emotional work and long-term disaster recovery. *Emotion, Space and Society, 5*(1), 60-69.

Widmann, T. (2022). Fear, Hope, and COVID-19: Emotional Elite Rhetoric and Its Impact on the Public During the First Wave of the COVID-19 Pandemic. *Political Psychology*, 43(5), 827-850.

Winter, S., & Neubaum, G. (2016). Examining characteristics of opinion leaders in social media: A motivational approach. *Social Media+ Society, 2*(3), 2056305116665858.

Wolfe, D., & Murphy-Teixidor, J. M. (2022). Mass Shootings in the US: Fast Facts. *CNN*, September 20, 2022. Retrieved from: https://edition.cnn.com/2021/07/06/us/mass-shootings-fast-facts

Wollebæk, D., Karlsen, R., Steen-Johnsen, K., & Enjolras, B. (2019). Anger, fear, and echo chambers: The emotional basis for online behavior. *Social Media + Society*, *5*(2), Article 2056305119829859.

Yin, J., Lampert, A., Cameron, M., Robinson, B., & Power, R. (2012). Using social media to enhance emergency situation awareness. *IEEE Intelligent Systems*, *27*(6), 52-59.