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Religious Violence and Twitter: Networks of Knowledge, Empathy and Fascination

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Abstract: Twitter analysis through data mining, text analysis, and visualization, coupled with the application of actor-network-theory, reveals a coalition of heterogenous religious affiliations around grief and fascination. While religious violence has always existed, the prevalence of social media has led to an increase in the magnitude of discussions around the topic. This paper examines the different reactions on Twitter to violence targeting three religious communities: the 2015 Charleston Church shooting, the 2018 Pittsburgh Synagogue shooting, and the 2019 Christchurch Mosque shootings. The attacks were all perpetrated by white nationalists with firearms. By analyzing large Twitter datasets in response to the attacks, we were able to render visible associations among actors across religions communities, national identities, and political persuasions. What this project revealed is that if we apply actor-network-theory and data visualization to look at networks created by human/non-human (text, computer, phone, meme, tweet, retweet, hashtag) actors, we can see that knowledge, empathy, and fascination drive communication around mass violence against religious communities.

1. Introduction: Religious Violence and the Social Media Response

Religious violence has unfortunately always been a part of human history. Extremists target houses of worship to intimidate and terrorize members of a certain faith. People of all faiths generally denounce such acts of violence attacking civilians, particularly in a place of peace and submission, as an unacceptable act of hate and violence. Such attacks have taken many forms over the years, but shootings have been increasing in number in the past few years (Taylor 2019).

Mass shootings have been on the rise in the past decade with shooting occurring in schools, malls, workplaces, and houses of worship. These include the elementary school shooting at Sandy Hook, CT (Doré et al. 2015), the city hall shooting in Kirkwood, Missouri (Nizza and Baranauckas 2008) and the Orlando, FL nightclub shooting (Baucum et al. 2020). Those mass shootings generated strong international media coverage and continue to generate voluminous discussion on social media, with people expressing their emotions and analyzing the cause and sequence of events (Croitoru et al. 2020; Porfiri et al. 2019).

As these mass shootings and the responses to them on Twitter indicate, human beings are increasingly enmeshed in a network of relationships that are technological, mechanized, digital, and social. To understand the mediated response to these events, we merge two methodological strains from disparate fields—computer data analysis and actor-network-theory—following Bruno Latour's description of actor-network-theory to "trace connections *between* the controversies themselves" (Latour 2005, p. 22). Rather than impose on the actors a grouping or interpreting their semiotic responses in the sole context of a particular religious, national, or racial identity, this study, in disaggregating and re-integrating Twitter datasets, reveals a network of associations driven by the actors,

not an overarching ideology of how they are expected to respond. David Krieger takes the implications of this form of analysis a step further (Krieger and Belliger 2014, p. 16), arguing:

> Networks are doing the interpreting, as well as being interpreted. In both cases what is at stake is the construction of meaning. This implies that rationality consists in making associations. From the perspective of new media studies, this view leads to a definition of rationality as the particular kind of networking that results from the social operating system.

This study reveals that when we trace the network of associations to look for meaning in the responses to these crises, we can learn about how networks are created within the frameworks of knowledge development to create meaning, empathic responses to create affiliation, and attention consolidation to create fascination. By focusing on three crises that shared similar technologies (gun violence), affiliation (religion), and emotional responses (grief and gawking), this study engages the potential of qualitative research provided through digital humanities methods, as Melissa Freeman argues: "Controversies open up spaces where formations of networks and matters of concern are more easily visible" (Freeman 2019, p. 461).

Controversies on social media range from celebrity missteps, egregiously prejudiced commentary, outrageous behavior, viral hashtags, and catastrophic incidents. When a major news event occurs, it is usually followed by a flurry of tweets both spreading the story and reacting to it. In this study, we focus on the Twitter reactions in the aftermath of religious violence at three houses of worship for three different faiths to make the networks of heterogenous groups visible. We chose these attacks based on their high volume of media coverage and the public response from religiously affiliated groups who were not necessarily aligned.

In each of the three cases, the perpetrator was a white supremacist. The first event was the Emanuel African Methodist Episcopal Church shooting in North Carolina, USA, on 17 June 2015. Nine African American worshippers were shot and killed during a Bible study meeting by declared white supremacist, Dylann Roof. The second event was the attack on the Tree of Life Synagogue in Pittsburg, PA, on 27 October 2018. The shooter was Robert Bowers and he killed 11 worshippers, most of whom were elderly. The third event was the shooting of 51 worshippers at two mosques in Christchurch, New Zealand, on 15 March 2019. Once again, the shooter was a declared white supremacist, Brenton Tarrant. The victims were mainly Muslim emigrants to New Zealand.

Each of these shootings generated a massive outpouring of grief, a sense of national reckoning over issues of white supremacy, gun control, anti-Black racism, antisemitism, anti-Muslim, anti-immigrant, mental illness, and the contagion of gun violence. These events also reflect the need to consider the human/non-human networks of interpretation called for by actor-network-theory. John Law (Law 1992) and Bruno Latour (Latour 2005), among others, have demonstrated that human beings are so embedded in technology that we can only truly understand human agency, decision making, and even identity through the networks of technology, nature, language, humans, microbes, instruments, etc. One way to make these complex associations visible is to collect a dataset generated by actors and apply digital humanities techniques of mapping, visualization, word frequency, patterning, and sentiment analysis to the corpus.

Our study is guided by overarching research questions to trace the network of actors in these events: Do the responses to these events contribute to knowledge building to create meaning? What role do empathic responses of grief and solidarity play in the development of new network affiliations? Do the traces of networks created by these events register a sinister fascination with violence and the figure of the lone shooter that works against the empathic affiliations? Data visualization will demonstrate the time lapse in responses; the magnitude of the responses by individuals, influencers, and organizations; and the linguistic networks revealed in the responses.

2. Literature Review

Twitter has quickly evolved as a major player in the field of social media since its launch in 2006. It has become the preferred social media platform, with 426 million users in 2021, according to Statista (2021). Its global connectivity, diverse userbase, and active user participation make it the premier qualitative and quantitative source from which data can be extracted and analyzed. Consequently, we used Twitter as our social media platform for conducting this study.

Public discourse on social media reflects people's attention and sentiment, and we are arguing that it also shapes and quantifies the attention given to certain events and topics. Following David Krieger's analysis of New Media Studies, hermeneutics, and ANT, "the network is the actor, and the actor is the network" (Krieger and Belliger 2014, p. 20). This treasure trove of data is extensively analyzed to measure the sentiment of the public toward a certain issue, and how it was shaped over time. As Twitter provides a space for individuals and organizations to comment on, interpret, and interact with each other and the world, it creates a type of human/non-human media that reveals patterns. In our dataset of religious violence, we observed patterns and gestures of grief, solidarity, sympathy, racism, anti-racism, antisemitism, prejudice, and religious fervor.

To understand the value of data collection on Twitter, we need only look to the business sector, which has been one of the most active data collectors and analyzers over the years, as a deep knowledge of current sentiment and interest creates actionable intelligence. Bhor et al. (2018) explore the use of digital social media mining of current trends in consumer interest to direct marketing campaigns over digital media. Hasson et al. (2019) studied the use of social media to gain insight into customer satisfaction with different products as an alternative to customer feedback forms and reviews. Though perhaps not analyzing deep issues linked to identity, such as religious affiliation or extremism, consumer analysis revealed the potential for tracing networks of attention and action.

Political discussion, and the resulting analysis, are also extremely popular on social media, particularly Twitter. Research on the political discussion is plentiful and insightful. Hanteer et al. (2018) examine the participation of an "imagined audience" on social media in political discussions and uses the analysis to create virtual communities of mutual understanding. This research suggests that networks can be revealed even through subtle, indirect messaging on Twitter. Rojas and Boguslavskaya (2018) studied the participation of women in the political discussion on social media, suggesting that traditional alliances are disrupted by the new media, and Kleftodimos et al. (2018) examine the Greek political Twittersphere, recognizing previously unseen interconnections. Social media is also heavily used in the preparation for, and aftermath of, natural disasters. Aziz et al. (2019) and Niles et al. (2019) study the rate and topics of social media posts about earthquakes, hurricanes, tornadoes, and flooding events. Catastrophes and crises bring out unlikely or invisible associations. Twitter analysis in the context of actor-network-theory can make these traces apparent.

Critical to understanding how social media posting creates networks that can be counterintuitive is the fact that it often mirrors and shows a person's personality and characteristics. Sumner et al. (2012) perform an interesting analysis on tweets to detect three negative personality traits: narcissism, Machiavellianism, and psychopathy, which are known as the "Dark Triad." They conclude that machine learning can detect those traits, although there are ethical implications about drawing conclusions from personal information embedded in social media sites. Similarly, Chatzakou et al. (2017) use feature extraction and a random forest classifier to detect aggressors and bullies using a large dataset of 1.6 million tweets. When we analyzed datasets in response to these mass shootings, the potential fascination with and popularization of the shooters was unmistakable. Negative personality traits were drawn to these dark events, and religious interest was matched by the negation of religion, or even a glorification of evil.

The study of terrorism and violence on social media is our main area of interest; the literature in this area is growing because the implications for prevention are clear, but the

ethical issues of privacy are prevalent. Almoqbel and Xu (2019) present a survey about recent computational mining of social media research in the field of curbing and analyzing terrorism. Hate speech on social media has garnered a lot of attention, with excellent analysis by Evolvi (2018), whose sustained analysis of Islamaphobia identifies online and offline attacks. The crossover from the virtual Twittersphere to in-person hate speech, or worse, violence, is a growing issue. Mathew et al. (2019) determine that hate speech travels online at a much higher velocity than other forms of speech, and Guberman et al. (2016) work at quantifying online aggression on a large scale. Albadi et al. (2018) provide an interesting analysis of hate speech in the Arabic Twittersphere which seeks to find the ways that sectarian language inflames religious prejudice. Tracing the subtlety of this language requires careful digital/coding/interpretive tools. As we have discovered in our study, language on Twitter must be located within a system and context that is often changing. Analysis that diligently traces nuances of communication and attends to the human and non-human interchanges is essential.

Violent attacks, particularly mass shootings, generate and proliferate Twitter responses that almost feel viral (Zhang et al. 2017). Burnap et al. (2014) study the tweet frequency and lifetime after a particular terrorist attack. They define the term "survival rate" to measure how long a tweet is retweeted until it stops, and deduct that survivability depends on the sentiment and emotional factor in a tweet. Doré et al. (2015) analyzed the online reaction to the Sandy Hook Elementary School massacre. Jones et al. (2016) and Saha and Choudhury (2017) examined the reaction to college-campus violence, both on a local scale and generally in the online community. In the wake of mass violence, Twitter provided a way to assess the negative mental health outcomes in a community in these studies. Our contribution in this work is to trace the networks made visible by the analysis of Twitter datasets on gun violence in religious communities that suggests and interrelationship between identity and the reaction to religious violence in terms of knowledge, empathy, and fascination.

In terms of the three specific events chosen for this work, there are competing issues of religion, race, white extremism, gun violence, etc. The shooting in Charleston had both racial and religious overtones. The reaction to the event was studied by Brown and Matusitz (2019) who examined the response to the shooting by US church leaders, while Cassidy et al. (2018) studied how journalists covered the event in traditional media. Chebrolu (2020) studied the event as an aspect of racial anxiety and white nationalist rhetoric on social media that could attract other white nationalists. The shooter was also a subject of study himself. Bass (2021) reflected on the psychoanalysis of the nature of the shooter and his personality. Boyce and Brayda (2015) concentrated on the writings of Dylann Roof as an example of South Carolina's tradition of white supremacy (2015). The network which facilitated Dylann Roof's radicalization via social media platforms is considered by Chebrolu and is an alternative network analysis to this essay, but methods of data collection and mining could be useful to studies of white nationalism/supremacy on social media platforms. This research aimed to elucidate why this event happened and how the shooter was radicalized.

Antisemitism on dark social media platforms was the main topic of interest in studying the synagogue shooting. McIlroy-Young and Anderson (2019) studied the use of the online social network "Gab" in promoting violence and its effect on the synagogue shooting. Mathew et al. (2019) also studied the effect of hate messages on Gab as well as looking at multiple events including the Pittsburgh shooting. The reaction of the public and news media were not studied or analyzed after this violent event. In contrast, the Christchurch Mosque event was heavily analyzed, as it encompasses multiple topics: immigration, faith, gun control, and social media influence. New Zealand was swift to enact new gun control laws days after the massacre, a move that was very unusual. Every-Palmer et al. (2020) present a compelling study of the event and its media themes: a nameless and faceless gunman, focusing on the victims, causal attribution—no agency to blame, and gun control.

New Zealand had attempted for years to enact new gun control policies, and this event was the catalyst to finally get them passed almost without objection. The reaction after the

event was also a popular topic of study: Hashemi and Na (2021) analyzed the news reports about the event in traditional media. More comparable to our study of Twitter reactions, Besley and Peters (2020) looked at the witness accounts for the event. Additionally, Leander et al. (2020) studied the bias observed in the public reaction to violent events, using the Pittsburgh Synagogue shooting and the Christchurch Mosque shooting as examples. The shooter in this event was not given much coverage or analysis in general. This was in response to a message from New Zealand's prime minister: "*He is a terrorist. He is a criminal. He is an extremist. But he will, when I speak, be nameless. And to others, I implore you: speak the names of those who were lost rather than the name of the man who took them. He may have sought notoriety but we, in New Zealand, will give nothing—not even his name.*" (Arden 2019). In fact, more studies have been carried out on these events in terms of radicalization than in terms of community response. Our goal is to study the reaction of the public on social media by collecting tweets written in reaction to those events and measuring their attention, reaction, and sentiment.

3. Data Collection

Twitter hashtags are a key method to support searching for and identifying trending topics on Twitter. They allow tweeters to categorize their messages and to signal the context within which the tweet occurs. We rely on Twitter hashtags in our data collection.

Our datasets were downloaded from Twitter in three separate batches using the Twitter Capture and Analysis Toolset (DMI-TCAT) (Borra and Rieder 2014), as well as the "TwitteR" library in the R programming language (Gentry 2015). Several well-known hashtags were used to collect relevant data for each event. We started by collecting tweets using the known hashtags for the events published in the "trending" news page in Twitter. The main well-known trending hashtags were #Charlestonshooting, #Synagogueshooting and #christchurch for the three events. We then recursively collected all the other hashtags found in the text of those tweets, until the new tweets yielded very few new tweets to add to the dataset.

Table 1 show the hashtags used for the church, synagogue, and mosque shootings in that order. Some hashtags were very general, such as #tarrant and #treeoflife, and had to be manually cleaned to remove tweets not related to this event. Data were collected weekly until 12 October 2020, and we collected over 900,000 unique tweets and their replies.

Table 1. Hashtags used for data collection.

Charleston Massacre		Synagogue Massacre		Mosque Massacre	
Hashtag	**Count**	**Hashtag**	**Count**	**Hashtag**	**Count**
#CharlestonShooting	272,791	#SynagogueShooting	91,010	#Christchurch (cleaned)	246,224
#DylannRoof	38,097	#Bowers (Cleaned)	39,508	#Newzealandshooting	49,033
#PrayforCharleston	18,388	#TreeofLife (Cleaned)	9450	#Tarrant (Cleaned)	24,868
#CharlestonStrong	15,714	#SquirrelHill (Cleaned)	4296	#Newzealandmosqueattack	19,048
#AMEshooting	15,492	#RobertBowers	2391	#Christchurchterrorattack	15,206
#CharlestonMassacre	6654	#TreeofLifeSynagogue	437	#Christchurchattack	14,636
#EmanuelAME	5910	#PittsburghShooting	362	#Nzmosqueshooting	14,405
#Charleston9	5839	#PittsburghStrong	286	#ChristChurchShooting	12,178
#Emanuel9	5720	#SynagogueMassacre	253	#Christchurchmosque	8399
#MotherEmanuel	4213	#PittsburgSynagogue	238	#Christchurchmosqueshooting	6849
#StandwithCharleston	3918	#RobBowers	70	#Brentontarrant	3515
#DylannStormroof	2616	#PittsburghShooter	42	#Mosqueshooting	2472
#AMEmassacre	1953	#RobertGregoryBowers	38	#Newzealandattack	2112
#CharlestonTerrorist	1575	#PittsburghSynagogueShooting	36	#Christchurchmassacre	1020
#Emanuelnine	414	#PittsburghMassacre	34		
#AMEterrorism	171				
All hashtags	383,288	All hashtags	147,320	All hashtags	400,901

There was a large discrepancy in the overall number of tweets between the mosque and church shooting, compared to the synagogue. The church and mosque shooting had approximately the same number of tweets (383,288 and 400,901), but the synagogue had a significantly fewer number of tweets (147,320, even though it occurred chronologically between them and was very similar to the church shooting in both the method of attack and the number of victims. However, there are about 15 million followers of the Jewish faith compared to about 2.5 billion Christians and 1.9 billion Muslims, so the event garnered a relatively large number of reactions.

Another observation is the choice of words used in the hashtags. The location of the event was an important hashtag, as well as the name of the shooter and the words "shoot," "attack," and "massacre." Interestingly, the only positive hashtags, #PrayforCharleston and #StandwithCharleston, were used only in the Charleston church massacre.

The names of the shooters were a popular hashtag in all three events: Dylann Roof was used as a hashtag around 40,000 times (10.6% of tweets) in the church shooting; Robert Bowers was used 40,000 times (28.5% of tweets) in the synagogue shooting; and Brenton Tarrant was used 27,000 times (7% of tweets) in the mosque shooting, a small percentage given that the shooting was live streamed on social media and the shooter desired publicity for the event.

Conversely, news outlets published the names of the attackers far less often than users on Twitter. In the three months following the Christchurch shooting, almost 1000 reports were published in major news outlets in New Zealand. Less than 10% of news reports published by major media outlets mentioned Tarrant's name. Every-Palmer et al. (2020) suggested that the media made a moral choice to deny Tarrant exposure and not sensationalize his views, deviating from how similar events internationally were covered in the media. The court required the media to pixelate Tarrant's face when covering the legal proceedings; thus, within New Zealand, he remained largely faceless and nameless. Instead, media coverage focused largely on the victims and their families.

The datasets include the owner of the tweet, text of the tweet, number of retweets, likes, replies, followers of the tweeter, and the date and time of the tweets. Table 2 summarizes the tweets' statistics. It is of note that the Synagogue and Mosque events had more engagement than the Church event, as they had more replies, likes and retweets in general. The kind of data analysis shown in Table 2 reveals networks and relationships that are only intelligible in this kind of work. For example, while we observed a great discrepancy in the overall number of tweets in the three events, the engagement, number of tweets per person, and replies may tell a different story. Figure 1 shows the most liked and retweeted tweet in each dataset. None of them were about the events themselves, but the issues surrounding them: racism, hate, and gun control.

Table 2. Tweet statistics for the three massacres.

	Church Massacre	Synagogue Massacre	Mosque Massacre
Number of Tweets	383,288	147,320	400,901
Number of Tweeters	164,339	74,338	198,286
Avg number of likes per tweet	4.06	15.74	17.87
Average number of retweets per tweet	4.86	5.78	6.26
Average number of replies per tweet	0.40	1.13	1.11

(**a**)

(**b**)

(**c**)

Figure 1. Most liked and retweeted tweet in each dataset. (**a**) Most liked and retweeted tweet in the Church massacre dataset by an entertainer (tweet currently deleted). (**b**) Most liked and retweeted tweet in Synagogue dataset by Political Commentator Wajahat Ali (2018). (**c**) Most liked and retweeted tweet in the Mosque dataset by Politician Alexandria Ocasio-Cortez (2019).

Influencers

We define influencers as tweeters who have more than one million followers; in our datasets, they were mainly news sources, government, and politicians. However, there were also some celebrities from the entertainment and sports fields. Table 3 shows the

numbers and percentages of influencers, their tweets, likes, replies, and retweets. As the table shows, influencers represent a very small percentage of tweeters (less than 0.3%) in all datasets but have a much bigger percentage of all interactions: 20% of likes, 23% of replies, and 18% of retweets. This is to be expected due to the large number of followers and name recognition.

Table 3. Role of influencers in the discussion.

Event	Influencers	Tweets	Likes	Replies	Retweets
Church massacre	243 (0.14%)	2357 (0.61%)	298,952 (19.2%)	36,491 (23.6%)	341,852 (18.3%)
Synagogue massacre	208 (0.28%)	1528 (1.04%)	467,726 (20.2%)	44,989 (27%)	169,943 (19.9%)
Mosque massacre	368 (0.18%)	3752 (0.93%)	1,869,664 (26%)	116,527 (26.1%)	522,816 (20.8%)

4. Data Cleaning

After collecting the data, the next step is to prepare the text of the tweets for text analysis. The following operations were performed. We start by removing all the tags, images, videos, URL links, punctuation, non-alphabet characters, emoticons, and any other kind of character that might not be a useful part of the tweet. This cleaning step involves using regular expressions, which can be used to filter out most of the unwanted texts. The next step is to view the tweet as individual words and convert them all to lowercase. Then, all stop words are removed. Stop words are words which are used very frequently such as "of," "are," and "the". The last step is lemmatization, which is used to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form.For example, "organizer", "organizes", "organization", "organized" are all reduced to a root term, "organize". Figure 2 shows two sample tweets before and after the data clean operation was performed.
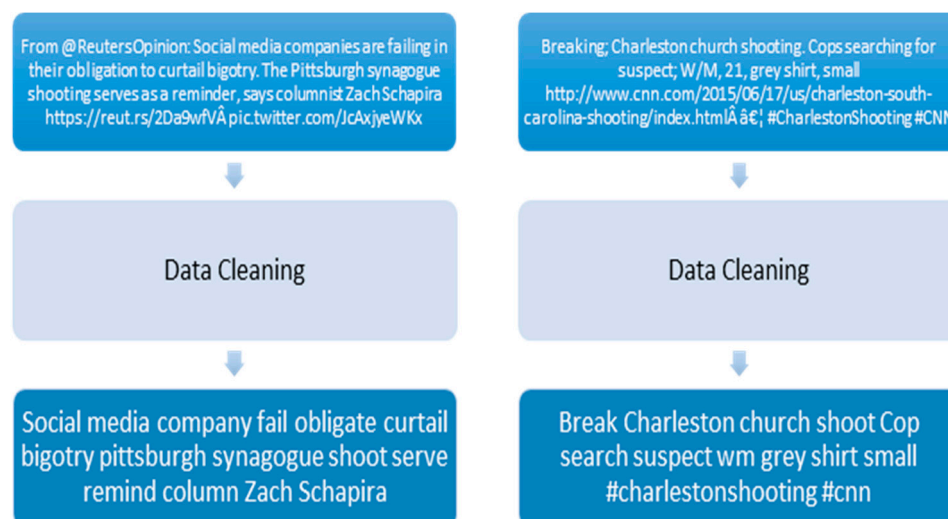

Figure 2. Sample tweets before and after cleaning and stemming.

5. Time Analysis

After the data were cleaned and prepared for processing, we carried out a time analysis of the tweets and when they occurred, as well as a study of the words used in the tweets themselves and a sentiment analysis of the tweets. Our findings are described in the next sections. We compared the number of tweets over time for the three massacres to measure how intense and how long the discussion was about each of these events, irrespective of the content of the tweets themselves. The massacres happened at different times, in 2015,

2018, and 2019. For all events, the timeline shows an initial peak and then the discussion tapers off in a long tail.

By concentrating on the first 30 days of each massacre, we noticed a difference in reaction, as shown in Figure 3. Both the church and the mosque datasets had an almost equal number of tweets, but the church massacre has a much higher tweet count in the first day before quickly tapering off, in strong contrast with the mosque massacre. This is due to the fact that the mosque massacre generated discussion about gun control and social media streaming immediately after the event, thus keeping interest high. Interestingly, the synagogue massacre received less discussion even though it was of a similar nature to the other two events. We believe the reason behind this reaction is the fact that it was not linked to a secondary discussion, such as racial tension for the church massacre and gun control and social media violence streaming for the mosque massacre. The ADL also reports that Twitter is rife with anti-semitic attacks, so people looking for comfort after an anti-semitic attack like the one perpetrated on the Tree of Life Synagogue may not look to Twitter as a site of solace (Anti Defamation League 2018).
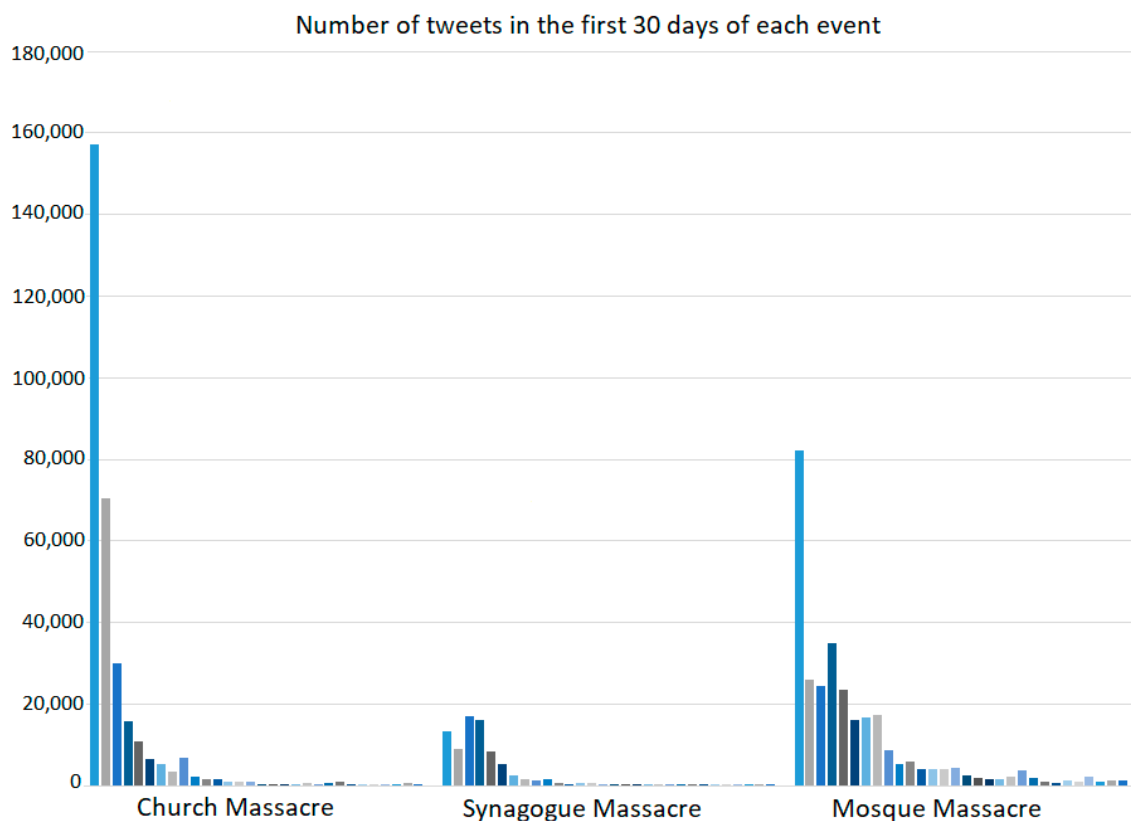

**Figure 3.** Number of tweets in the first 30 days.

Table 4 shows the numbers of tweets for each event in the first day and the first month, and it shows that the synagogue massacre, although it had a smaller number of tweets originally, had a longer lifetime, as only 56% of the tweets were sent in the first month. It was also discussed over time as many more anti-semitic acts continued to take place, such as the shooting at a synagogue in Poway, California.

Key to our subsequent analysis is the observation that there was a huge spike in Twitter activity regarding the Charleston shooting when a linked event, the synagogue shooting, happened. This renewed activity concerning the Charleston incident suggests that the public quickly perceived these two incidents to be related. Actor-network-analysis can help us understand these findings. Figure 4 shows the peak in chatter of the Charleston massacre tweets when the synagogue massacre (Figure 4a) and mosque event happened

(Figure 4b). Similarly, there was an increase in discussion about the synagogue shooting after the mosque shooting (Figure 4c).

Table 4. Tweet percentage over time.

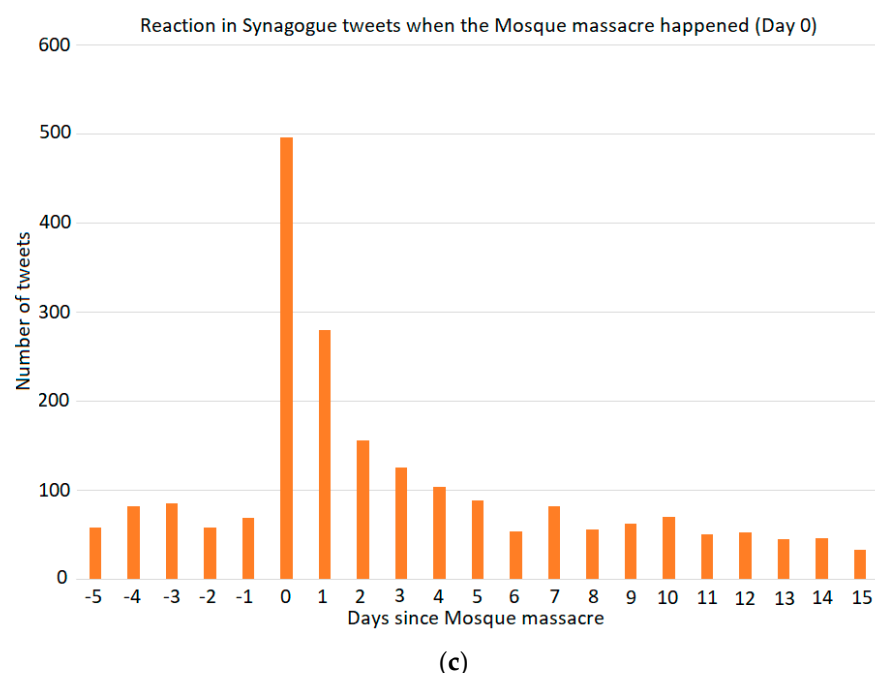| Event	Total Number of Tweets	Number of Tweets on the First Day	Number of Tweets in the First Month
Church	383,139	171,170 (44.6%)	322,718 (84.2%)
Synagogue	147,315	13,376 (9.08%)	83,646 (56.8%)
Mosque	400,876	82,249 (20.51%)	304,858 (76.05%)

(a)

(b)

Figure 4. *Cont.*

(c)
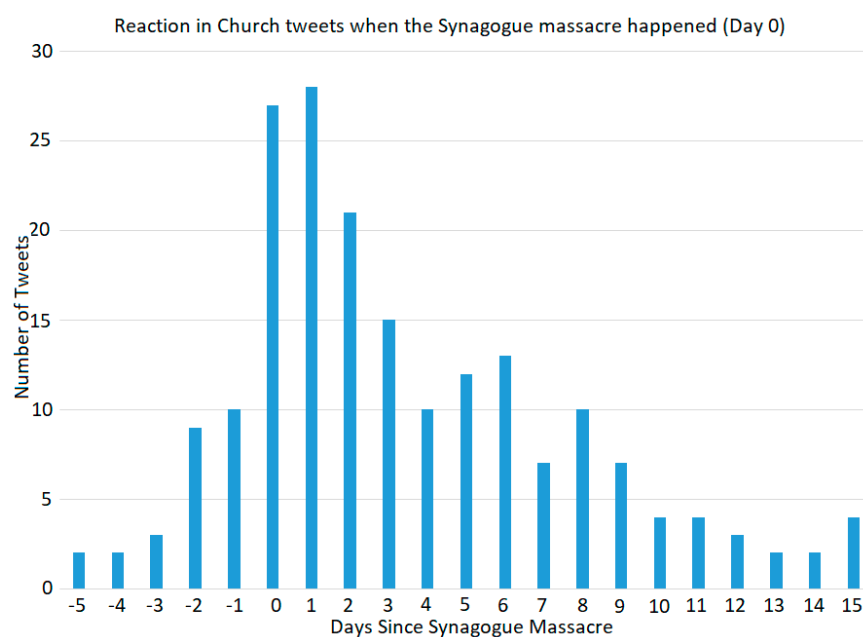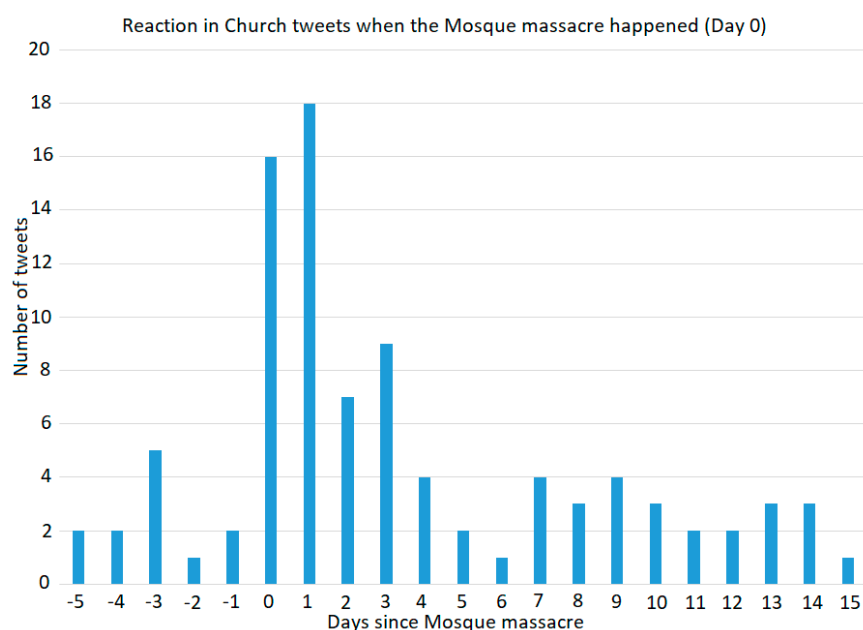
Figure 4. Re-invigoration of discussion in reaction to new violent events. (**a**) Reaction of Church massacre tweets when Synagogue massacre started; (**b**) reaction of Church massacre tweets when mosque massacre started; (**c**) reaction of synagogue massacre tweets when mosque massacre started.

6. Word Frequency

Word frequency analysis is a productive way to compare the use of language in response to each of the three events and compare the choice of words used in each. A simple word frequency count shows a lot about the language used in a discussion and makes contexts intelligible that might otherwise be obscured. An electronic word frequency analysis has an inherent flaw, which is the disregard of negative connotations, humor, sarcasm, and word ordering in a sentence. This method also does not consider the semantic relation between words. However, given such a large corpus, it is a reasonable measure of word choice and usage.

Another aspect we take into consideration is "retweets." A retweet signals a strong opinion of the retweeted message and, thus, gives it a larger audience (Tanupabrungsun and Hemsley 2018). Thinking of Latour's description of actors and flat ontology, these retweets must be considered as part of the network of associations created in response to these events. In other words, we need to find ways to analyze and reveal these data that puts the iterations of communication on the same plane—from hashtag creation, to thread, to reply, to retweet, to quote tweet, etc. How do we square this understanding of interpreting networks with the sense that not all tweets are equal? Many tweets are posted by people with no following, no likes, no replies, and no retweets. These tweets should not have the same weight as a tweet with extensive engagement, such as thousands of retweets. Hence, it was useful to include the number of retweets in the word frequency count. It is also possible to include the number of followers to give tweets different weights depending upon the audience size. Thus, patterns and networks become more intelligible.

Tables 5–7 show the word frequency counts of tweets with and without counting in the retweets. Notice that we added the names of the shooter (first and last together) as one word since they all refer to the same person (manual stemming). Violent words are shown in a red font, and the shooters' names in a blue font.

As can be seen from Table 5, the racial element of the Charleston shooting dominated the discussion with words like "black," "white," "confederate," "race," and "flag." However, even in designating "flag" as a racially coded term, we are interpreting the network to draw in traces of conversations other than religion. Additionally, the shooter's name was

the most frequently used word after the event location. His name was used a lot more frequently than words related to the victims: "black," "people," and "victim".

Table 5. Word frequency of the Church massacre.

	Top 20 Words without Retweets	Word Count	Top 20 Words with Retweets	Word Count
1	#charlestonshooting	269,904	Charleston	2,126,667
2	dylann roof (Shooter)	82,183	Shoot	2,036,365
3	Charleston	50,516	#charlestonshooting	1,683,008
4	Black	37,180	dylann roof (Shooter)	1,081,853
5	Race	34,878	Pray	383,835
6	Hate	33,075	Black	324,463
7	church	31,619	Kill	318,351
8	people	31,106	White	311,918
9	pray	28,738	Church	268,918
10	shoot	27,261	Emanuel	243,891
11	terror	26,402	Terror	239,887
12	white	26,034	People	238,914
13	victims	24,619	Race	215,337
14	gun	24,327	Gun	181,497
15	confederate	21,006	Suspect	173,277
16	family	20,948	News	156,191
17	flag	20,481	Hate	152,750
18	emanuel	19,818	Victims	138,269
19	kill	19,384	#ameshooting	115,750
20	#prayforcharleston	18,172	Flag	113,194

Table 6. Word frequency for the Synagogue massacre.

	Top 20 Words without Retweets	Word Count	Top 20 Words with Retweets	Word Count
1	shoot	107,446	Shoot	860,833
2	synagogue	101,680	Synagogue	753,062
3	robert bowers (Shooter)	63,232	robert bowers (Shooter)	634,860
4	pittsburgh	43,036	trump (President)	488,377
5	trump (President)	37,974	Pittsburgh	379,361
6	jew	20,423	Jew	286,028
7	suspect	18,455	Treeoflife	277,505
8	hate	18,338	Victim	246,358
9	treeoflife	17,807	Kill	203,012
10	victim	15,164	America	199,380
11	people	12,764	Hate	180,476
12	dead	12,617	White	170,134
13	poway	10,315	Life	169,871
14	kill	10,157	People	137,737
15	gun	9601	Terror	97,600
16	california	8527	Murder	95,245
17	#synagogueshooting	7786	Muslim	91,652
18	news	7693	Gun	90,757
19	white	7647	Suspect	87,260
20	life	7198	Caravan	82,697

Table 7. Word Frequency for the Mosque massacre.

	Top 20 Words without Retweets	Word Count	Top 20 Words with Retweets	Word Count
1	christchurch	368,140	Zealand	3,564,512
2	zealand	212,161	Christchurch	3,209,930
3	media	166,781	Terror	2,329,111
4	terror	101,384	Attack	1,796,107
5	attack	97,104	Mosque	1,660,428
6	shoot	90,284	Shoot	1,451,827
7	mosque	74,959	Muslim	1,377,070
8	muslim	59,904	Kill	877,323
9	brenton tarrant (Shooter)	46,290	jacinda arden (Prime Minister)	681,693
10	kill	45,915	Islam	517,641
11	people	44,023	Gun	441,283
12	victim	38,038	People	396,772
13	jacinda arden (Prime Minister)	34,045	White	393,068
14	gun	31,737	Pray	378,346
15	white	30,064	Victim	359,457
16	islam	28,369	Act	319,030
17	hate	25,658	Call	315,935
18	world	24,214	Hate	287,635
19	massacre	23,899	brenton tarrant (Shooter)	264,619
20	news	22,819	Ban	24,4321

Of note is the use of the word "pray" and the popularity of the hashtag #prayfor-charleston. This popularity is unique to the Charleston shooting; hashtags similar to this one were rarely found in the other two datasets. Additionally, the word "hate" dropped from number 6 to number 17 on the list when retweets were taken into account, and the word "pray" rose from number 9 to number 5 on the list, suggesting that tweets with a positive sentiment tend to be more popular and have a better chance of being retweeted than negative tweets. Notably, in the top 20 words used in relation to the shooting at the church, there is no mention of Christ, Christian, or Christianity. Emanuel and AME are mentioned, but far down the list. In the response to the synagogue and mosques shootings, there are specific indications of religion given—Jew, Jewish, Muslim, Islam—and invoked in each event, not only the one connected to each specific religion.

Table 6 shows the choice of words in reaction to the synagogue massacre. This was very similar in action to the church massacre, but the discussion is very different. The dominant words are "shoot," the location, and the shooter's name. We took special note of the inclusion of President Trump's name frequently, while President Obama was never popular in the church shooting discussion. The shooter referenced Trump, thus opening a discussion about white supremacy, and caravans of migrants (Abdelkader 2020). By invoking Trump in his manifesto, Bowers engaged an entire network of associations such as fearmongering about the "immigrant caravans" on the Southern border of the United States. It is also unusual that the word "Muslim" is 17th on the list; this is due to the large number of tweets that compared this incident to the one at the New Zealand mosque in 2019, as well as the discussion of the Muslim ban, which characterized the early days of Trump's presidency. Word frequency analysis reveals associations and affiliations that were energized by the event.

In the mosque massacre tweet set (Table 7), the shooter's name is used less than in the other tweet sets because there was a concerted effort to keep his name and photo out of the media. This is the only set where the victims were discussed more frequently than the shooter, as shown by the prominence of words like "Muslim," "Islam," and "victim." In contrast, the Prime Minister was prominent in the discussion and was cast in a good

light because of her empathy to the victims and the quick push for gun control laws (Every-Palmer et al. 2020). Oddly, the main word used to describe the event was "terror" and "attack" as opposed to "shoot" like the other events.

Notably, in this dataset is the drop in the shooter's name from position 9 to position 19 when retweets are taken into consideration, while New Zealand's Prime Minister Jacinda Arden rose from position 13 to position 9. She played a major positive role in the aftermath of the shooting and was heavily covered in international media. This reinforces the observation that positive tweets receive more retweets than negative ones. Figure 5 shows the comparative bubble charts for the three events. Public figures, like Trump and Arden, figure prominently in word frequency when their role in instigating or quelling the crises is well-known.
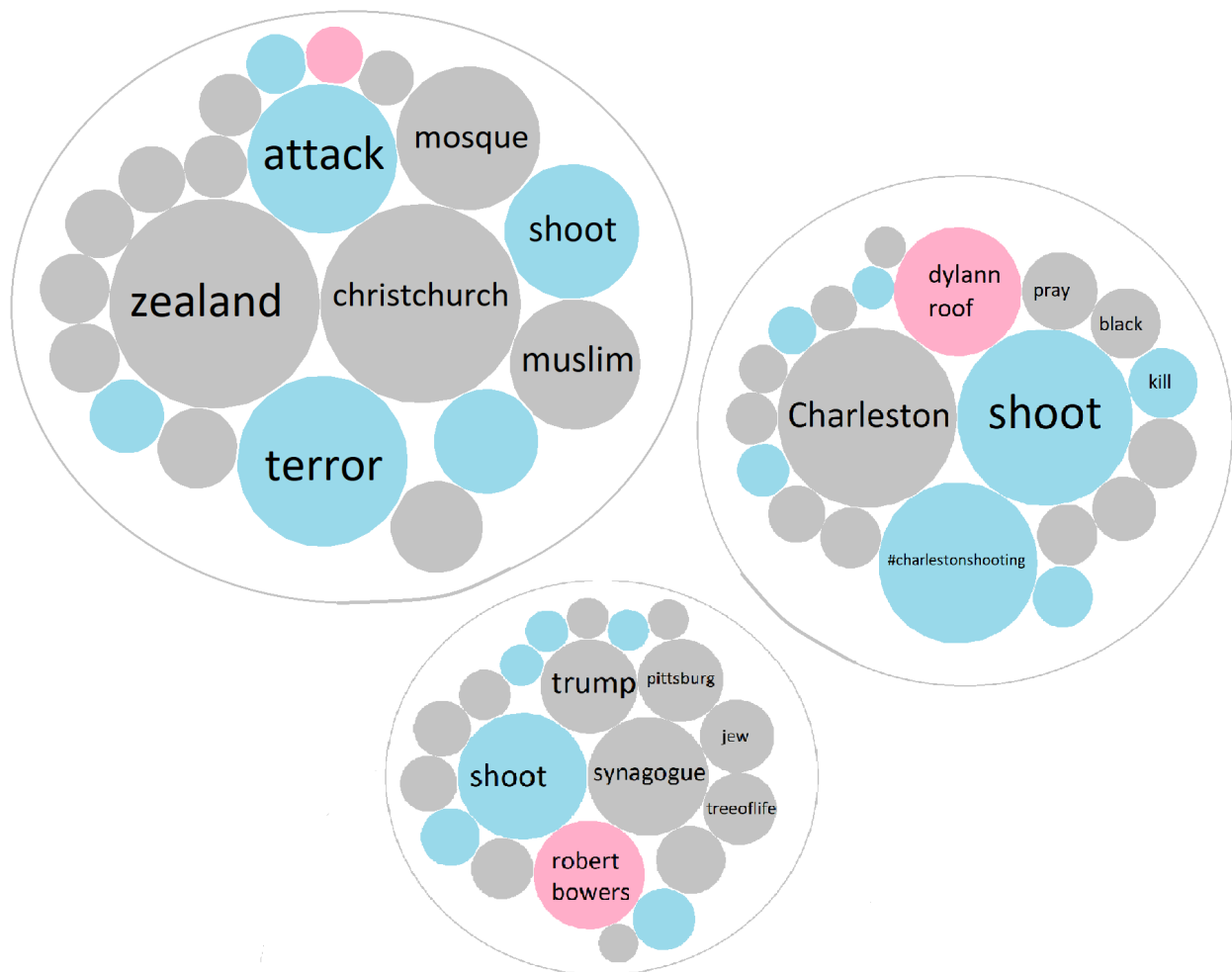

Figure 5. Word bubble for the three datasets word frequency (Mauri et al. 2017).

These word frequencies demonstrate the way these religiously motivated violent acts intersect with other issues of social justice; they seem to energize related affiliations. The Charleston shooting triggered questions of race relations, confederacy, white supremacy, mental illness, and racism. The synagogue shooting incited language of immigration, Trump, American fascism, and outsiders. The Christchurch shootings brought up language of islamophobia, the war on terror, gun violence. The attendant networks of cause and effect that these frequencies suggest reveal that the long-standing roots of anti-religious violence are deeply political.

7. Hateful Words

All three datasets contain a lot of violent and negative words such as "shoot," "terror," "kill," and "hate." This was expected due to the nature of the subject being discussed. It is, therefore, difficult to determine if a tweet is particularly vile or just describing the event using words that reflect the violence and hate. Manual parsing would be required for that, and that is particularly difficult due to the enormous number of tweets. However, we can easily detect hate tweets that use offensive words. A list of offensive words was obtained from the Hatebase Hatebase Project (2020) site. Table 8 shows a sample of those hate-filled tweets. Of note is the fact that those accounts typically had zero or very few followers and hardly any likes or retweets, and they relied mainly on common hashtags to obtain an audience.

Table 8. Sample of hate-filled tweets found in the datasets.

Event	Sample Hate-Filled Tweets
Church massacre	"#CharlestonShooting it's about time whites start fighting back. Fuck you #niggers" "Payback for all the murders of whites. #CharlestonShooting fucking niggers need to hang."
Synagogue massacre	"You know that the Jewish people couldn't let Christians get all of the media attention, because of Sri Lanka. So they decided to shut the Christians down with a #synagogue shooting. To them, one Jewish life is worth more than 250 goyim lives."
Mosque massacre	"It was not a MASSACRE it was a CULL. No more MOSQUES no more MUSLIMS. ISLAM IS TERRORISM."

The total number of all words in all three datasets is 9,613,855 but only 1522 offensive hate words were found (67 different words), such as "nigger," "monkey," "raghead," and "goyim." This is testimony to the effective anti-hate culture implemented by Twitter (Twitter Hateful Conduct Policy 2021). Still, these terms got through and, even more disturbing, these tweets point to an invocation of a return to violence that may be even deeper and more ancient than gun violence. The tweets around the Church massacre invoke lynching; the hate tweets around the synagogue invoke the ancient mythology of Jewish sacrifice of Christians; the suggestion of culling implies a dehumanizing extermination. These hate tweets invigorate old and grotesque images of past stereotypes to complement the modern technological massacres by gun violence.

8. Conclusions

In this study, we compare the online reaction on social media to incidents of religious violence against different religions. Three shootings were chosen because of the similarity in how they were carried out: the shooting at the AME church in Charleston, SC, church in 2015; the shooting in the Tree of Life synagogue in Pittsburgh, PA, in 2018; and the dual shooting of the Christchurch mosque, New Zealand, in 2019. Over 900,000 tweets in response to these events were collected and analyzed.

By applying the analytical lens of actor-network-theory, we argue that the analysis of Twitter in relation to religiously motivated violence allows us to interpret networks in three key areas: knowledge, empathy, and fascination. Twitter allows for people to respond to national and international events in a participatory and interdependent way by following a hashtag, retweeting something or liking something. This is a mobilization of collective action. Our task is to find a method through ANT to make visible in our research the networks that are activated. Some of our work aligns with qualitative research in visual network analysis, described by Mathias Decuypere (2020). In our tables, graphs, and word bubbles, we attempt to draw out and visualize the critical responses to these instances of religious violence.

As we laid out in the beginning, the three interpretive processes that the tweeters participated the most in were knowledge, empathy, and fascination. First, for knowledge, we observed that one of the key features of tweets, retweets, replies, etc., was to create and share knowledge about the event. Most of the hashtags in Table 1 center around information—place, geography, building, shooting, name of shooter, and the name of the religious entity. Through these hashtags, people could learn the details of the massacres, signal their interest, and connect with others. The tweet statistics and most-liked tweets in Table 2 record a more complex level of response that contributes to the network of knowledge building we noticed. The most liked tweets of each event make connections and synthesize information. They are not tagged as emotional or grief-stricken tweets, but rather forge a set of ideas about underlying causes and interpretations of these events. The tweets show a network of associations that people are making: religion, evangelism, white supremacy/gun violence, white supremacy, anti-immigration, terror/racism, and mental illness. The bubble graph of most frequent words used also demonstrates the desire to find the root causes of these events. Words like "terror," "Trump," "gun," "flag," "Black," and "white," are reaching for a critical interpretation of the events.

In tweets that make visible efforts at empathy, influencers and time analysis demonstrate these networks. First, the interest in, and connection to, these events is not always a simple correlation of one's religious identity. This becomes apparent in the groups of influencers and importantly in the time analysis of the tweets. There is a strong correspondence and sympathy with the events that reinvigorates tweets about one event in the wake of another. Even though there were years between these events, a new catastrophe could elicit more tweets on the earlier event (Figure 4). People see patterns in these events and encode them in a network of responses on Twitter. Therefore, it is impossible to argue that the network of associations is only built on a singular identity, such as a religious identification. The network of tweets seems to suggest that there are associations between terror victims, gun-violence victims, activists, and sympathetic or empathetic human relations being manifested in Twitter responses. The emphasis on prayer seems indicative of religious sentiment and empathy. Like the calls for unity and solidarity in the face of grief as seen after the Boston Marathon shooting, #Charlestonstrong resonated on Twitter.

Counterintuitively, the analysis of these datasets also revealed a network of associations that distinctly moved away from empathy to gawking and fascination. The heavy emphasis on the name of the shooters, and violent language in general, suggests that people were also attracted to the horror and violence of the events. The shooters dominated the conversation in the church and synagogue shootings but not in the mosque one, this was due to an effort by the New Zealand government not to give him any publicity. Additionally, the verb used to describe the events was mainly "shoot" for the church and synagogue, but it was "terror" for the mosque event, showing the association of the word "terror" with Muslims in general even when they were the victims.

We discovered that interpreting these data through a complex web of interdependencies and relationships is important. The use of the word "terror" in relation to the New Zealand shooting of course echoes the way Muslim identity has been reinscribed by the history of 9/11. Invoking the confederate flag in response to the Charleston shoot engenders networks of racial animus and white supremacy. As well, government intervention and policies can direct discussion about these events. For example, the New Zealand government's reaction to the event was to immediately move to discussion about gun control and social media responsibility as the event was live-streamed and shared (Chew and Tandoc 2020).

A positive takeaway from our study is that only a small number of tweets contained offensive or hate-filled language. Some conclusions can be drawn with this analysis of the reaction to religious violence on Twitter. First, that Twitter provides a space to demonstrate community support, as evidenced by the positive tweets. Second, Twitter provides an analytical sphere where tweeters can connect different events and synthesize their reactions to find common ground. Finally, Twitter's efforts to monitor hate speech seem to be

effective; however, the interest in the shooter's name as primary in all cases suggests to us that Twitter still provides its audience fascination and the glorification of violence. The virtual community of Twitter, as well as the tweets, replies, actors, organizations, and technology create a complex space of communication, one that seems to value or replicate for knowledge, empathy, and fascination or attention. These three forms are not all ethically neutral, and therefore, it is important to attend to the production of networks in social media, especially as new platforms develop. This kind of research can open up wide-ranging interpretation to understand the networks of responses to crisis, trauma, and religious violence.

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