DOI: 10.1111/1745-9133.12486

CRIMINOLOGY & Public Policy

SPECIAL ISSUE ARTICLE

COUNTERING MASS VIOLENCE IN THE UNITED STATES

Responses to mass shooting events

The interplay between the media and the public

Arie Croitoru[1] | Sara Kien[2] | Ron Mahabir[1] | Jacek Radzikowski[1] | Andrew Crooks[1] | Ross Schuchard[1] | Tatyanna Begay[3] | Ashley Lee[3] | Alex Bettios[4] | Anthony Stefanidis[1]

[1]George Mason University

[2]Northern Arizona University

[3]Dine College

[4]Langley High School

Correspondence
Arie Croitoru, Georgraphy and Geoinformation Science, George Mason University, 2204 Exploratory Hall, Fairfax, VA 22030.
Email: acroitor@gmu.edu

Research Summary: Public mass shootings tend to capture the public's attention and receive substantial coverage in both traditional media and online social networks (OSNs) and have become a salient topic in them. Motivated by this, the overarching objective of this paper is to advance our understanding of how the public responds to mass shooting events in such media outlets. Specifically, it aims to examine whether distinct information seeking patterns emerge over time and space, and whether associations between public mass shooting events emerge in online activities and discourse. Towards this objective, we study a sequence of five public mass shooting events that have occurred in the United States between October 2017 and May 2018 across three major dimensions: the public's online information seeking activities, the media coverage, and the discourse that emerges in a prominent OSN. To capture these dimensions, respectively, data was collected and analyzed from Google Trends, LexisNexis, Wikipedia Page views, and Twitter. The results of our analysis suggest that distinct temporal patterns emerge in the public's information seeking activities across different platforms, and that associations between an event and its preceding events emerge both in the media coverage and in OSNs.

Policy Implication: Studying the evolution of discourse in OSNs provides a valuable lens to observe how society's views on public mass shooting events are formed and evolved over time and space. The ability to analyze such data allows tapping into the dynamics of reshaping and reframing public mass shooting events in the public sphere and enable it to be closely studied and modeled. A deeper understanding of this process, along with the emerging associations drawn between such events, can then provide policy and decision-makers with opportunities to better design policies and communicate the significance of their goals and objectives to the public.

Public mass shootings in general, and school shootings in particular, have a long history in the United States. The earliest recording of a school shooting event dates back to 1764, but most school shooting events were recorded from 1840 to present day (Paradice, 2017). Although not a formally defined government statistic in the United States, many researchers have generally considered public mass shooting as "a multiple homicide incident in which four or more victims are murdered with firearms, within one event, in at least one or more public locations, such as, a workplace, school, restaurant, house of worship, neighborhood, or other public setting" (Krouse & Richardson, 2015, p. 2; see also Dahmen, 2018; Murray, 2017; Silva & Capellan, 2019; Towers, Gomez-Lievano, Khan, Mubayi, & Castillo-Chavez, 2015.). Moffat (2019) tallied 70 mass shooting events in the United States with 620 casualties and more than 1,000 wounded in the period beginning with the Columbine event in 1999 and concluding with the Parkland shooting in 2018. Although mass shooting events occur in various countries around the world, the United States seems to be exceptional in terms of the sheer volume of such events, positioning it well above any other country (Lankford, 2016). Lankford (2016) noted that globally the United States also had a disproportionately high number of offenders (accounting for 31% of global public mass shooters) compared with its share of the global population (5%). Moreover, public mass shootings have been on the rise in the United States over the last decade (Blair & Schweit, 2014; Katsiyannis, Whitford, & Ennis, 2018).

These events tend to capture the public's attention and receive substantial news coverage. For example, in 2012, news editors, in an Associated Press year-end poll, placed mass shootings as the leading news stories for that year (Fox & DeLateur, 2014). Similarly, *The New York Times* ranked mass shooting stories among its 100 most read stories in 2015, 2017, and 2018. In addition to such traditional media outlets (i.e., newspapers and television news), online social networks (OSNs), such as Twitter or Facebook, have recently emerged as a prominent source of information about breaking news, including mass shootings. In the United States, OSNs recently surpassed traditional print newspapers as a primary source for news and continue to gain traction on other traditional news sources such as television and radio (Mitchell et al., 2018). This combination of traditional and emerging media can be seen as a novel news ecosystem comprising both traditional news sources and online platforms (e.g., news websites/apps and social media) that is highly participatory and fosters citizen engagement

(Mahabir, Croitoru, Crooks, Agouris, & Stefanidis, 2018). Consequently, in addition to their well-established saliency in traditional media, mass shooting events have become a salient topic for public engagement and digital activism in OSNs.

The substantial attention given to the coverage of public mass shootings in the media is rooted, at least in part, in the interplay between the interest among the general public to seek and consume information, and the motivation of media outlets to provide information about such events. The interest of the general public in mass shooting events can be attributed to a range of motivations, from general curiosity or a desire to obtain information about current news to a concern for public and personal safety (Gunn, Ter Horst, Markossian, & Molina, 2018; Menachemi, Rahurkar, & Rahurkar, 2017). Levin and Wiest (2018) recently explored public interest in information after mass shootings (specifically school shootings) identified information seeking, specifically in the context of public and personal protestation and safety, as a generally strong motivator for consuming news about such an event. At the same time, they found notable public interest in information about specific aspects of shooting that provide a "silver lining" to the event, such as acts of heroism or stories about victims and survivors. Media outlets, however, do not always mirror entirely the public's need for information. For example, even though the general public seeks information about mass shooting events to reduce uncertainty, media outlets often have a significant financial interest in providing "what the public desires to consume" (Murray, 2017).

It is also important to note that different public mass shooting events may be covered differently in the media, depending on the characteristics of the event. For example, Silva and Capellan (2019) recently examined *The New York Times* coverage of public mass shooting events between 1966 and 2016 and found a distinct discrepancy between the most common characteristics of such events in the United States and the characteristics highlighted by the media. For instance, even though the most common public mass shootings involve perpetrators that are middle aged, White, and nonideological, the media highlights public mass shootings that involve younger, Middle Eastern, ideological perpetrators. After exploring the specific issue of the event location, Silva and Capellan (2019) found that school shootings in particular influenced the media's decision to dedicate coverage to a mass shooting event. Similarly, after comparing photographic coverage between perpetrators and victims of three mass school shooting events, Dahmen (2018) found that much greater attention was given to perpetrators than to individual deceased victims.

The extensive coverage of certain public mass shooting events, specifically school shootings, in the media and on OSNs has repeatedly raised a concern that such coverage may increase the possibility of "copycat" violent behavior by other individuals who see a recent public mass shooting as a model for imitation (e.g., Abrutyn & Mueller, 2014; Fox & DeLateur, 2014; Langman, 2018; Lankford & Madfis, 2018). Mullen (2004), for example, in his forensic evaluations with five pseudocommando mass shooters, reported that most perpetrators acknowledged being influenced by previous mass killers who had received significant media attention. This view is widely shared among the public, with 70% of media consumers agreeing that media coverage is responsible for the increase in mass shootings (Schildkraut & McHale, 2018). This concern is also supported, at least in part, by drawing a parallel from the study of imitation behavior in suicide attempts and, more recently, terrorist attacks. In an extensive meta-analysis, Stack (2002) explored media coverage as a risk factor in suicide based on 42 scientific studies and, as a result, indicated that even though most evidence for a copycat suicide effect is indirect, some evidence shows support for the existence of an imitation behavior factor in suicide incidents. Specifically, it has been found that media coverage of suicides of prominent entertainers and political celebrities seem to be more strongly associated with such behavior, which indicates that imitation behavior in suicides results from differential identification among victims (Ueda, Mori, Matsubayashi, & Sawada, 2017). More recently, Fink, Santaella-Tenorio, and Keyes (2018) explored the relationship between a prominent entertainer's suicide (i.e., Robin Williams) and the increase in suicide cases that followed, which showed further support for this finding. Therefore, in addition to traditional media, OSNs are becoming a noteworthy risk factor in suicide imitation behavior (Fink et al., 2018). Media coverage of mass shooting events and the public engagement that follows in OSNs as a potential risk factor, however, is still not fully understood.

Motivated by this gap, the overarching objective of this article is to advance our understanding of the public's response to public mass shootings. Here, we are specifically interested in how the public responds to mass shooting events, for example, by seeking additional information or exchanging opinions about them in media coverage (e.g., newspaper articles) and through online sources of information (e.g., Google Trends, Wikipedia, and OSNs). Consequently, we have to consider association patterns between the mentioned sources of information. In the context of this article, we consider an association pattern as a conceptual link that one perceives and identifies among the events themselves. Our understanding of these patterns is, however, still limited.

This knowledge gap is further compounded by the evolution in the way the general public consumes and produces information about public mass shooting events, from a reliance on printed press and broadcasted news to a two-way interaction with an entire media ecosystem that includes OSNs (Knoll & Annas, 2016). In particular, we explore, on the one hand, how information about public mass shootings is being made available and accessed in digital news outlets, and, on the other hand, how the public seeks and contributes information online. The focus of the analysis in this study is therefore on discovering observable temporal as well as geographic patterns that may emerge from data related to these information-production and -seeking activities.

A key principle in our approach is that rather than attempting to find temporal patterns between mass shooting events, we explore whether the public's response to mass shooting events provides any evidence of association patterns when it seeks, consumes, or produces information about such events. By doing so, we postulate that the association effect should be seen not only in the narrow context of the epidemic-like spread of shooting incidents but also in the broader context of the spread of public engagement with information about sequences of such events. As a result, we explore five research questions, the first four (RQ 1–RQ 4) are focused on online search patterns, whereas the last (RQ 5) is focused on OSN contributions:

RQ 1. Are there discernible online search patterns for public mass shooting events?

RQ 2. Given a current event, how are past events manifested in the corresponding online search patterns?

RQ 3. What is the relationship between online search patterns and news coverage of an event?

RQ 4. Are there discernible geographic patterns of online searches?

RQ 5. Do OSN contributions exhibit patterns comparable with online searches or news coverage?

Combined, these questions are focused on the issue of online public engagement with mass shooting events, ranging from consuming and accessing information to producing online contribution.

The remainder of this article is structured as follows. In the Data and Method section, we describe the different data sources used in this study, their characteristics, and the methods used in our analysis. Then, we present and discuss the results of the analysis that was conducted for each research question and summarize the key findings. Finally, in the Conclusion and Policy

Recommendations section, we examine the broader implications of the study result for policy and decision-making.

1 | DATA AND METHOD

1.1 | Study Scope

In this study, we focus on the 9-month period after the seminal 2017 Las Vegas shooting. This event is considered seminal as the sheer volume of victims (58 dead and 851 injured) put renewed attention on gun laws. For our study period (from October 2017 to June 2018), we focused on a sequence of events with the highest number of casualties overall because total victim counts serve as the most salient predictor of increased media interest and coverage (Schildkraut et al., 2018). In accordance with this criterion, we selected the following five consecutive events to study: (1) the Las Vegas Route 91 concert shooting (October 1, 2017), (2) the Sutherland Springs church shooting (November 5, 2017), (3) the Marshall County school shooting (January 23, 2018), (4) the Parkland school shooting (February 14, 2018), and (5) the Santa Fe school shooting (May 18, 2018). Whereas the first two events occurred in public spaces in which people gather on their own accord, the remaining three events occurred in schools. A summary of the public mass shooting events in this study is provided in Table 1.

1.2 | Data

We build this study on three open-source data sets (i.e., Google Trends, Wikipedia page views, and Twitter messages) and one subscription-based sourced data set (i.e., LexisNexis) to address RQ 1 through RQ 5. These data sources were selected as proxies for the public's information-seeking activities (Google Trends and the number of Wikipedia page views), news availability (LexisNexis), and the public's engagement in OSNs (messages on Twitter). Specifically, the data were collected as follows.

To retrieve for each event the number of news articles per day from LexisNexis, a term-based search was carried out using a term relating specifically to the given event. The term used for each event comprised the name of the event and the term "shooting" (e.g., in the case of Las Vegas, the search term used was "Las Vegas shooting"). The articles that were retrieved by the search were then filtered manually to remove unrelated articles and non-news media entries (e.g., blog posts). The same keywords were also used to retrieve the Google Trends (GT) daily search volume index data for each event over time. This index, which ranges between 0 (low or no search interest) and 100 (maximum search interest), represents a relative measure of the overall interest in a given term over a predefined period of time. In the case of Wikipedia, the page of each event was manually identified and the number of views per day was retrieved using the Wikipedia Application Programming Interface (API). The extraction of the data from these three sources resulted in time series that were then clipped to predefined time periods of 269 days (the maximum time interval for which Google Trends data at daily granularity is publicly available) after each event. Table 2 provides a summary of the total counts of LexisNexis news articles and Wikipedia page views over the study period.

In addition to the generation of these time series, Google Trends was also used to capture a relative ranked search volume measure by state, thus, allowing subsequent geographic exploration of such data. Such relative ranked volume value can vary between 0 (representing low search volume for a specific search term and state) and 100 (representing the highest level of interest for a specific search term and state). It should be noted that when, for example, two different states have a ranked volume of 0, that value should be interpreted as "similar and low search volume" rather than as "zero search volume."

TABLE 1 Summary of mass shooting events resulting in greater than 10 deaths from October 1, 2017 through May 18, 2018

Event	Date	Killed	Injured	Description
Las Vegas Concert Shooting (Las Vegas, Nevada)	Oct. 1, 2017	59	418	[a]On October 1, 2017, gunman Stephen Paddock opened fire from his Mandalay Bay hotel room in Las Vegas, Nevada, onto the Route 91 Country Musical Festival crowd killing 58 and himself, while injuring 418.
Sutherland Springs Shooting (Sutherland Springs, Texas)	Nov. 5, 2017	27	20	[b]On November 5, 2017, gunman Devin Kelley fired into the congregation of the First Baptist Church of Sutherland Springs, Texas, killing 26 and himself, while injuring 20.
Marshall County school shooting (Draffenville, Kentucky)	Jan. 23, 2018	2	18	[c]Sixteen people were wounded, two of them fatally, after a shooter opened fire Tuesday morning at Marshall County High School, authorities said. Four others sustained various injuries.
Parkland School Shooting (Parkland, Florida)	Feb. 14, 2018	17	17	[d]On February 14, 2018, gunman Nikolas Cruz opened fire within the Marjory Stoneman Douglas High School in Parkland, Florida, killing 17, while injuring 17.
Santa Fe School Shooting (Santa Fe, Texas)	May 18, 2018	10	13	[e]On May 18, 2018, gunman Dimitrios Pagourtzis opened fire within the Santa Fe High School in Santa Fe, Texas (near Houston), killing 10, while injuring 13.

[a]http://archive.is/DVF9s
[b]http://archive.is/BYPVH
[c]http://archive.is/EmS1r
[d]http://archive.is/68csS
[e]http://archive.is/QSO9L

TABLE 2 Number of news articles and wikipedia page views after each event during the corresponding 269 days period

Data Source	Las Vegas	Sutherland Springs	Marshall County	Parkland	Santa Fe
LexisNexis articles	1,115	521	113	5,069	795
Wikipedia page views	2,337,317	1,064,938	126,470	3,418,554	609,932

TABLE 3 Overall tweet corpus volumes for each associated OSN mass shooting event conversation

Corpus	Collection Dates	Tweets	Retweets	Contributors
Las Vegas	Oct. 1–Oct. 30, 2017	17,260,101	13,258,233	2,925,808
Sutherland Springs	Nov. 5–Dec. 4, 2017	13,641,103	10,095,006	4,996,779
Marshall County	Jan. 23–Feb. 20, 2018	7,018,974	5,096,023	1,136,457
Parkland	Feb. 14–Mar. 14, 2018	974,203	802,227	425,941
Santa Fe	May 18–Jun. 22, 2018	14,856,795	11,688,269	5,262,635

In addition to these data sources, Twitter data were also collected for this study via the Twitter API for a period of approximately 1 month after the actual event date for each mass shooting event. In an effort to maintain a consistent collection paradigm for each event, the data were collected using a set of keywords that are related to mass shooting events but are not event specific: "shooting," "shot," "shots," "gunman," "gunfire," "shooter," and "active shooter." This collection approach enabled the creation of a broad corpus of data surrounding mass shootings, which was then further filtered to extract a subset of the data that is related to each shooting event using the same terms that were used to retrieve the GT and LexisNexis time series. In total, the data corpus harvested for all mass shooting events consisted of approximately 46.7 million tweets generated by slightly more than 13.6 million unique Twitter users. Table 3 provides a summary of the Twitter data corpus for each shooting event.

1.3 | Method

To address the specific research questions of this study, the analysis is carried out in two parts. In the first part of the analysis, we address research questions RQ 1 through RQ 4—that is, the association patterns of public information-seeking behavior (via Google Trends and Wikipedia page views)—and their relationship to media coverage of mass shooting events (via LexisNexis news articles). In the second part of the analysis, we address research question RQ 5, examining patterns of user contributions in an OSN (i.e., Twitter) and their relationship to online public information-seeking behavior.

Figure 1 provides an overview of the analysis performed for exploring RQ 1 through RQ 4. In the first part of the analysis, time series data from Google Trends, LexisNexis, and Wikipedia page views were examined. Specifically, we compared broad patterns of activity between events across the three different data sources and studied the structural patterns of activity across all events for the three different data sources. In so doing, we sought not only to identify overall association patterns in public-seeking behavior, and their relationship to news coverage, but also to explore the possible existence of markers (i.e., spikes, dips, or slope of the activity curve) that may be common to all events and/or specific data sources. Such information can be of interest as it can lead to a better understanding of the degree to which specific patterns that are characteristic of shooting events emerge from the data.

After the time series analysis was completed, we also examined broad geographical patterns in public-seeking behavior via Google Trends for the full study period (i.e., 269 days) at the aggregated state level. Use of such an analysis enabled us to examine whether, and if so which, geographic

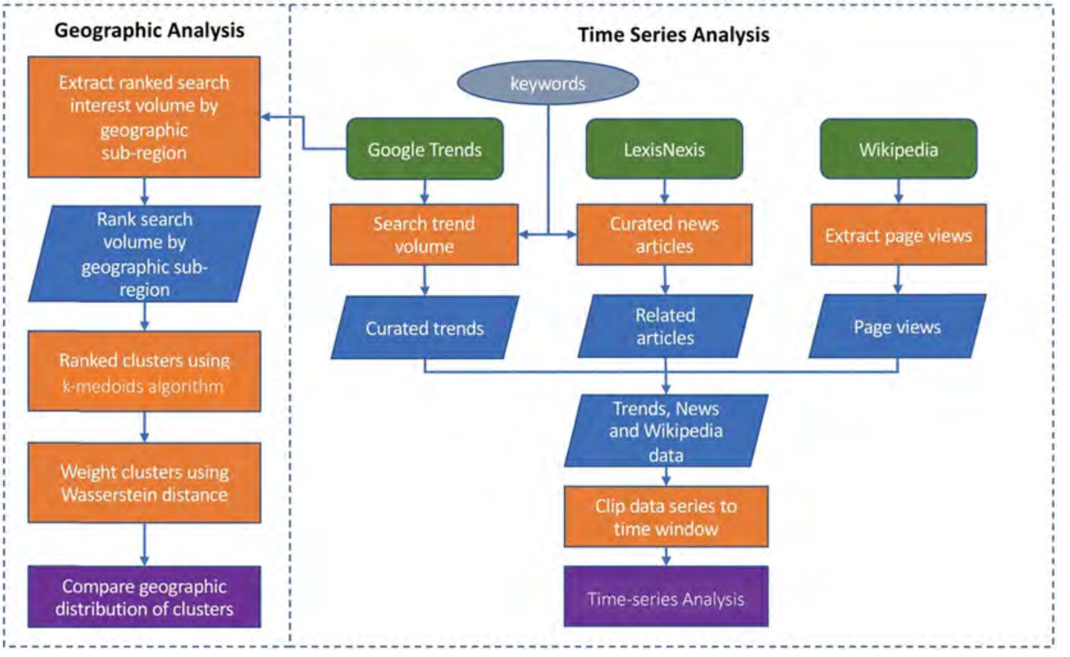

FIGURE 1 Framework for the analysis of temporal and geographical Trends (RQ 1–RQ 4) [Color figure can be viewed at wileyonlinelibrary.com]

patterns emerge in the public's information-seeking activity on mass shootings as events unfold. Data on Google Trends search index volume aggregated over the full study period and ranked at the state level were first clustered using the k-medoids clustering algorithm (Kaufman & Rousseeuw, 1990). The k-medoids algorithm is particularly appropriate for this analysis because methods that use second-order statistics to cluster data are less meaningful when applied to ranked data such as the Google Trends data used in this study. For each event, the optimum number of ranked clusters was determined using the "elbow" search method (Thorndike, 1953).

Another important consideration in analyzing the publicly available Google Trends data is that Google does not provide information on how it normalizes its trend data, making the calculation of absolute Google Trends value differences difficult to interpret. This issue can, however, be overcome by using the Wasserstein Distance (WD; Wasserstein, 1969) metric to weight each ranked k-medoids cluster within an event. In our analysis, the WD distance measure was used under the assumption that the within-distance values in each k-medoids cluster is negligible compared with the statistical distance between their cluster distributions when determining the relative weight of each cluster. For example, assuming that three clusters were found in the k-medoids clustering process, C_0, C_1, and C_2, where the values 0, 1, and 2 represent cluster ranks from lowest to highest respectfully, the cluster comparison starts by estimating the pairwise WD distance from the lowest ranked cluster C_0 to C_1, and C_2, that is, for the pairs C_0 C_1 followed by C_1 C_2. Then, the cumulative sum of WD distances up to the current cluster being examined is added to all of this cluster's rescaled values. Although following this approach does not produce an absolute weighting of clusters, it does enable a relative comparison between clusters, ensuring that both their rank and relative magnitude are preserved. After the weights are determined for state cluster groups, the geographic distribution between clusters is examined for each of the five mass shooting events.

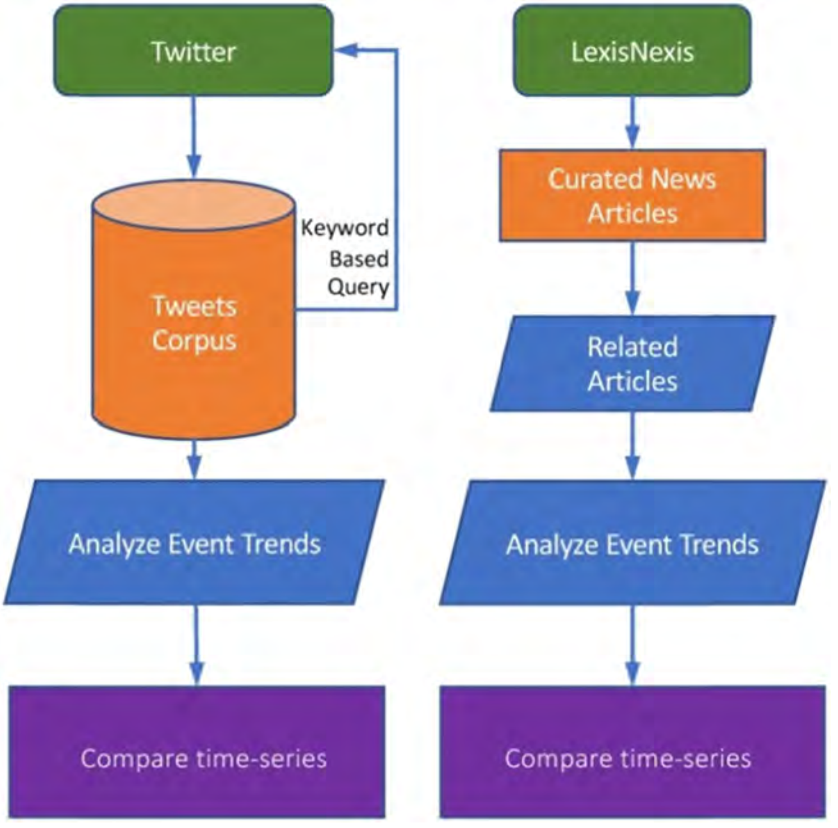

FIGURE 2 Analysis processes of Twitter and LexisNexis data [Color figure can be viewed at wileyonlinelibrary.com]

In the second part of our analysis, the relationship between news activity (via LexisNexis) and public engagement (via Twitter) is explored to address RQ 5. The collection of Tweets was first retrieved from the Twitter public API based on a set of mass shooting keywords that are not event specific. Then, the resulting tweets corpus was further filtered to derive data sets covering a 1-month period (as shown in Table 3) for each of the five events studied here using the name of each event. Similarly, the LexisNexis data set was generated by recording the number of LexisNexis news articles for each event occurring within the 1-month period for which Twitter data were collected. Using the resulting time series, we then compared (a) the evolution of news stories in LexisNexis and public engagement in Twitter for events over time and (b) co-mentions of past events as new events take shape. A summary of the analysis performed for RQ 5 is presented in Figure 2.

2 | RESULTS

The results of our analysis are presented in the subsections that follow. We first report on online search behavior for public mass shooting events (RQ 1), the association between these events (RQ 2), and their relationship to news coverage activity (RQ 3). Next, we report on the results of our geographic analysis to understand better how search interest in an event becomes geographically diffused between states when a mass shooting occurs (RQ 4). This section concludes with the results of our OSN analysis

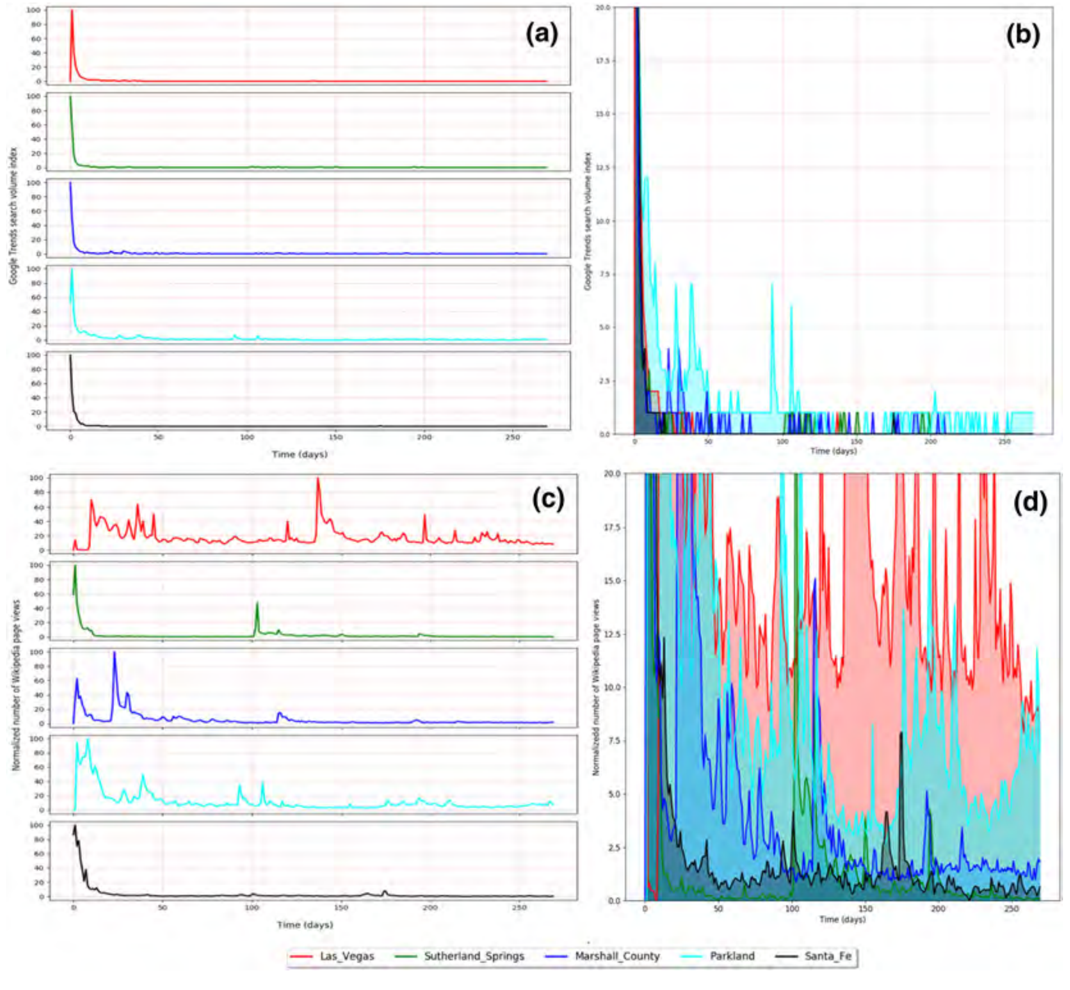

FIGURE 3 Online search activity index in Google Trends: (a) Each Event Separately (Normalized Values) and (b) Sequence of Events Overlaid. Number of Wikipedia Page Views: (c) Each Event Separately (normalized values), and (d) Sequence of Events Overlaid [Color figure can be viewed at wileyonlinelibrary.com]
Note. The *y*-axes in (b) and (d) are clipped at 20.0 to show the activity in the months after each event.

to understand the association patterns of activity between news coverage of mass shooting and public engagement via Twitter (RQ 5).

2.1 | RQ 1: Are there discernible online search patterns for public mass shooting events?

To address RQ 1, we examined the online search behavior in Google Trends for all five events during the 269 days after each event. Here, the analysis was carried out in two steps: an examination of the visual trends that emerge from the time series data, and a quantitative analysis of these trends. Figure 3 depicts these behaviors using five distinct colors that will be used throughout this article to represent the different events: Las Vegas—red, Sutherland Springs—green, Marshall County—blue, Parkland—cyan, and Santa Fe—black. The order in which these events are presented in Figure 3(a) will also be preserved throughout this article for all similar figures for convenience. Figure 3(a) demonstrates the overall transient nature of the public's information-seeking behavior after a mass shooting event: In all the events examined here, there is a distinct spike in the public's interest in finding information in the immediate aftermath of the event. As will be discussed, however, this activity is only short-lived as a sharp decline in public search interest soon follows. For all events except the Las Vegas shooting, peak online search activity occurred on the day of the event. In the case of Las Vegas, this event took place around 10:00 PM Pacific time on a Sunday night (around 1:00 AM Eastern time), leading to the largest spike occurring only on the day after the event.

Figure 3(b) shows the superimposition of the times series presented in Figure 3(a) for the five events. The *y*-axis (i.e., search index volume) in this figure, however, has been limited to 20.0 to reveal the more subtle activity that occurs during the weeks and months after the event. As can be seen, even though information-seeking activity was still taking place weeks and months after an event, this activity was much more nuanced in the case of Las Vegas, Sutherland Springs, and Santa Fe. Marshall County has several spurts of activity occurring within the first month of the event with more prolonged activity occurring in the case of Parkland. As it relates to Parkland, several organized efforts after this event (e.g., student school walkouts, protests, and marches; Grinberg & Muaddi, 2018) may have contributed to sustaining a much higher public interest in this event compared with other events. These results indicate that the public's interest in mass shooting events can vary considerably, from a loss of interest shortly after an event to renewed reoccurring interest in the months afterward. Although our data cannot provide any direct causal explanation of this phenomenon, we can offer two potential explanations for it. First, it is possible that the public's renewed interest in a historic event stems from the reframing of stories about the event by media outlets. For example, in our study, as the Marshall County event occurred within 269 of the Las Vegas event, it is possible that the reignited public interest in the Las Vegas event was "triggered" by the media's coverage of the Marshall County event that included references to the Las Vegas event. A second explanation, similar in nature, is driven by the public's own ability to create associations between shooting events that "trigger" information-seeking behavior. Notably, in both explanations, search patterns emerge as a result of the creation of associations between events—either by the media or by the public itself. These possible explanations are explored further in our analysis of RQ 2 and RQ 3.

To understand public search behavior after each event, we applied a quantitative analysis in which we fit a decay function model to the time series of each event in Google Trends and Wikipedia page views. Given the overall shape of the time series analyzed here [e.g., Figure 3(a)], the following decay function was used to fit each time series:

$$y = ae^{-bx} + c \tag{1}$$

where x is the data series and a, b, and c represent the y-intercept, the decay parameter (or exponent of the function), and a constant, respectively. The values for a, b, and c were all determined in a data-driven manner using the optimize curve-fitting module located in the Python programming suite (Jones, Oliphant, & Peterson, 2001).

In columns 2 and 3 of Table 4, the values of the decay parameter b from the decay functions that were fitted to Google Trends and Wikipedia page view counts are summarized. As can be seen from this table, the results of the decay parameter for Google Trends and Wikipedia page views exhibit overall a distinct decay trend in the public's information-seeking activity over time. At the same time, the results indicate that the rate of decay of the public's information-seeking activity is different across the two platforms; specifically, the decay in Google Trends tends to be faster than it is in Wikipedia. These results therefore suggest that information-seeking activity after mass shooting events can vary substantially across online platforms and further highlight the different role of each platform: Although Google

TABLE 4 Values of the model parameters for Google Trends and Wikipedia page views

Corpus	Decay Parameter (b) Google Trends	Decay Parameter (b) Wikipedia Page Views	Local Minima (in days) Google Trends	Local Minima (in days) Wikipedia Page Views
Las Vegas	0.756 ± 0.011	–0.005 ± 0.006	10	N/A
Sutherland Springs	0.729 ± 0.011	0.282 ± 0.020	10	19
Marshall County	0.790 ± 0.012	0.023 ± 0.004	9	90
Parkland	0.277 ± 0.018	0.000 ± 0.000	19	N/A
Santa Fe	0.684 ± 0.008	0.191 ± 0005	10	25

Note. N/A entries indicates a value that could not be computed within the analysis time periods.

Trends often reflect the emergence of trending yet transient themes, Wikipedia page views often reflect the public's search for curated information about shooting events that persist over time. It is also important to note that even though in Google Trends the decay parameter (or rate) of the information-seeking activity is similar (with the exception of the Parkland event), Wikipedia page views do not exhibit such overall consistency. In particular, in Wikipedia, each event page has a considerably different decay rate. For instance, although the Sutherland Springs event has the highest rate of decay, the Parkland event does not exhibit a distinct decay trend.

To examine the overall trends exhibited by the decay parameters in Table 4, we also calculated the location of the "knee point" (measured in days since the event) along the time series curve of event in both Google Trends and Wikipedia page views using a heuristic developed by Satopaa, Albrecht, Irwin, and Raghavan (2011). The "knee point," which often coincides with the point of maximum curvature along a curve, is significant to the understanding of the public's search patterns because it indicates the time at which the public's information-seeking activity changes its dynamics and becomes consistent (analogous to a "steady state") over time [a more detailed discussion of the "knee point" detection problem is presented in Satopaa et al. (2011)]. The results of these calculations are shown in columns 4 and 5 of Table 4. These estimated locations (in days) of the local minima points show a similar behavior to the results obtained for the decay parameter b in our previous calculation: With the exception of Parkland, Google trends exhibits consistent activity after approximately 10 days, whereas some Wikipedia page views reach such consistent activity over a widely variable period of time (19 to 90 days) and others do not reach such consistency within the period examined here (269 days). It should be noted that the "N/A" values in Table 4 indicate cases in which a "knee point" was not found, implying that a change in the overall seeking activity had not been reached within the study period.

2.1.1 | Summary finding

Overall, in Google Trends, there is a discernable online pattern of engagement for mass shooting events, manifesting itself as a substantial peak within the first 24 to 48 hours of the event and dissipating after 10 days. Activism can substantially prolong this engagement as was seen in the case of Parkland.

2.2 | RQ 2: Given a current event, how are past events manifested in the corresponding online search patterns?

The emerging search patterns that were observed in our analysis of RQ 1 give rise to the possibility that the public's search activities with respect to a current event could be driven, at least in part, by associating it with past events. To study this possible association, we examine the search activity of the first four consecutive events in Table 1, namely, the Las Vegas, Sutherland Spring, Marshall County,

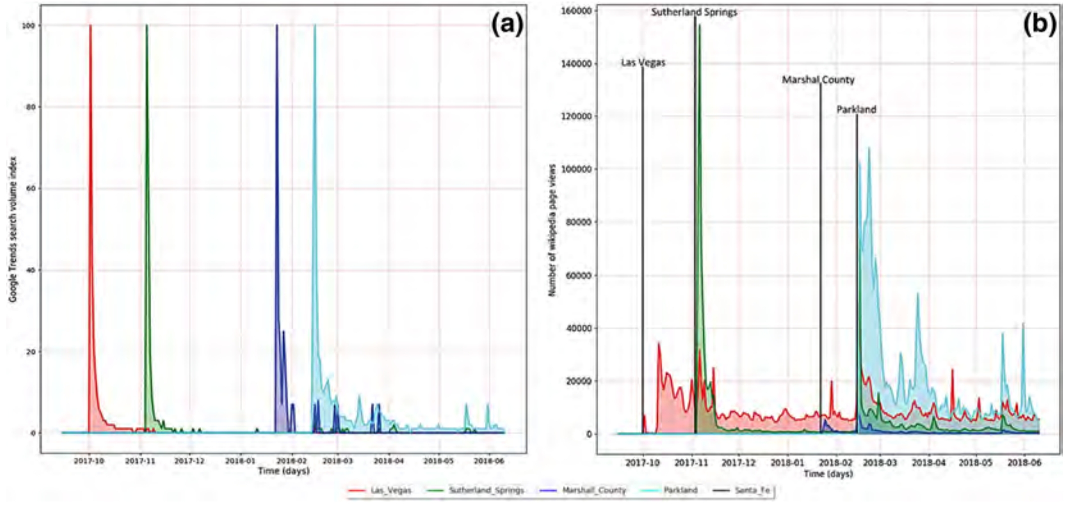

FIGURE 4 Chronologically ordered Google Trends search activity (a, left) and Wikipedia page views (b, right) [Color figure can be viewed at wileyonlinelibrary.com]
Note. Each vertical solid black line marks the occurrence of one of four shooting events examined in the analysis (as indicated by the line label).

and Parkland shooting events. The fifth event, Santa Fe, was omitted from this analysis as a result of Google Trends publicly available data time period limitation of 269 days (the Santa Fe event occurred only 40 days before the end of the 269 days period from October 1, 2017, thus, not providing a sufficient large time interval to examine search trends). Figure 4 depicts the search patterns in Google Trends and Wikipedia page views for each of the four events as they appear in chronological order. As this figure shows, there are some periods of time during which there is renewed public interest in searching information about a prior shooting event in the aftermath of a recent shooting event. For example, in Figure 4(a), a clear renewed interest in the Marshall County event emerges almost immediately after the Parkland event. Similarly, some search activity with respect to Sutherland Spring occurs after the Parkland event. The reemergence of public interest in prior events is even more pronounced in Wikipedia Page views [Figure 4(b)]. For example, a peak in the page view activity of the Las Vegas, Sutherland Springs, and Marshall County events reoccurs in conjunction with the distinct peak in the Parkland event in mid-February 2018. Combined, these results reveal that the public's information-seeking activity is not limited only to a currently occurring event but to the broader context of prior mass shooting events.

2.2.1 | Summary finding

The search patterns indicate an emerging association between these events, with preceding events recalled in the aftermath of a new mass shooting event.

2.3 | RQ 3: What is the relationship between online search patterns and news coverage of an event?

To understand better the interplay between media coverage of distinct shooting events and search patterns, we examined the relationship between news coverage of mass shooting events, the public's search activity, and other shooting events. In this analysis, we considered the number of news stories about

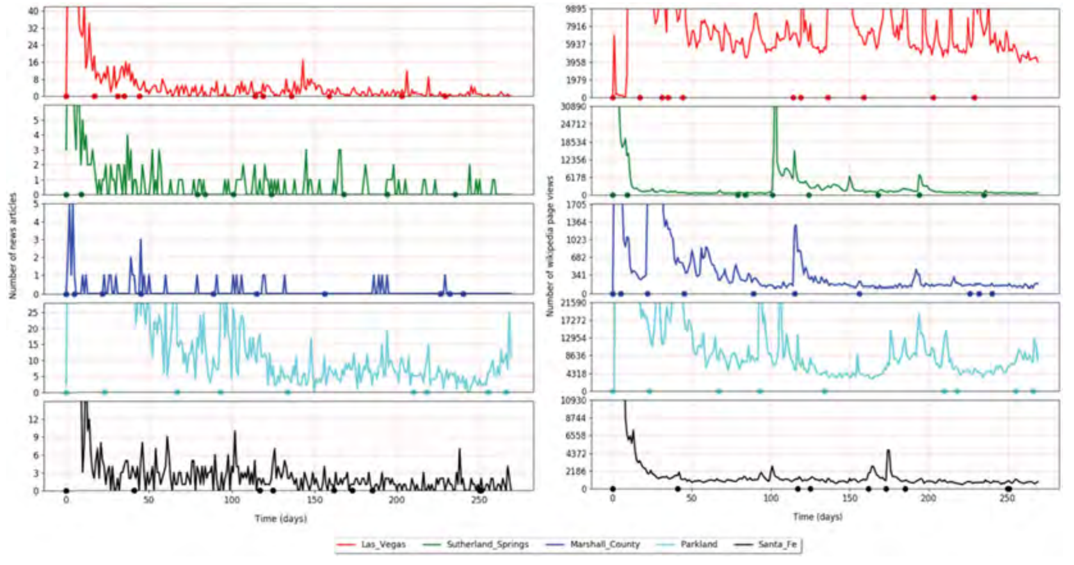

FIGURE 5 Volume of news stories from LexisNexis (left column) and Wikipedia page views (right column) for each mass shooting event studied [Color figure can be viewed at wileyonlinelibrary.com]
Note. Colored dots along the *x*-axis of each plot indicate a shooting event that occurred during the 269 days after each of the five studied events.

each of the five mass shooting events explored here as a measure of the news coverage, as well as how the number of Wikipedia page views correspond to these events as a measure of the public's information-seeking activity. Here, our focus on Wikipedia rather than on Google Trends stems from the results of our analysis of RQ 1, which indicated a much slower decay of the search activity in Wikipedia, thus, providing us a better opportunity to explore the relationship between the public's search activity and news coverage.

The time series of LexisNexis news articles and Wikipedia page views during a 269-day period after each event are shown in Figure 5. Similarly to the Google Trends activity previously observed in Figure 3(b), the *y*-axis of each figure is limited to a value lower than the maximum peak value to enable the examination of the finer fluctuations in the time series values (an exception is the LexisNexis data series for Marshall County, which was left unchanged as its largest value is five articles). For each time series, we also included the locations of all mass shootings during the specified period extracted from the Mother Jones (2019) online database; these locations are shown on the *x*-axis as circles for each event and are being used to study the extent to which the occurrence of an event impacts activity in news and online search behavior.

Figure 5 reveals some noteworthy observations regarding the relationship between news coverage and shooting events and between information-seeking activity and shooting events. First, it demonstrates that in general, large changes in the volume of news stories regarding each of the studied events are not always associated with the occurrence of subsequent shooting events (with the exception of the event itself). This is most noticeable in the volume of news stories regarding the Marshall County event, in which some subsequent events are not associated with any change in the volume of stories. In contrast, the number of Wikipedia page views exhibits a closer association with subsequent shooting events. Prominent examples of such an association can be seen in the case of Sutherland Springs, where a shooting event on approximately day 100 results in a spike in Sutherland Springs page views, as well as in the case of Marshall County, where an event on approximately day 120 results in a spike

TABLE 5 Values of the decay parameters for LexisNexis news articles

	LexisNexis News Stories	
Corpus	**Decay Parameter (*b*)**	**Local Minima (in days)**
Las Vegas	0.151 ± 0.009	29
Sutherland Springs	0.113 ± 0.011	35
Marshall County	0.142 ± 0.031	30
Parkland	N/A	N/A
Santa Fe	0.137 ± 0.008	30

in Marshall County page views. These results therefore further clarify the relationship between news coverage and online information-seeking activity, which indicates that the association between events tends to be driven by the public rather than by the media.

To examine the relationship between news coverage and the public's search patterns, a decay model was calculated for the LexisNexis time series of each of the five events using Equation 1 from which the value of a decay parameter b was derived. Additionally, the location of the knee point (in days since the event) along the time series curve of each event was calculated similarly to the analysis done for RQ 1. The results of these calculations are summarized in Table 5. In comparison with the decay parameters of the five events in Google Trends and Wikipedia, decay parameters that were derived for the five cases in LexisNexis indicate that media coverage decays substantially slower than Google Trends. Therefore, media outlets tend to sustain their reporting on mass shooting events for periods of time longer than the period during which the public seeks immediate information about such events. This idea is further supported by the location of the local minima, which is approximately 1 month (31 days on average) compared with approximately 10 days for Google Trends (Table 4).

2.3.1 | Summary finding

Media coverage of such events tends to last longer (31 days) than the public's engagement with the events themselves (10 days). Also, Wikipedia search patterns seem to reveal that the public is associating these individual events into a longer sequence, whereas news coverage does not seem to follow this pattern.

2.4 | RQ 4: Are there discernible geographic patterns of online searches?

Although public interest in seeking information about mass shooting events exhibits temporal patterns, it may also exhibit some geographic patterns. To explore this issue, we examined the results of Google Trends in Figure 6 using the Jenks natural breaks algorithm (Jenks, 1967). As the results in this figure show, there is substantial information-seeking activity in states in which shooting events have occurred; however, this interest is also variable across different states. Specifically, for the Las Vegas event, a large volume of search interest occurred in the western United States with most other states interested in this event as well. Given the high mortality and morbidity levels associated with this event (see Table 1), national interest in this event is also present but to a lesser extent (e.g., northeast United States). For Sutherland Springs, there seems to be almost a longitudinal pattern in search interest from Texas in the south to Montana in the north, and in the case of Marshall County, there was only search interest in immediately surrounding states. For Parkland, several surrounding states to Florida had high search interest, with a high volume of search activity in Wyoming. Like Sutherland Springs, there is also search interest in states surrounding Florida. Finally, for the Santa Fe event, there was overall similar search interest in surrounding states.

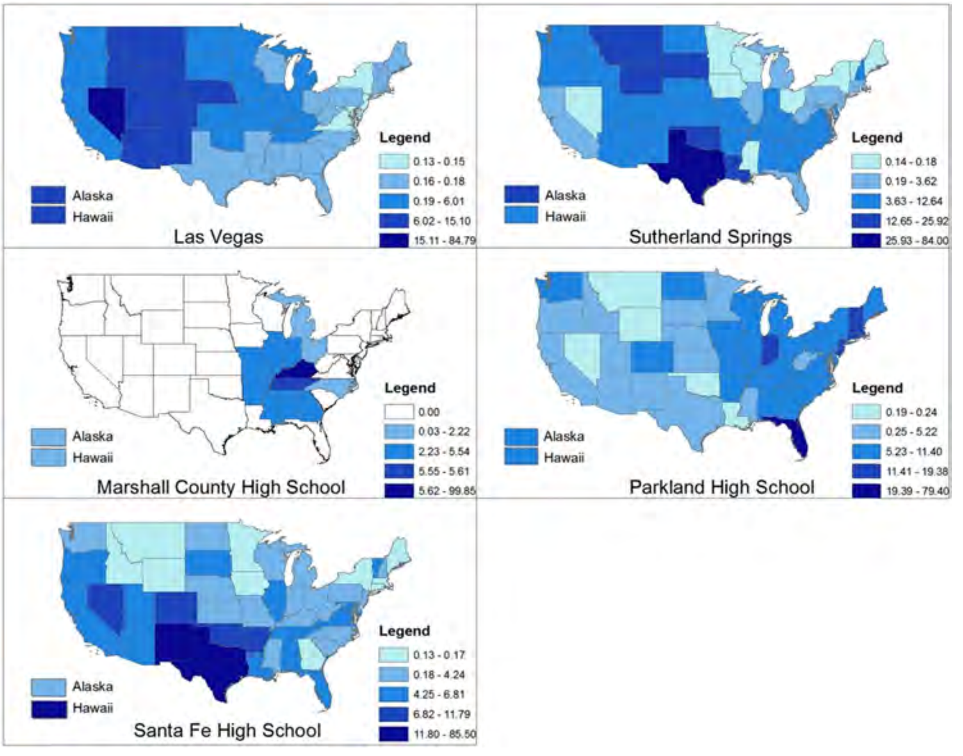

FIGURE 6 Geographic patterns in online search activity in google Trends for five events in our study [Color figure can be viewed at wileyonlinelibrary.com]

To examine the emergence of spatial patterns, we also compared search activity across events. Figure 7 shows bar charts with rescaled search volume values between 0 and 1 for each event based on our clustering results. The results in this figure are in line with the results in Figure 6 showing peak activity in states with mass shooting events, with all other states accounting for at most 20% of search interest. Parkland showed similar levels of search interest across all states outside of Florida with the exception of Montana and North Dakota. There are also similarly low levels of search interest for Sutherland and Santa Fe for several midwestern states (Wyoming, Colorado, New Mexico, Oklahoma, and Louisiana). For all other states, search interest in Sutherland Springs was slightly higher, but similar patterns were observed for these two Texas shooting events overall. Finally, for Las Vegas, search interest centered mainly on the western United States.

2.4.1 | Summary finding

There is a spatial pattern with respect to search interest in mass shootings. In general, we observe that the state affected by the mass shooting has the highest search interest with some regional engagement patterns also emerging.

2.5 | RQ 5: Do OSN contributions exhibit patterns comparable with online searches or news coverage?

As OSNs have emerged as a new platform for media communication and public discourse, it is of interest to explore the patterns of public engagement in them and to assess how such patterns compare

FIGURE 7 Normalized geographic patterns in online search activity in Google Trends Across United States for five events in our study [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 6 Values of the decay parameter (b) for Google Trends, Wikipedia page views, and LexisNexis news articles over a period of approximately 1 month

	Decay Parameter (*b*)			
Corpus	**Google Trends**	**Wikipedia Page Views**	**LexisNexis News Articles**	**Twitter Messages**
Las Vegas	0.815 ± 0.028	0.000 ± 0.005	0.345 ± 0.020	0.660 ± 0.090
Sutherland Springs	0.715 ± 0.028	0.270 ± 0.040	0.230 ± 0.060	0.260 ± 0.080
Marshall County	0.882 ± 0.022	0.060 ± 0.330	0.030 ± 0.004	0.061 ± 0.023
Parkland	0.320 ± 0.070	–0.010 ± 0.050	0.000 ± 0.025	0.240 ± 0.060
Santa Fe	0.670 ± 0.021	0.189 ± 0017	0.138 ± 0.031	0.000 ± N/A

Note. N/A entries indicates a value that could not be computed within the analysis time periods.

with information-seeking activities online (e.g., Google Trends). Towards this goal, we performed two analyses with the Twitter data (described in Table 3) that were collected on each of the five events studied here. In the first analysis, the decay parameter (based on Equation 1) of the public's engagement in Twitter was examined, whereas in the second analysis, the extent to which associations are made between events in the Twitter discourse was examined.

The results of the first analysis are summarized in Table 6. For comparison purposes, this table also includes the decay parameter values for Google Trends, Wikipedia page views, and LexisNexis for same corresponding period of time covered by the Twitter data set for each event. The decay parameter results for Twitter indicate that the public's engagement patterns in OSNs generally does not follow the search patterns observed in Google Trends. Engagement in Twitter shows a comparable decay behavior with Google Trends in the case of Las Vegas (0.660 and 0.815 in Twitter and Google Trends, respectively) and Parkland (0.240 and 0.320 in Twitter and Google Trends, respectively), and similar to the media in the case of Sutherland Springs (0.260 and 0.230 in Twitter and LexisNexis, respectively) and Marshall County (0.061 and 0.030 in Twitter and LexisNexis, respectively). As mentioned in RQ

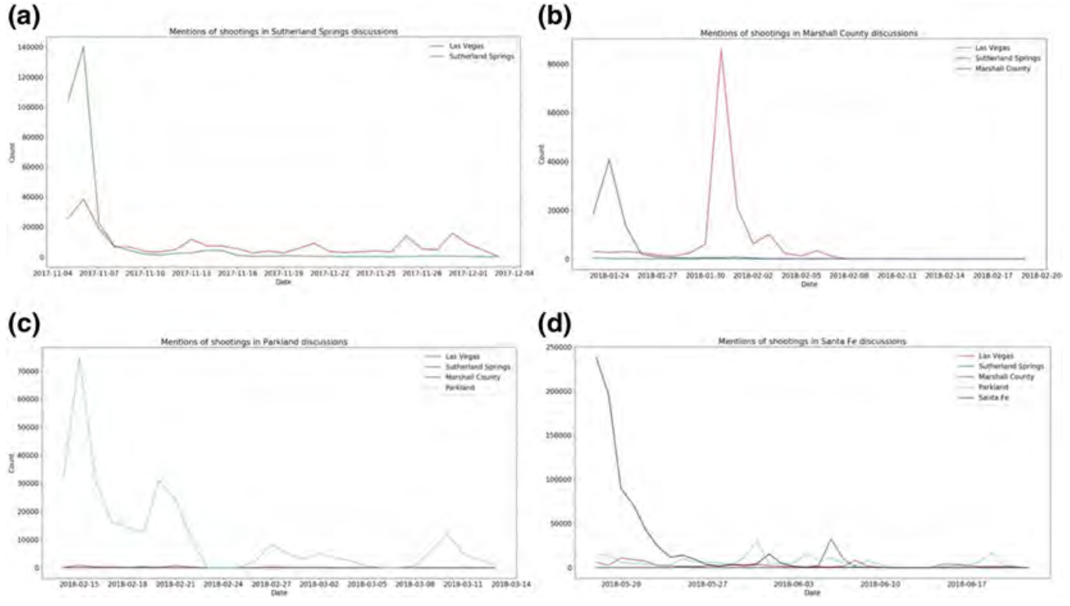

FIGURE 8 Mentions of prior events during first approximately 1-month period after each event in each event studied: (a) Sutherland Springs, (B) Marshall County, (C) Parkland, (D) Santa Fe [Color figure can be viewed at wileyonlinelibrary.com]

1, a reported decay parameter value of N/A in Table 6 (i.e., in the case of Santa Fe for Twitter) during the first month after an event is reflective of its ongoing nature in the context of this study.

In the second analysis, we explored the degree to which associations are made in Twitter between a current event and prior shooting events when a current event is being discussed. This analysis is similar in nature to the analysis presented for RQ 2, resulting in the time series shown in Figure 8. It should be noted that the Las Vegas event is not included as it was chronologically the first event in our event sequence. As can be seen from the figure, the discourses on Twitter regarding each of the five events do include references to prior events within the first month after each event. Therefore, associations are likely being made between an occurring event and the events preceding it. As with the associations between events that are being made in search activities in our exploration of RQ 1, the associations we observe in Twitter can be a combination of public-driven and media-induced reporting interests. For example, in the case of the Marshall County event, the association of that event with the Sutherland Springs and the Las Vegas events seem to be sustained over time, with the occurrence of a continual low (relative to the overall activity) intensity public-driven association between the three events. At the same time, the rapid increase and decrease in this association around January 31, 2018, seem to be driven more by news regarding the emergence of a second “person of interest” in the event. This combination of public-driven and media-driven association between events can, at least in part, be explained by the fact that media outlets often use OSNs as a platform for reaching a broader audience and for disseminating news stories quickly.

To conclude the examination of RQ 5, and specifically to gain some insight into the nature of the associations between events in Twitter, we constructed a hashtag network from the Twitter data set of each event. These networks were constructed by parsing all the Twitter messages for each event; afterward, all occurrences of unique hashtag pairs were identified and counted. In this network, nodes represent unique hashtags and edges between nodes indicate the co-occurrence of two hashtags in the

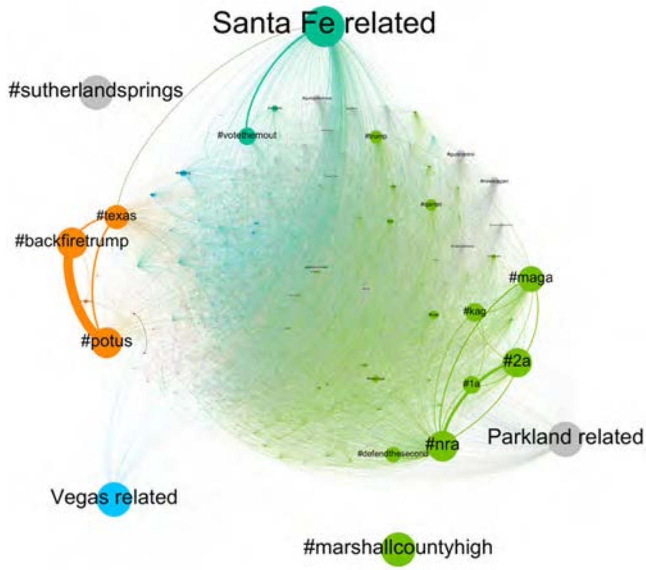

FIGURE 9 Hashtag network derived from Santa Fe event [Color figure can be viewed at wileyonlinelibrary.com]
Notes. Node size and edge width in this network are proportional to the degree centrality and the number of times two connected hashtags co-appear in a Twitter message, respectively. Different node and edge colors represent different clusters in the network.

same tweet. It should be noted that each edge in this network is associated with a weight, which is equal to the number of times two hashtags co-appeared in tweets. As the number of possible hashtag pairs is high, each network was filtered and aggregated as follows: (a) All network nodes with a degree centrality of 5 or less were eliminated, and (b) nodes that are explicitly related to the name of one of the five events examined were aggregated into a single node labeled with the name of the event. The discovery of the nodes related to each event was done by a combination of keyword searches and manual inspection of each network. Once constructed, a community detection algorithm was applied to identify emerging hashtag clusters in each network using a modularity-maximization algorithm.

An example of the networks that were constructed using this approach is shown in Figure 9, which depicts the network for the Santa Fe event. As this network shows, the Twitter discourse related to the Santa Fe event (dark green on the top) comprises hashtags related to this event as well as hashtags related to all four events preceding it, namely, Las Vegas (blue node on the bottom right), Sutherland Springs (gray node on the top left), Marshall County (green node on the bottom), and Parkland (gray node on the bottom left). The links between the different events, however, tend to be indirect, passing through one or more nodes that relate to the theme of mass shootings or another emerging topic in the discourse (e.g., the Vegas node is connected to the #sutherlandsprings node through the #texas node). Such indirect links indicate that the associations made between different events are driven by an underlying (e.g., a policy or an activism-related) theme.

2.5.1 | Summary finding

Overall, a discernable online pattern of engagement for mass shooting events is evident in Twitter that appears as a substantial peak within the first 24 to 48 hours after an event. This is similar to the pattern observed in Google Trends in RQ 1. In addition, associations between an event and its preceding events emerge in the online discourse.

3 | CONCLUSION AND POLICY RECOMMENDATIONS

As our society is grappling with the ongoing and expanding crisis of mass shootings, data analytics can provide a valuable tool to advance our understanding of the collective and evolving perception of this crisis and the policy issues associated with it. In this article, we provided representative examples of how data analytics can be leveraged to provide snapshots of public awareness and resulting collective opinions, as well as to monitor their evolution over time in response to subsequent mass shooting events. This is particularly important in today's hyper-engaged world, in which the general public continually accesses and contributes news and views on a scale unimaginable a couple of decades ago. Data analytics methodologies like the ones presented in this article can form the basis of a broader data-informed policy-making framework, wherein policymaking is constantly informed by public opinion and views, and the evolution of societal stances on relevant issues.

Toward this goal, the findings of our study contribute to our understanding of the interplay between the public and the media in relation to mass shooting events. Overall, distinct discernible patterns in both time and space were found in the public's online information-seeking activities. More specifically, public interest peaks during the first 24 to 48 hours after an event. Google Trends indicate that this interest is then gradually decaying over a period of approximately 10 days, indicating a short period of interest on the story. This finding expands on earlier work by Menachemi et al. (2017) on Sandy Hook and corresponding Yahoo! search engine queries, which showed a comparable period of engagement. When it comes to Wikipedia, however, which is a curated record of the event, public engagement displays more complex patterns, lacking the high peaks of Google Trends but also lacking the corresponding distinct decay (as shown in Figure 4). Compared with these processes, media coverage of mass shooting events, as captured by LexisNexis, tends to extend over a longer period of approximately 31 days. This is likely indicative of the media's own dynamic reframing process of such events (Muschert & Carr, 2006). The results of our study also indicate discernible online information-seeking patterns in geographic space, with a focal area of interest in the state in which the shooting event occurs, surrounded by a region of reduced interest. In addition, therefore, online information-seeking activities are likely driven, at least in part, by geographic proximity to mass shooting events.

Another key finding of our study is the emergence of associations between successive mass shooting events as we showed by analyzing social media references to them. These associations manifest themselves as references to prior events when discussing the current one and by sharing common terms when referring to such events. This is indicative of the public's view of them as sequences rather than as individual events.

In our study, such associations were shown to be present not only in the public's discourse in Twitter but also in information-seeking activities in Wikipedia. Our results show, however, that such associations are often made indirectly by linking different events through other related emerging topics in the overall discussion. Guggenheim, Jang, Bae, and Neuman (2015) suggested that a reciprocal relationship exists in the framing of mass shooting narratives between traditional media and OSNs. Similar to that earlier study, we found support for the idea that OSNs do not simply follow the media when it comes to associating different mass shooting events. Instead, such associations often originate from the public and provide a distinct context to the online discourse about this topic. Combined, these findings indicate that the interplay between OSNs and the media is not linear but based on complex dynamics that involve competing associations (or competing frames; Chong & Druckman, 2007).

Although we showcase the potential of our methodology for studying the interplay between the media and the public in mass shooting events in this article, this methodology could be further expanded toward the development of a more comprehensive research framework in several ways. First, it would be beneficial to explore how analyses such as the ones presented here could be better integrated with theories of risk communication (Palenchar & Heath, 2007) and the social amplification of risk (Kasperson et al., 1988). A second area of future exploration could involve the design of a more robust statistical analysis approach for examining and comparing the different data sources used here. Specifically, it would be of interest to examine how recent causation tools (e.g., recent work by Eberhardt & Scheines, 2007) could be used to improve understanding of the interplay between media coverage and public attention.

As stated, we believe that the methodology and findings of this study provide some noteworthy opportunities and challenges related to policy and decision-making related to the phenomenon of public mass shootings in the United States. The current richness of OSNs in terms of diversity and availability of large volumes of data and the timeliness of such data provide a unique opportunity to gain valuable insights into how the public perceives and frames such events over time and space. By studying the evolution of discourse in OSNs through such "big data," we are provided with a lens to observe how society's views on certain issues of broad interest are formed and evolve. As we pursue this goal, it is important to remain cognizant of the particularities of such online discourse ecosystems. They comprise echo chambers (formed by clusters of users that share common views and opinions) and open forums (where users of diverse views debate the issue (Williams, McMurray, Kurz, & Lambert, 2015). The complex dynamics of each component separately, and both jointly, help shape public opinion. Echo chambers are strengthening opinion bases, whereas open forums are refining arguments and counterarguments, in the process setting the discourse agenda and framing its conduct.

This process of discourse conduct and public opinion shaping online has strong policy implications. Höchtl, Parycek, and Schöllhammer (2016) referred to this complex and evolving interplay between policy-making and public discourse in social media as "e-policymaking," in which the public is constantly polled during dynamic policy-making cycles (Höchtl, Schossböck, Lampoltshammer, & Parycek, 2017) rather than as a separate step at the end of the policy-making process (Ferro, Loukis, Charalabidis, & Osella, 2013, Misuraca, Mureddu, & Osimo, 2014). This would allow for tapping into the dynamic process of reshaping and reframing public mass shooting events in the public sphere and enable it to be modeled. The deep understanding of this process, along with the associations drawn between such events, can then provide policy and decision makers with opportunities to communicate better the significance of their goals and objectives.

The utilization of such data analytics approaches for policymaking in the context of public mass shooting events is, however, not without challenges. Chief among such challenges is the risk of manipulation of the discourse about such events in OSNs. Although OSNs are particularly convenient for publishing and consuming content about breaking events, they have proven to be more susceptible to manipulation compared with more traditional media outlets. In particular, OSNs have often been used to spread and amplify incorrect, misleading, or false narratives to achieve certain public opinion goals (Bolsover & Howard, 2017; Lazer, Baum, & Benkler, 2018; Starbird, 2017; Schuchard, Crooks, Stefanidis, & Croitoru, 2019; Vosoughi, Roy, & Aral, 2018). Such manipulations can lead to fallacious changes in public opinion that could then propagate to and influence the policy-making process. The incorporation of such data in e-policymaking practices, therefore, places the burden of judging the accuracy of information about mass shootings on the data users.

Beyond policy- and decision-making, the ability to understand better the media ecosystem and the results of this study have some potential practical implications for addressing mass shooting events. As noted by Lankford and Madfis (2018), the nature of the coverage of such events in traditional media and OSNs has several real implications that have the potential to affect victims and shooters of past events as well as potential future events. This idea is further supported by the findings from a recent study in which a correlation between the occurrence of a mass shooting and the rate of growth in firearm acquisition was identified (Porfiri, Sattanapalle, Nakayama, Macinko, & Sipahi, 2019). Given such implications, Lankford and Madfis (2018) proposed a possible communication strategy for deterring possible future offenders from considering action. We believe that such strategies could be further improved by considering the dynamics of the coverage and reframing process, and the associations made between events and themes in addition to considering what is being covered in the media ecosystem.

ENDNOTE

[1] https://archive.is/YalhQ.

ORCID

Arie Croitoru https://orcid.org/0000-0002-8470-9273
Sara Kien https://orcid.org/0000-0003-2533-902X
Ron Mahabir https://orcid.org/0000-0002-5553-5366
Jacek Radzikowski https://orcid.org/0000-0001-9542-2190
Andrew Crooks https://orcid.org/0000-0002-5034-6654
Ross Schuchard https://orcid.org/0000-0003-0070-6030
Anthony Stefanidis https://orcid.org/0000-0002-8165-0667

REFERENCES

Abrutyn, S., & Mueller, A. S. (2014). September). Reconsidering Durkheim's assessment of Tarde: Formalizing a Tardian theory of imitation, contagion, and suicide suggestion. *Sociological Forum*, *29*(3), 698–719. Retrieved from https://doi.org/10.1111/socf.12110

Blair, J. P., & Schweit, K. W. (2014). *A study of active shooter incidents, 2000-2013*. Washington, DC: Texas State University and Federal Bureau of Investigation, U.S. Department of Justice.

Bolsover, G., & Howard, P. (2017). Computational propaganda and political big data: Moving toward a more critical research agenda. *Big Data*, *5*, 273–276. Retrieved from https://doi.org/10.1089/big.2017.29024.cpr

Chong, D., & Druckman, J. N. (2007). Framing public opinion in competitive democracies. *American Political Science Review*, *101*(4), 637–655.

Dahmen, N. S. (2018). Visually reporting mass shootings: US newspaper photographic coverage of three mass school shootings. *American Behavioral Scientist*, *62*(2), 163–180. Retrieved from https://doi.org/10.1177/0002764218756921

Eberhardt, F., & Scheines, R. (2007). Interventions and causal inference. *Philosophy of Science*, *74*(5), 981–995.

Ferro, E., Loukis, E. N., Charalabidis, Y., & Osella, M. (2013). Policy making 2.0: From theory to practice. *Government Information Quarterly*, *30*(4), 359–368.

Fink, D. S., Santaella-Tenorio, J., & Keyes, K. M. (2018). Increase in suicides the months after the death of Robin Williams in the US. *PLoS One*, *13*(2), e0191405. Retrieved from https://doi.org/10.1371/journal.pone.0191405

Fox, J. A., & DeLateur, M. J. (2014). Mass shootings in America: Moving beyond Newtown. *Homicide Studies*, *18*(1), 125–145. Retrieved from https://doi.org/10.1177/1088767913510297

Grinberg, E., & Muaddi, N. (2018). How the Parkland students pulled off a massive national protest in only 5 weeks. *CNN*.

Guggenheim, L., Jang, S. M., Bae, S. Y., & Neuman, W. R. (2015). The dynamics of issue frame competition in traditional and social media. *The ANNALS of the American Academy of Political and Social Science*, *659*(1), 207–224.

Gunn, L. H., Ter Horst, E., Markossian, T. W., & Molina, G. (2018). Online interest regarding violent attacks, gun control, and gun purchase: A causal analysis. *PLoS one*, *13*(11), e0207924. Retrieved from https://doi.org/10.1371/journal.pone.0207924

Höchtl, J., Parycek, P., & Schöllhammer, R. (2016). Big data in the policy cycle: Policy decision making in the digital era. *Journal of Organizational Computing and Electronic Commerce*, *26*(1-2), 147–169.

Höchtl, J., Schossböck, J., Lampoltshammer, T. J., & Parycek, P. (2017). The citizen scientist in the epolicy cycle. In *Government 3.0–next generation government technology infrastructure and services* (pp. 37–61). New York, NY: Springer.

Jenks, G. F. (1967). The data model concept in statistical mapping. *International Yearbook of Cartography*, *7*, 186–190.

Jones, E., Oliphant, T., Peterson, P. et al. (2001). SciPy: Open source scientific tools for Python. Retrieved from http://www.scipy.org/

Kasperson, R. E., Renn, O., Slovic, P., Brown, H. S., Emel, J., Goble, R., & Ratick, S. (1988). The social amplification of risk: A conceptual framework. *Risk Analysis*, *8*(2), 177–187.

Kaufman, L., & Rousseeuw, P. J. (1990). Partitioning Around Mediods (Program PAM). In *Finding groups in data: An introduction to cluster analysis* (pp. 68–125). Hoboken, NJ: John Wiley & Sons.

Katsiyannis, A., Whitford, D. K., & Ennis, R. P. (2018). Historical examination of United States intentional mass school shootings in the 20th and 21st centuries: Implications for students, schools, and society. *Journal of Child and Family Studies*, *27*(8), 2562–2573. Retrieved from https://doi.org/10.1007/s10826-018-1096-2

Knoll, J. L. I. V., & Annas, G. D. (2016). Mass shootings and mental illness. In L. H. Gold & R. I. Simon (Eds.), *Gun violence and mental illness* (pp. 81–104). Arlington, VA: American Psychiatric Association.

Krouse, W. J., & Richardson, D. J. (2015). *Mass murder with firearms: Incidents and victims* (pp. 1999–2013). Washington, DC: Congressional Research Service.

Langman, P. (2018). Different types of role model influence and fame seeking among mass killers and copycat offenders. *American Behavioral Scientist*, *62*(2), 210–228. Retrieved from https://doi.org/10.1177/0002764217739663

Lankford, A. (2016). Are America's public mass shooters unique? A comparative analysis of offenders in the United States and other countries. *International Journal of Comparative and Applied Criminal Justice*, *40*(2), 171–183. Retrieved from https://doi.org/10.1080/01924036.2015.1105144

Lankford, A., & Madfis, E. (2018). Don't name them, don't show them, but report everything else: A pragmatic proposal for denying mass killers the attention they seek and deterring future offenders. *American Behavioral Scientist*, *62*(2), 260–279. Retrieved from https://doi.org/10.1177/0002764217730854

Lazer, D. M. J., Baum, M. A., Benkler, Y. et al. (2018). The science of fake news. *Science*, *359*, 1094–1096. Retrieved from https://doi.org/10.1126/science.aao2998

Levin, J., & Wiest, J. B. (2018). Covering mass murder: An experimental examination of the effect of news focus—killer, victim, or hero—on reader interest. *American Behavioral Scientist*, *62*(2), 181–194. Retrieved from https://doi.org/10.1177/0002764218756916

Mahabir, R., Croitoru, A., Crooks, A., Agouris, P., & Stefanidis, A. (2018). News coverage, digital activism, and geographical saliency: A case study of refugee camps and volunteered geographical information. *PloS one*, *13*(11), e0206825. Retrieved from https://doi.org/10.1371/journal.pone.0206825

Menachemi, N., Rahurkar, S., & Rahurkar, M. (2017). Using web-based search data to study the public's reactions to societal events: The case of the Sandy Hook shooting. *JMIR Public Health and Surveillance*, *3*(1), e12. Retrieved from https://doi.org/10.2196/publichealth.6033

Misuraca, G., Mureddu, F., & Osimo, D. (2014). Policy-making 2.0: Unleashing the power of big data for public governance. In *Open government* (pp. 171–188). New York, NY: Springer.

Mitchell, A., Simmons, K., Matsa, K. E., Silver, L., Shearer, E., Johnson, C., … Taylor, K. (2018). In Western Europe, public attitudes toward news media more divided by populist views than left-right ideology. *Pew Research Center*, Retrieved from http://www.journalism.org/2018/05/14/in-western-europe-public-attitudes-toward-news-media-more-divided-by-populist-views-than-left-right-ideology

Moffat, B. S. (2019). Medical response to mass shootings. In *Disasters and Mass Casualty Incidents* (pp. 71–74). New York, NY: Springer.

Mother, Jones (2019). US mass shootings, 1982–2019: Data from Mother Jones' investigation. Retrieved from https://www.motherjones.com/politics/2012/12/mass-shootings-mother-jones-full-data/

Mullen, P. E. (2004). The autogenic (self-generated) massacre. *Behavioral Sciences & the Law*, *22*(3), 311–323. Retrieved from https://doi.org/10.1002/bsl.564

Murray, J. L. (2017). Mass media reporting and enabling of mass shootings. *Cultural Studies↔ Critical Methodologies*, *17*(2), 114–124. Retrieved from https://doi.org/10.1177/1532708616679144

Muschert, G. W., & Carr, D. (2006). Media salience and frame changing across events: Coverage of nine school shootings, 1997–2001. *Journalism & Mass Communication Quarterly*, *83*(4), 747–766.

Palenchar, M. J., & Heath, R. L. (2007). Strategic risk communication: Adding value to society. *Public Relations Review*, *33*(2), 120–129.

Paradice, D. (2017). An analysis of us school shooting data (1840–2015). *Education*, *138*(2), 135–144.

Porfiri, M., Sattanapalle, R. R., Nakayama, S., Macinko, J., & Sipahi, R. (2019). June 24). Media coverage and firearm acquisition in the aftermath of a mass shooting. *Nature Human Behavior*. Retrieved from https://doi.org/10.1038/s41562-019-0636-0

Satopaa, V., Albrecht, J., Irwin, D., & Raghavan, B. (2011). *Finding a "kneedle" in a haystack: Detecting knee points in system behavior*. Paper presented at the 2011 31st IEEE International Conference on Distributed Computing Systems Workshops.

Schildkraut, J., & McHale, R. (2018). Covering rampage: News consumers' perceptions about mass shootings in the media. Paper presented at the annual meeting of the Academy of Criminal Justice Sciences, New Orleans, LA.

Schuchard, R., Crooks, A., Stefanidis, A., & Croitoru, A. (2019). *Bots fired: Examining social bot evidence in online mass shooting conversations*, New York, NY: Palgrave Communications.

Silva, J. R., & Capellan, J. A. (2019). The media's coverage of mass public shootings in America: Fifty years of newsworthiness. *International Journal of Comparative and Applied Criminal Justice*, *43*(1), 77–97. Retrieved from https://doi.org/10.1080/01924036.2018.1437458

Stack, S. (2002). Media coverage as a risk factor in suicide. *Injury Prevention*, *8*(suppl 4), iv30–iv32. Retrieved from https://doi.org/10.1136/ip.8.suppl_4.iv30

Starbird, K. (2017). Examining the alternative media ecosystem through the production of alternative narratives of mass shooting events on Twitter. Paper presented at the Eleventh International AAAI Conference on Web and Social Media.

Thorndike, R. L. (1953). Who belongs in the family? *Psychometrika*, *18*(4), 267–276.

Towers, S., Gomez-Lievano, A., Khan, M., Mubayi, A., & Castillo-Chavez, C. (2015). Contagion in mass killings and school shootings. *PLoS one*, *10*(7), e0117259. Retrieved from https://doi.org/10.1371/journal.pone.0117259

Ueda, M., Mori, K., Matsubayashi, T., & Sawada, Y. (2017). Tweeting celebrity suicides: Users' reaction to prominent suicide deaths on Twitter and subsequent increases in actual suicides. *Social Science & Medicine*, *189*, 158–166. Retrieved from https://doi.org/10.1016/j.socscimed.2017.06.032

Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, *359*, 1146–1151. https://doi.org/10.1126/science.aap9559

Wasserstein, L. N. (1969). Markov processes with countable state space describing large systems of automata. *Problemy Peredachi Informatsii*, *5*(3), 64–73.

Williams, H. T., McMurray, J. R., Kurz, T., & Lambert, F. H. (2015). Network analysis reveals open forums and echo chambers in social media discussions of climate change. *Global Environmental Change*, *32*, 126–138.

AUTHOR BIOGRAPHIES

Arie Croitoru is an Associate Professor at the Department of Geography and Geoinformation Science at George Mason University and the Director of the College of Science Center for Geospatial and Open-Source Intelligence at Mason. He received his Ph.D. in Mapping & Geoinformation Engineering in 2002 and was a postdoctoral fellow at the National Center for Geographic Information and Analysis (NCGIA) at the University of Maine. His expertise is in geoinformatics, with a particular focus on geospatial data mining and knowledge discovery from social media and other emerging open data sources.

Sara Kien received her PhD in Cognitive Psychology from Northwestern University in 2008. Her research focuses on culture and cognition, including cultural differences in folkbiological thought and implications for culturally-based STEM education. Her recent research examines the role of media in normalizing mass shootings. She is dedicated to increasing diversity in the psychological sciences, having collaborated with Indigenous communities for 15 years and serving as Chair of Social and Behavioral Sciences at Diné College on the Navajo Nation, during which time she spearheaded development of the culturally-based Navajo Psychology BA program. She is currently developing an Indigenous Psychology program in the Department of Psychological Sciences at Northern Arizona University.

Ron Mahabir is an Assistant Professor in the Department of Computational and Data Sciences at George Mason University. His research focuses on the use of geospatial data science tools and techniques applied to different areas of urban and rural systems, in order to explore and understand the different components of these systems, and to provide solutions that will contribute towards smart, resilient and sustainable cities. More information about his research can be found at: http://www.digitalgeo.org

Jacek Radzikowski holds Master of Science degrees in Computer Science (from Warsaw University of Technology) and Computational Sciences (from George Mason University), and is currently working on his PhD degree in Earth Systems Geoinformation Sciences ate GMU. His area of expertise is collection, processing and geospatial analysis of information collected from social media.

Andrew Crooks is an associate professor of Computational Social Science within the Department of Computational and Data Sciences at George Mason University. His research interests relate to exploring and understanding of the natural and socioeconomic environments using geographical information systems (GIS), social network analysis, and agent-based modeling methodologies. More information about his research can be found at: http://gisagents.org.

Ross Schuchard received his PhD in Computational Social Science from the Department of Computational and Data Sciences at George Mason University. His primary research interests focus on exploring social complexity through the lens of simulation modeling and social network analysis. Prior to his PhD studies, Ross worked in the defense industry developing cyber analytics.

Tatyanna Begay received her Bachelor's degree in Psychology from Diné College in May 2019. Her degree emphasizes in the Indigenous and Western psychology aspects to promote holistic well-being for individuals, families, and communities. Within the collaboration between Diné College and George Mason University, her recent research focuses on the social media content within the contagion period of mass shootings. Tatyanna's academic interests are to continue the psychology research field with an Indigenous approach that will promote positive solutions for health disparities that Native American communities experience. Currently, she is contributing to her community by developing a non-profit community clean up organization that targets illegal dumpsites around Tuba City, Arizona, in hopes to reverse generational learned habits of illegal dumping.

Ashley Lee obtained her Bachelor's degree in Psychology from Diné College in the spring of 2019. Her recent research focuses on the role of media in mass shootings, studies which were facilitated through a collaboration between Diné College and George Mason University. Her research interests range from mass shootings, grief in a cultural context, and as an Indigenous researcher she is directing her focus to issues on the Navajo reservation. She is currently employed as a Research Assistant with Johns Hopkins University, aiding in a Diné hydration project on the Navajo Nation.

Alex Bettios is a senior at Langley High School in McLean, Virginia. His work featured in this paper is the result of a summer internship with the CINA COE and the Center for Geospatial Intelligence at GMU. He will be attending William & Mary in September of 2020 studying Computer Science. Alex's interests include computer programming, computer game design, data science, and cybersecurity.

Anthony Stefanidis is a Professor of Computer Science at the College of William & Mary. His work featured in this paper was performed in his prior appointment as Director of the Criminal Investigations and Network Analysis (CINA) DHS Center of Excellence at George Mason University. His research interests focus on a variety of geospatial applications, including the analysis of crowdsourced content and social media contributions to monitor issues of broad societal interest.

How to cite this article: Croitoru A, Kien S, Mahabir R, et al. Responses to mass shooting events: The interplay between the media and the public. *Criminol Public Policy*. 2020;19:335–360. https://doi.org/10.1111/1745-9133.12486