

## Analysis of Social Media Based on Terrorism — A Review

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With the ever-growing number of online social media platforms, the world has shrunk even further with regards to communication and knowledge-sharing perspective. However, communication, at times, can be deterrent when misused using such widespread social media tools. The acts of terrorism become seemingly convenient as the barrier of communication is nullified. This propagation of hateful content becomes much more easier and even recruiting anti-socials gets easier. Oddly, these social media platforms are the ones that prove essential during such crisis situations. This paper reviews most of the works reported by various authors in the last 10 years on the use of social media during a time of terrorist attack to addressing how to use social media for public communication with the emergency organization and military or police during terrorist attack, how to perform post-attack social media analytic and how to detect acts of terrorism, unrest, and hatred using social media analytic. With this objective, the authors also hope to inspire other researchers to work in this direction and use this review as a guide for instigating future research to counter-attack terrorism as it is the need of the hour for our country in the wake of recent Uri and Pulwama attack.

*Keywords:* Social media analytics; terrorism; sentiment analysis.

### 1. Introduction

Social media today, plays a very essential part in the life of not only an individual but also in the functioning of a government. Statistics show that the current world population is 7.8 billion as of February 2020 whereas internet users are not less than a billions. The power of social networking is such that the number of worldwide users is expected to reach 3.02 billion monthly active social media users by 2021. The impact of social media on society, people and the corresponding data that generates in the wake of it, has been discussed comprehensively in Refs. 1–4. The progress of 21st

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century can barely be anticipated without the indication of social media in it. It would not be overstating to say that social media is ubiquitously present in all spheres of life be it education, health care, business, disaster management, politics, tourism industry, and of course, the use of media sharing and entertainment needs no mention. Apart from all such conveniences provided by the social media, it does have a darker side to cast.<sup>5</sup> Misuse of social media which is the other side of the coin, also needs to be accounted for. On one hand, this may seem to abridge the communication gap and faster news delivery among people; on the other hand, it is being heavily misused by many; misuse on a level of genocide, murders, bombings, conspiracies, etc. In a study conducted by Medina,<sup>6</sup> the author states that about 90% of terrorist activities online are conducted via social media platforms while 76% of U.K. terrorists engage in the internet to research and strategize their actions. In 2013, ASG, a terrorist organization, kidnapped Australian Warren Rodwell and held him for about 472 days. The group made use of YouTube and Facebook for ransom videos and to demonstrate the proof of life. A robust literature conducted by Borau and Wamba,<sup>7</sup> revealed the extensive use of social media by terrorist organizations to advertise their ideology and enroll members and supporters. The usage of proactive social media tactics by three extremist-related groups operational in Asia Pacific has been examined by Droogan *et al.*<sup>8</sup> This study explains how these groups afford numerous opportunities to exploit their reach, impact, and effect using social media. Another such misuse of social media has been examined by Fisher,<sup>9</sup> who present the social media activity and their online presence and circulate propaganda content online. The ISIS and social media involvement have been briefly examined and presented by Hutchinson *et al.*<sup>10–12</sup>

On a positive note, social media can also be of a great help for military, defense, and public with regards to safety during an unfortunate terrorist event as those reported by Teodorescu *et al.*,<sup>13,14</sup> The overview of social media in conflict areas of Ukraine, Palestine, Syria, and Republika Srpska has been presented as a case study by Aal *et al.*<sup>15</sup> A comprehensive review of how social media tools are being used in disasters by the public, emergency organizations, and academic institutions have been well reported by Simon *et al.*<sup>16</sup> It discusses the literature related to the use of social media in emergencies from 2007 to 2014. Another detailed and semi-systematic review describing the growing contours of social media research in the sphere of counter-terrorism has been presented by Bartlett and Miller<sup>17</sup> It suggests a method, potentially for usage considered by the various researchers to be widely applicable to the purpose of countering terrorism. The behavioral side of social media has been explored by Kapoor *et al.*<sup>18</sup> to assess the evolution of social media and social networking from 1997 to 2017. Policing of terrorism using the data from social data and the countermeasures to be taken against it are lucidly explained by Pelzer *et al.*<sup>19,20</sup> Figures 1 and 2 show the evolution of terms *social media analytics* in India and worldwide on the Internet over region and time.

An overall perspective on the goodness and evil of social media in today's global scenario has been described by Dwivedi *et al.*,<sup>21</sup> wherein the author discusses the

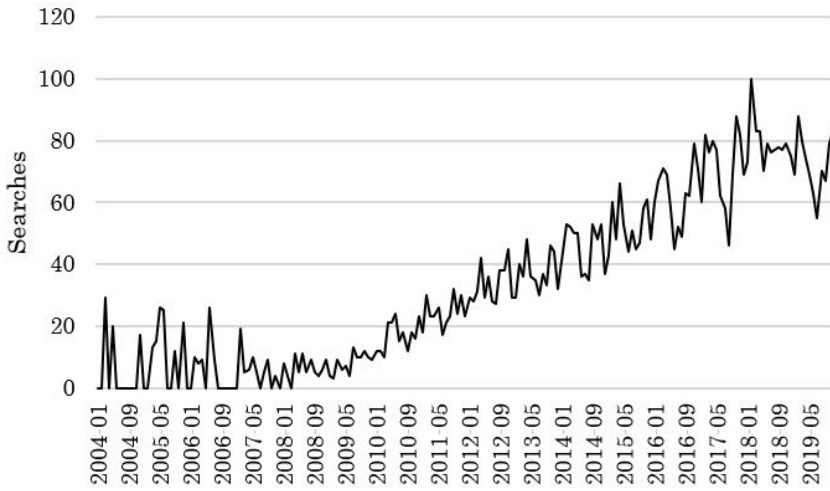


Fig. 1. Web search of term Social Media Analytics of Worldwide from 2004-present (Using Google Trends).

seemingly endless benefits of social media and the taboo that it brings with it in various walks of life. With the ever-growing use of some popular social media like Twitter, Facebook, Youtube, Instagram, LinkedIn, etc., there have been several other social media platforms surfacing and gaining a strong foothold on the grounds of the virtual world. A list and details of such social media platforms have been tabulated in Table 1. More the number of networking options, the greater is the danger of facing such unfortunate crises. The terrorist attacks, religious hypocrisy, and cultural incompatibility among the people of various sects, region or country

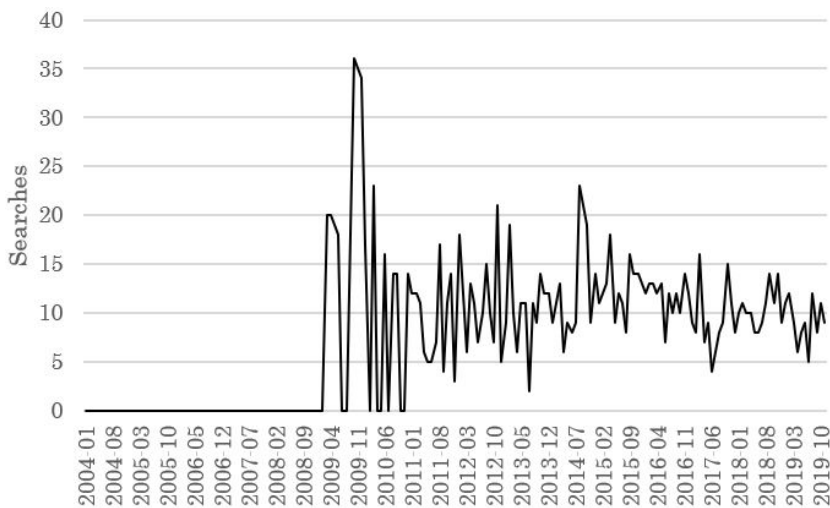


Fig. 2. Web search of term Social Media Analytics of India from 2014-present (Using Google Trends).

Table 1. List of popular social networking websites.

Platform	Type	Active users/month
Facebook	Social networking site	1.59 billion
WhatsApp	Communication-based	1 billion
QQ	Communication-based	853 million
WeChat	Communication-based	697 million
QZone	Social networking site	640 million
Tumblr	Micro blogging	555 million
Instagram	Media Sharing Networks	400 million
Twitter	Social networking site	320 million
Google+	Media Sharing Networks	300 million
Skype	Communication-based	300 million
Sina Weibo	Microblogging social platform	222 million
VKontakte (VK)	Social networking (Russia)	100 million
Pinterest	Media Sharing Networks	100 million
LinkedIn	Social networking platforms	100 million
Reddit	Social networking	100 million
Taringa	Social networking (L America)	75 million
Renren	Social networking (China)	30 million
Tagged	Friendship and dating	25 million

drives enough hatred to give rise to ghastly attacks. It is extremely necessary to manage peace, safety measures, and counter-terrorism using the fastest way possible. The use of social media is one of the ways in this digital era.

Hence, the current paper focuses on collecting all the relevant studies, works and researches reported by various authors in last 10 years concerning the use of social media during a time of terrorist attack to address following issues:

- (1) How to use social media for public communication with the emergency organization and military or police during a terrorist attacks?
- (2) How to perform post-attack social media analytics?
- (3) How to detect acts of terrorism, unrest and, hatred using social media analytic?

The current review discusses the foundations of terrorism as well as the nature and geography of terrorist groups. It is essential to understand that terrorism has a long history, it is not new. Terrorism has been defined in multiple forms and emerges from diverse sources. Terrorists usually aim civilians or non-participants and are mostly sub-national or hidden groups. Terrorism has many types like the connectivity between international terrorist groups of a certain era and is defined by three characteristics:

- (1) a cycle of activity in a given time period showing expansion and contraction phases,
- (2) international character, and
- (3) a prime energy that drives and shapes the group characteristics and relationships.

As reported by Rapoport,<sup>22</sup> the most usual root of terrorism includes civilizations or religious globalization, Israeli–Palestinian conflict, culture clashes, or the Russian invasion of Afghanistan. More personal or individual-based reasons for terrorism are frustration, deprivation, negative identity, narcissistic rage, or moral disengagement.

The four strains have identified by Parker and Sitter<sup>23</sup> all date from the same period, and although they have mostly developed separately since, they do occasionally combine and mutate. These four horsemen of terrorism are:

- (1) Nationalism,
- (2) Socialism,
- (3) Religious Extremism, and
- (4) Social Exclusion.

With this objective, the authors also hope to inspire other researchers to work in this direction and use this review as a guide for instigating future research to counter attack terrorism as it is the need of the hour for our country in the wake of recent Uri and Pulwama attack.

## 2. Event-Based Studies

Social media have gained grounds firmly since last decade. Any unfortunate event across a globe is not a distant crisis anymore. Within a few minutes almost every digitally active citizen of every country gets the detailed knowledge of these events. Such kind of social media data has been evaluated, examined, and used as a tool for safety, precaution, detection, and future-prevention strategies by many researchers. This section discusses some major terrorist event occurrences and the role of social media in it. The graph plotted based on the total number of tweets during emergencies that occurred in the year 2008 to 2017 is shown in Fig. 3.

### 2.1. Manchester Bombing, UK — 22 May 2017

The Manchester bombing on 22nd May 2017, was a suicide bombing attack where a homemade bomb as the crowd was departing from the Arena after a concert of the American singer Ariana Grande. This was seen as an act of terrorism. Around 23 citizens died, including the perpetrator, and about 139 were wounded with most of them being children. Convergence Behavior (CB) on social media during this crisis situation was studied by Mirbabaie *et al.*<sup>24</sup> This study identified the Helpers to be the CB Archetypes who were the most to retweet all over the crisis. On the other hand, the Mourners had the highest impact by retweeting the most. This indicated that those users who create emotional content tend to retweet the most. Additionally, the Detectives disseminated information into other communities, the most. The authors not only extended the knowledge on how users converge on social media in crisis situations, but also help the crisis managers to get more insight into users behavior. Knowing which type of behavior on social networks has

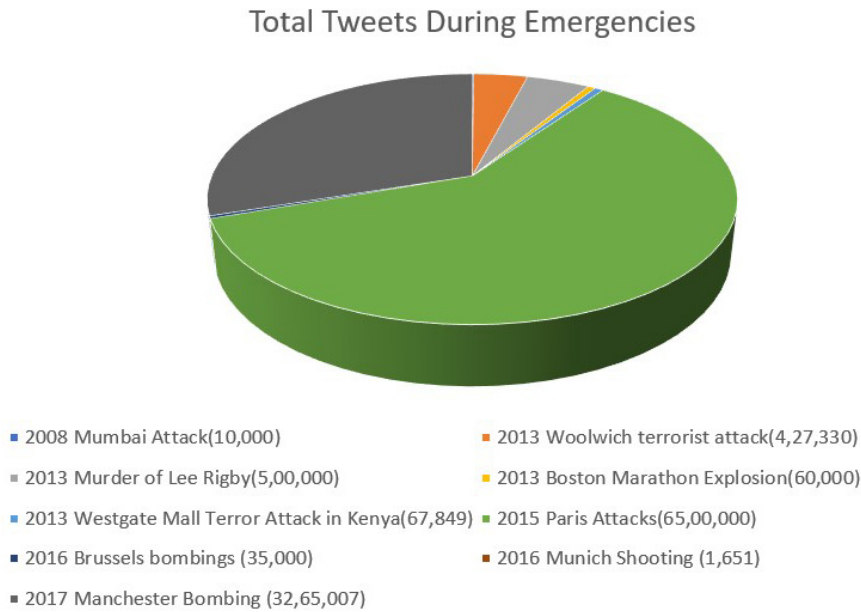


Fig. 3. Total No. of tweets posted during emergencies between 2008 to 2017.

an effective impact, might help in controlling the amount of data that is generated during a crisis situation.

**2.2. UK terrorist attacks, UK — 22 March, 22 May, 3 June and 19 June 2017**

Four terrorist attacks took place in the UK in 2017 as tabulated in Table 2. All these four attacks were studied as a whole by Innes *et al.*<sup>25</sup> Their investigation aimed at manifesting the role of rumors, conspiracy theories, false news and propaganda in affecting public understanding of the gravity of the situation using twitter generated data. More specifically, it detects three digitally influenced engineering techniques, namely, spoofing, truthing and social proofing. They believe these are related to the communication of misinformation and disinformation. Also the possibilities for evidence-informed after-event preventative interventions have been comparatively ignored in the conceptualization of counter-terrorism strategies. These informational

Table 2. List of four terrorist attacks in UK in 2017.

Date	Attack location
22 March 2017	Westminster Bridge
22 May 2017	Manchester bombing
3 June 2017	London
19 June 2017	Finsbury Park

forms are especially influential on public attitudes and behaviors in moments of emergency and crisis, such as terrorist attacks. This paper seeks to develop an understanding of how digital communications are used to influence the ways publics think, feel and behave during and after terrorist event.<sup>25</sup>

2.3. Munich Shooting, Germany — 22nd July 2016

Another study of CB on social media has been reported by Bunker *et al.*<sup>26</sup> who explained the behavior of individuals who choose to remain passive, i.e. by-standers. The authors believe that Bystanders play an important role due to their proximity to the conflicted event and their function as an eye-witness. To investigate the role of bystanders in crisis communications, the authors analyzed Twitter communication, generated from the 2016 Munich Shooting event. On 22 July 2016, an 18-year-old Iranian-German, David Ali Sonboly, started shooting fellow teenagers at a McDonald’s cafe and bystanders on the street outside and then inside the mall. About nine citizens were shot dead and 36 others were injured. Sonboly shot himself before getting caught. The social media convergence behavior study on bystanders revealed that by gathering and sharing information close to where the event is occurring, an impassive convergence behavior archetype (CBA) can act upon a crises situation as a passive as well a rational eye-witness as described in Fig. 4.

2.4. Brussels Bombings, Belgium — 22nd March 2016

Three coordinated suicide bombs exploded in Belgium on 22 March 2016. About 32 people and three bombers died, and more than 300 people were wounded. The Islamic State of Iraq and the Levant (ISIL) took the responsibility of the bombing. Social Media Analyses, in this case Twitter, was conducted<sup>27</sup> to detect potential users and their role. Further, they also performed content and sense-making analyses to determine the type of content that spreads to measure the sense-making. The findings reveal that regularly retweeted users categorized as information starters and

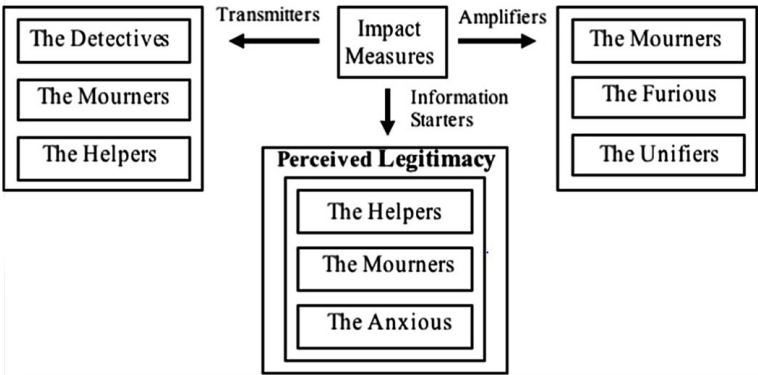


Fig. 4. The top three most impactful CBA of each role.<sup>24</sup>

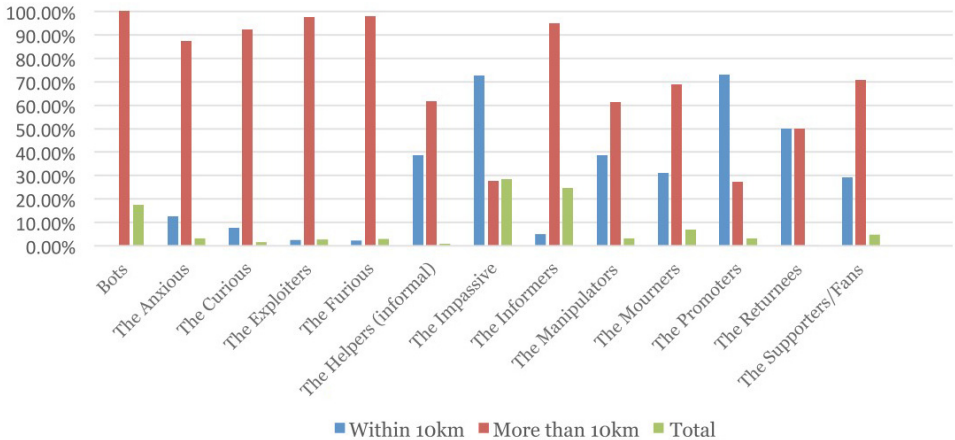


Fig. 5. Frequencies of archetypes according to their distance to the incident.<sup>26</sup>

those having the most followers categorized as amplifiers abridges the communication gap through tweeting and retweeting new information. Moreover, users can bridge various communities categorized as transmitters shared numerous opinions, that helps in sense-making substantially.

2.5. Orlando Nightclub Shooting, Florida — 12th June 2016

A 29-year-old security guard started mass shooting inside a nightclub in Orlando, Florida, United States, on 12 June 2016. This killed 49 people and injured 53 others. Figure 5 shows the overall percentage of tweets by convergence behaviour archetypes. After a three-hour standoff, Orlando Police Department officers shot and killed him. The fear and anger that germinates in a wake of such a terror attack were studied by Baucum and John.<sup>28</sup> They believe that both, fear and anger can unambiguously contribute to policy attitudes and risk-avoidance characteristics. They investigated 36,259 tweets surfaced in response to the Orlando nightclub shooting and studied how fear and anger related expressions vary with time and spatial distance from the location of the attack. It was seen that fear-related words acutely attenuated over time, although the pattern was dominant at positions near the shooting, whereas anger-related words marginally decreased over time but soared with distance from attack. Relating these findings to users pre-attack language indicates that distant users remained both fearful as well as angry after the nightclub shooting, whereas users near to the shooting were angry but hastily reduced expressions of fear to pre-attack levels.

2.6. Paris attacks, France — 13th November 2015

Three suicide bombers struck outside the Stade de France stadium in Saint-Denis while there was a soccer match between France and Germany. The attack was followed by several bombings and shootings in the city at various



cafes and restaurants. About 130 people were killed, 352 people injured. On 14 November, the Islamic State of Iraq and the Levant, claimed responsibility for the attacks.

This event was analyzed in multiple phases by Gupta *et al.*<sup>29</sup> One of these phases was a Twitter analysis related to this attack. This study investigated four keywords related to the attack: Paris attacks, Bataclan, Paris, and Porte verte. This revealed some facts which were not reported in major newspapers. They constructed the timeline of the attack using the 6.5 million tweets.

A similar study of this attack was reported by Lin *et al.*,<sup>32</sup> who gathered more than 18 million tweets from 15,509 tweeter users in Paris on 13 November 2015. They measured the level of their anxiety, anger, and sadness post-attacks. The authors proposed the use of computational focus groups and a completely novel investigation framework to evaluate a social media stream that archives user location and history. The study resulted in outcomes that would be unlikely to manifest through other media or methods.

### **2.7. Westgate Mall Terror Attack, Kenya — 21st September 2013**

During the four day siege, Twitter became an essential channel of communication between the emergency responders, government, and the public. This highly facilitated the emergency management of the crises. A comprehensive analysis of understanding crisis communication trends mediated by social media was studied by Simon *et al.*<sup>31</sup> TwitterMate was used to collect the data generated during tweets and also to analyze it. It also identifies the main hashtags surfaced by the crowd and specific Twitter accounts of individuals, NGOs, and emergency responders. A total of 67,849 tweets were gathered and examined. Four primary types of hashtags were detected: social support, terror attack, geographical locations, and organizations.

This terror attack has been also examined by Ishengoma.<sup>32</sup> They investigated the number of tweets, the geographical location of tweets, and user demographics. They also evaluated if users in developing countries are inclined to tweet, retweet, or reply during the event of a terrorist attack. They define new metrics about reach and impression of the tweet. They reported that, users from developing countries are inclined to tweet more initially and a critical period of the terrorist occurrence. Furthermore, the hefty number of tweets originated from Kenya with 23% from women and 73% from men. Also, original posts had the highest number of tweets followed by replies and retweets.

### **2.8. Boston Marathon Bombing, Massachusetts — 15th April 2013**

In the annual Boston Marathon on 15 April 2013, two homemade pressure-cooker bombs detonated in the vicinity of the finish line of the race. This killed three people and several 100 others were injured. About 16 people lost limbs. The social media posts uploaded instantly after the bombings were examined by Cassa *et al.*<sup>33</sup> They found specific keywords to appear regularly before the official

public safety and media reports. People adjacent to the explosions posted messages within minutes via Twitter. This helped to detect the location and details of events. This showcases the role of social media in the ahead of time identification and portrayal of emergency events.

The study of this event was also undertaken by Lee *et al.*<sup>34</sup> They examined the influence of features of the tweet on the dispersion of two categories of messages marathon tragedy, namely, real and rumor related (both in the context of the Boston tragedy). Negative binomial analysis showed that tweet features like usage of the hashtag, number of followers, and reaction time have an impact on tweet message diffusion during the bombing. The number of followers illustrated a positive relationship with message dispersion. However, the relationship between reaction time of tweet and message dispersion was negative. Interestingly, messages that without hashtags were spread more than those with hashtags.

## 2.9. Woolwich terrorist attack, London — 23rd May 2013

On 22 May 2013, Fusilier Lee Rigby, a soldier in the British Army of Fusiliers Royal Regiment, was killed by Michael Adebolajo and Michael Adebowale, British of Nigerian descent, in Woolwich, London. On 19 December 2013, they were found guilty of Rigby's murder. Adebolajo and Adebowale were converted to Islam but raised as Christians. This event in Woolwich, London in 2013 was studied by numerous researchers, namely, Burnap *et al.*,<sup>35</sup> Williams and Burnap,<sup>36</sup> Roberts *et al.*,<sup>37</sup> Innes *et al.*,<sup>38</sup> using social media analysis.

A model to predict information flow size and survival was developed by Burnap *et al.*,<sup>35</sup> with the help of data fetched from one of the popular social networking website Twitter. The information flow size and survival were modeled using zero truncated negative binomial (ZTNB) regression method and Cox regression technique, respectively. Using a sample of 427,330 Twitter data, they reported a novel outcome that identified the sentiment expressed in the tweet which was found to be statistically predictive of both size as well as the survival of information flows of such nature. Additionally, the co-occurrence of URLs and the time lags among retweets and hashtags also proved substantial.

In a similar study, Williams and Burnap<sup>36</sup> reported how an investigation of open-source communications data gathered through social media platforms could elucidate the inter and intra-community conflict dynamics, surfacing in the wake of such unfortunate events. They claimed that the Twitter data gathered after the murder of Fusilier Lee Rigby, convincingly supports the Collins three phases of conflict dynamics. They also analyzed two key claims, first regarding the interactive nature of the conflict, and second on how the detail provided by the digital data gives compelling insights into the complex network of relationships that come forth and develop throughout such dispute.

Another interesting study of this event was reported by Roberts *et al.*,<sup>37</sup> who worked this case study as a part of computational criminology. They showed the

temporal variation in cyberhate that is relative to concepts of much criminological theory, like the diffusion, duration, escalation, and de-escalation of crime. Analysis of social reactions to the murder of Lee Rigby, was studied by Innes *et al.*,<sup>38</sup> using data collected by systematic monitoring of twitter. They investigated some online behaviors with offline effects.

**2.10. Mumbai terrorist attacks, India — 26 November 2008, 13 July 2011**

On 26 November 2008, terrorists staged multiple attacks on Mumbai. The role of circumstantial information as a cause of terrorist’s opportunistic decision-making in the volatile and extreme environment of the Mumbai terrorist attack has been studied by Oh *et al.*<sup>39</sup> Using Situation Awareness (SA) theory, they examined the content of Twitter posts of the Mumbai terror incident, explored the vulnerabilities of Twitter as a participatory emergency reporting system in the terrorism context. The authors also suggested a conceptual framework for evaluating information control in the linguistic context of the terrorist acts. Another unfortunate attack on Mumbai took place on 13 July 2011, when three serial blasts occurred between 13:24 and 13:35 h. Gupta and Kumaraguru<sup>40</sup> performed a content and activity analysis of posts on Twitter immediately after the bomb blasts. They reported that the number of URLs and @-mentions in tweets soar during the time of the crisis in comparison to what researchers have exhibited for usual situations. Furthermore, they also showed empirically that the bulk of posts on Twitter during the crisis originates from non-authority users on 26/11.

Table 3 shows List of Hashtags on twitter according to different location of attacks for related tweets. The range of different emergencies and responses to them have produced attempts to categorize the use of social media. The aim is to both promote systematical analysis of behaviors and interactions and to facilitate the use

Table 3. Hashtags according to location of attacks.

Attack location	List of hashtags
Manchester Bombing	#Manchester
UK terrorist attacks	Spoofed identity accounts was @SouthLoneStar
Munich Shooting, Germany	mnchen, prayformunich, munich, oez, @polizeimuenchen
Brussels Bombings, Belgium	#qldfloods, #brusselsbombing, brussels, bruxelles and brusselsattacks
Orlando Nightclub Shooting	#OrlandoShooting, #Orlando, or #pulseshooting
Paris attacks, France	#paris2015, #parisattacks, #Bataclan, #paris, and #porteouverte
Westgate Mall Terror Attack, Kenya	#Westgate, #Nairobi, #Kenya, #Terrorist
Boston Marathon Bombing, Massachusetts	#BostonMarathon
Woolwich terrorist attack, London	#woolwich
Mumbai terrorist attacks, India	#tajattack,#mumbaiterroristattack

Table 4. Overview of selected cases and sample studies in the literature.

References	Cases	Contribution
Mirbabaie <i>et al.</i> <sup>24</sup>	Manchester Bombing 2017	Web 2.0-use of Information and Communication Technologies (ICT), such as social media like Twitter or Facebook, have emerged as an important technological trend. Social Network Analysis (SNA) using the tool Gephi.
Bunker <i>et al.</i> <sup>26</sup>	Munich Shooting 2016	(1) Active crisis involvement, i.e. returnees; helpers, exploiters; detectives or manipulators; or (2) passive crisis bystander, i.e. anxious; curious; fans (or supporters); and mourners status. (3) self-developed Java tool, for data tracking.
Mirbabaie and Zapatka <sup>27</sup>	Brussels bombings 2016	Frequently retweeted users (information starters) and those with the most followers (amplifiers) guide the gap bridging through tweeting and retweeting new information.
Gupta <i>et al.</i> <sup>29</sup>	2015 Paris Attacks	Network developed by Valdis Krebs from open sources and R. A series of attacks shook Paris in the year 2015. They were well coordinated attacks by the terrorist organization ISIL.
Simon <i>et al.</i> <sup>31</sup>	2013 Westgate Mall Terror Attack in Kenya	During the crisis, Twitter became a crucial channel of communication between the government, emergency responders and the public, facilitating the emergency management of the event. TwitterMate, a system developed to collect, store and analyze tweets.
Cassa <i>et al.</i> <sup>33</sup>	2013 Boston Marathon Explosion	Individuals immediately adjacent to the explosions posted messages within minutes via Twitter which identify the location and specifics of events, demonstrating a role for social media in the early recognition and characterization of emergency events
Burnap <i>et al.</i> <sup>35</sup>	2013 Woolwich terrorist attack	R statistical software toolkit, Weka toolkit was used to build the machine-learning models,. Sentiment analysis was performed on the content of tweets using the SentiStrength tool.
Innes <i>et al.</i> <sup>38</sup>	2013 Murder of Lee Rigby	Data collection: by systematic monitoring of social media platforms, Data analysis: identifies a number of online behaviors: reporting; requesting, responding; recruiting; risking; retaliating; rumouring; remembering; reheating; and resiliencing.

and development of qualified technology. There are different cases of disaster with their references and contribution are given in Table 4.

3. Social Media Platform-Based Studies

Number of works are available in the literature that studies the social media analytics, not on a specific event<sup>41,42</sup> but based on a particular platform like Twitter, Facebook, Youtube, Reddit, etc.

### 3.1. Twitter

A recent study reported by Kalpakis *et al.*,<sup>43</sup> was based on analyzing specific traits of terrorism-related content posted on Twitter. They aimed at distinguishing terrorism-related twitter accounts from others. After collecting a dataset of terrorism related content from Twitter by searches based on terrorism-related keywords, they examined various spatial, textual, temporal, and social media features of the collected posts and their metadata and compared them against neutral Twitter content. This way, they unveiled some distinguishable characteristics of extremism and terrorism-related accounts. This would aid in developing automated tools that identifies distinct traits of terrorism-related accounts for an early perception of terrorist and extremist content.

Another study addressed by Cunningham *et al.*,<sup>44</sup> was more specifically based on identifying the online presence of ISIS on social media platform, Twitter. Authors believe that Twitter serves as a platform for their supporters to send and receive messages, videos, images, and links to and from a wide range of audiences. The swiftness at which users can communicate information via Twitter suggests that an evaluation of ISIS-related user accounts can contribute to a better understanding of its overall narrative. They examined ISISs online presence by filtering the semantic networks of its most authoritative users from Twitter. A shift may be occurring, as the authors reckon, in the ISIS narrative, from one that pays attention on the near enemy to one on the far enemy. Among those who called for violent jihad debate emerged in the 1970s about whether to focus their efforts on the near enemy (the local ruler) or the far enemy (the Israeli state at that time), the author argued that the movement could not take on the far enemy until the near enemy was defeated.<sup>45</sup> In an interesting study of Oliveira and Huertas-Roig,<sup>46</sup> they investigated how the destination marketing organizations (DMOs) of Barcelona and Cambrils communicated information about the terrorist attacks they experienced. The tweets on the Barcelona and Cambrils profiles were assessed using a content analysis method on the terrorist attacks, the steps by the DMOs to manage them, and the tourism-related decisions that were taken for recovering the image of these destinations.

Identification of key players in terrorism-related social media networks using centrality measures has challenges of its own. To this end, a novel centrality measure, Mapping Entropy Betweenness (MEB), has been proposed by Gialampoukidis *et al.*<sup>47</sup> that simulates targeted attacks that remove the most central nodes of the network. The results reveal that the MEB affects the robustness of this terrorist network more than well-established centrality measures. Ghajar-Khosravi *et al.*,<sup>48</sup> explored the Twitter content of female users who seem to be sympathetic towards the Islamic State in Iraq and Syria (ISIS). Oddly, they demonstrated that tweets of ISIS fan-girls differ from non-radicalized, teenage girls. This difference, they proposed, can be identified by the automated text analysis techniques. In a study of lighter magnitude than terrorism, Agarwal *et al.*,<sup>49</sup> studied the civil unrest by a characterization study on open source Twitter data-set to evaluate the practicability

of building event forecasting model and also demonstrated a statistical-based forecasting model by conducting experiments on real world Twitter data. Analysis using twitter maps has been reported by Lieberman.<sup>50</sup> Six types of Twitter social media networks have been studied viz.,

- (1) Polarized,
- (2) In-group,
- (3) Brand/Public topic,
- (4) Bazaar,
- (5) Broadcast,
- (6) Support

An exploratory study published by Reuter *et al.*,<sup>51</sup> was in fact about a fight against terrorism in social media. They analyzed the state of research in the field of terrorism, its propaganda, and combat in social media explained using sample data from Twitter.

Studies have shown that people use Twitter for different purposes (Java, 2007; Ramage, 2010; Naaman, 2010) studied the aims of 94,000 Twitter users with more than 1.3 million tweets and concluded that users make use of Twitter in the following major areas:

- (1) Chatting. Most Twitter users are for discussion of day-to-day activities.
- (2) Conversations. Some of the Twitter users engage in the conversation using replies mechanism.
- (3) Information exchange/Sharing. Twitter users share and exchange information through Twitter posts contains URLs.
- (4) News. Reporting and commenting on breaking news and the latest news is another type of peoples usage on Twitter.

### 3.2. Facebook

NodeXL is a graphics program, which clusters and synthesizes social network data. A Facebook Social Network Analysis map has been explored using NodeXL by Lieberman.<sup>50</sup> It has the ability to mine Facebook Likes pages without a password. The authors analyzed the local network and reported the capability of this technique of visualization of social media data. A very intricate study reported by Awan,<sup>52</sup> addressed the following queries in his research:

- (1) The type content, if any, that is being used via Facebook to stereotype and demonize Muslims
- (2) The threats both, physical and non-physical, that are being used against Muslims through Facebook, and
- (3) In what way is Facebook being used to depict Muslims as a danger to national (British) security issues?

For this, the authors examined about 100 Facebook pages, posts, and comments. They found 494 instances of particularly anti-Muslim hate-speech. A generalized study on the role of social media especially Facebook, during crises situation particularly after the 2011 terror attack at Utoya in Norway has been addressed by Nilsen *et al.*<sup>53</sup> A total of 112 interviews were conducted with survivors 1415 months after the attack and examined using thematic analysis. Authors identified five reasons for social media usage, namely: information exchange, conveying social support, mourning, performing several symbolic actions, and participating in discussions and debates regarding the terror.

#### 4. Proposed System

In the proposed system, real-time Twitter messages will be collected using Twitter/Facebook streaming APIs. As an unstructured form of data will be gathered to find out the only relevant data by using modeling techniques and using term occurrence, data will be filtered, we extract the tweets related to Uri and Pulwama attack so tweets will be classified to an appropriate cluster. Comments or tweets of Facebook and twitter also provide geolocation analysis to analyze the people's view for that particular area which might help the government to manage situation or find culprit if possible related to terrorist attack. Current trend analysis of tweets from hashtags (e.g. #uriattack, #pulwama, #surgicalstrike etc.) will be useful for classification of tweets. Major topics can be also analyzed by clustering of all tweets/comments using methods of different algorithms.

For the implementation of this system following algorithms will be used:

- Algorithm 1: Tweet Processing  
Let T be the set of downloaded tweets.
  - Input: T
  - Output: A processed tweets with all unwanted word, space, and special character removal
- Algorithm 2: Volume Analysis  
Let T be the set of preprocessed tweets.
  - Input: T
  - Output: A top hashtags, top active users, and top trends.

Steps:

- Preprocess all tweets to remove unrecognized Unicode, garbage numbers, etc.
- Transfer all tweets from Local filesystem to HDFS.
- All tweets are split into words with whitespace as a separator and mapped to one, in the map phase.

$$\text{map}\langle q_1, p_1 \rangle = \text{list}\langle q_2, p_2 \rangle \quad (1)$$

- All similar words are counted and written to the dataset, in reduce phase.

$$\text{reduce}\langle q_1, p_1 \rangle = \text{list}\langle q_2, p_2 \rangle \quad (2)$$

here map and reduce are functions and  $p_1, q_1, p_2, q_2$  are sample pairs

- Transfer all tweets of output to local file system.
- Sort all tweets according to the count and filter all with hashtags, users and trends.
- Put all top hashtags, users, and trends.
- Visualize results for better prospects as per speed. The speed improvement can be calculated by the formula:

$$\text{SpeedUp} = \frac{\text{Serial Processing Time} - \text{Parallel Processing Time}}{\text{Serial Processing Time}} * 100 \quad (3)$$

• Algorithm 3: K-Means Clustering Algorithm

*K-Means Clustering Algorithm- Using Geo-Location*

- Input: Let X be Set of geolocation points where,  
 $X = \{X1, X2, \dots, Xn\}$   
 Let V be Set of centers where,  
 $V = \{V1, V2, \dots, Vn\}$
- Output: Formation of Clusters
- Steps:
  - \* Pre-processing: where all tweets pre-process separately and find out unique terms and TF-IDF of each unique term.
  - \* Create a set of tweet vectors by using a dictionary of unique terms.
  - \* Provide the numbers of clusters to be quantified.
  - \* For initial Centroids of the clusters, provide the TF-IDF values for centroid from vectors randomly.
  - \* Transfer clusters and vectors from Local filesystem on dataset
  - \* Repeat
    - Determine closeness by Euclidean Distance in terms of TF-IDF of each vector with every cluster centroid, in the map phase. Euclidean Distance between two points: If  $p = (p_1, p_2)$  and  $q = (q_1, q_2)$  then the distance is given by

$$d(p, q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2} \quad (4)$$

- Assign vectors to cluster which is most close to centroid of cluster, in the reduce phase. Assigning each point to the nearest cluster: If each cluster centroid is denoted by  $c_i$ , then each data point  $x$  is assigned to a cluster based on

$$\arg \min(c_i \in C) \text{dist}(c_i, x)^2 \quad (5)$$

where  $\text{dist}()$  is the Euclidean distance



- \* Until
  - No more changes in the center of clusters
  - or
  - Cluster's object is not changed further
- Algorithm 4: Naive Bayes Classifier
 

The orientation of users towards attacks, related topics can be analyzed from tweets. As per naive Bayes algorithm, the map Reduce version will be resolved to classify tweets into positive, negative, and neutral classes.

Steps:

  - Create data for the classifier
    - \* Creation of a list of positive words
    - \* Creation of a list of negative words
    - \* Provide a tweet file which we have to be analyzed
  - Design a Classifier
    - \* Extraction of the word feature list from the list with its frequency count
    - \* Using this words-list, create feature extractor which contains the words which will be matched with a dictionary created by us showing which words are contained in the input passed
  - Training the Classifier using the dataset of training.
    - \* Generate Label of Positive-Probability which contains the total number of positive words in the input file
    - \* Generate Label of Negative-Probability which contains the total number of Negative words in the input file
  - Calculate the score probability for the positive and the negative word for individual tweet

$$p(t) = \sum_{k=1}^m \text{score}(w) \quad (6)$$

Here,  $t$  represents tweets,  $m$  is the length of  $t$ ,  $w$  is the weight of  $t$  while  $p(t)$  is polarity of tweets (positive, negative, or neutral).

- \* Calculate score of Positive tweets by the total number of positive words in the tweet divided by Positive-Probability
- \* Calculate score of Negative tweets by the total number of Negative words in the tweet divided by Negative-Probability
- Compare this probability to identify the tweet category as positive, negative or neutral that is anger, anxiety, and sadness related to attack.

Following steps shown how to download the tweets

Steps:

- Registers on Twitter/Facebook development account to access APIs
- Issues the consumer Token and Secret key
- Enters Credentials
- Validate Credentials and issues OAuth verifier
- Request access token using OAuth verifier, Consumer Token and Secret key
- Issues Access Token and Secret key
- Request for content using access token and secret key
- Responds with requested Information

## 5. Conclusions

The current review presents the studies related to social media analysis particularly dealing with acts of terrorism. These studies need to be brought under a common platform to manifest the progression of counter-terrorism strategies in this digital world. We systematically present the past usage of social media during the times of terrorist attacks in a number of bombings, shootings, blasts that happened across the world. Further, we also discussed some of the studies specifically relating to the data analysis of twitter and Facebook which are the top most used social media platforms. Considering the studies reported and analysis performed hitherto, the authors find it to be the need of the hour to increase the magnitude of data analysis on a much larger scale and more so on a regular basis. This should be done not only to identify the acts of terrorism on social media but also as a safety tool, preventive measures, and post-attack examination.

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