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# Mainstream Media Power and Lost Orphans: The formation of Twitter networks in times of conflict

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## Executive Summary

This paper is an attempt to add to our understanding of social media use during times of political and social crisis by presenting an analysis of the use of Twitter during a specific event: the terrorist attack in Garissa, Kenya in 2015. In particular: how networks were generated on the social media platform in the aftermath of this event; what these networks may be able to tell us about how information flows following democratic conflict events; and, what the type of actors located at the centre of these flows tell us about the nature of Twitter communication.

- The results of the study show, at least in terms of the use of Twitter during the Garissa case study, that mainstream news organisations maintain a significant portion of their historical currency when it comes to both providing information and having information forwarded from their accounts. In particular, the BBC, CNN and Reuters emerged as key actors and network nodes.
- Other actors emerged as important, particularly local bloggers and activists. These results point to the role of local social media 'celebrities' and activists in media ecologies.
- Evidence of the broader challenge of self-published user-generated content (either in the form of single tweets and/or more formal publication) to 'established' journalism did not materialise in the data analysed in this study, with our defined 'Broadcasters' and 'Networkers' still dominated by established journalistic organisations. At least in terms of spread and sharing, this form of journalism was paramount. Thus, Twitter proved to be an important vehicle for mainstream journalism to both spread information and promote their brands during this particular event.
- The results of the study, and the identification of the key network nodes also points to an issue raised in both popular and scholarly literature: the rather narrow levels of use of the platform, and the elite-centric nature of Twitter users. Unlike Facebook, which has much broader user base but tends to be used for fewer, or in-depth postings and comments, Twitter is a platform that lends itself well to 'live', on-the-spot updates (including videos and image) but has a much smaller number of users, many of whom are journalists, politicians, celebrities, activists.

## Introduction

In the tech world, a decade is a long time, and it is precisely ten years since Twitter was first launched in the summer of 2006. Over that decade, the social media platform has gone through a series of shifts in terms of both popularity and popular image. It would be fair to say that while platforms such as Facebook or YouTube were associated (at least in their formative years) with what we might describe as the informal/entertainment side of social media, Twitter cemented its reputation (internationally) via political events and social movements. The 2009 Iranian elections and subsequent protests, democratic uprisings in Tunisia, Egypt and Libya between 2010 and 2012, and the Gezi protests in Turkey in 2013 are but a few examples of events where Twitter is reported to have played a role in activist coordination and the spread of information (both inside and outside of the countries in question). The architecture of the Twitter platform—with its 140 character maximum, a relatively simple interface and a primacy of instantaneous communication—meant that it was often favoured for on-the-spot messaging over other platforms such as Facebook. The improvement in mobile connection and download speeds with the advent of 3G and 4G led to better video and audio capabilities, thus enhancing Twitter's real-time utility.

A fundamental task for researchers has been to not only more precisely describe and analyse the aforementioned role of social media platforms during times of protest, dissent, upheaval, violence or political crisis, but also to more precisely describe and analyse social media use. During the early years of Twitter, for example, the term "Twitter Revolution" was bandied about in mainstream media outlets, suggesting a well-defined connection between social media use and political change. This popular technological discourse saw its start in relation to Iran in 2009, and its peak during the so-called "Arab Spring" between 2010 and 2012. And, in the United States, much power was attributed to social media during the 2008 Presidential elections, which saw Barack Obama come to power. In all of these cases, however, the popular understanding of both the use and role of social media was primarily anecdotal. For obvious temporal reasons, research was still thin on the ground, but as time has gone by, academic work on the use of platforms such as Twitter has shown that things are, in fact, more complicated than popular understanding(s) of social media would have us believe.

In this paper, we will attempt to add further layers of nuance to our academic understanding of social media use during times of political and social crisis by presenting an analysis of the use of Twitter during a specific event: the terrorist attack in Garissa, Kenya (Garissa University College) in 2015. In particular, we will focus on the networks that were generated on the social media platform in the aftermath of this event, and what these networks may be able to tell us about how information flows following democratic conflict events, and what the type of actors located at the centre of these flows (the 'nodes') also tell us about the nature of Twitter communication. It is important to note that this is not an analysis of the content of the tweets in question, but rather a presentation of the networks formed and the implications of those networks. The hope is that this chapter will allow for a greater understanding of who the central actors are during times of acute political and social crisis, and how that identification can help us to more precisely define the role of social media during such crises beyond vague notions of platforms as simply 'sources of information'.

## Research/Theory

The study of the use of Twitter has seen an exponential increase in recent years. As mentioned previously, the platform architecture, combined with smartphone ubiquity and improved download and upload speeds have all impacted Twitter's reputation as a central cog in the contemporary informational wheel. Within this cluster of research, scholars have become increasingly interested in the formation of networks surrounding political events, war and protest. Bennett (2003, p.144) wrote that while 'many activists cite the importance of personal digital media in creating networks and coordinating action across diverse political identities and organizations,' questions remained regarding the true use, efficacy and impact of such technologies, and the problem of whether or not 'the ease of joining and leaving polycentric (multi-hubbed) issue networks' (ibid) leads to difficulties in controlling and maintaining movements. Of central importance to Bennett was the issue of if (and how) digital media allowed for the development of new forms of political networks which challenged mainstream, hierarchical systems. In examining the impact of digital media upon activists around the turn of the millennium, Bennett found that such media had a wide range of effects upon political activism, 'from organizational dynamics and patterns of change, to strategic political relations between activists, opponents and spectator publics.' Bennett also noted that participation patterns were impacted by communication networks which allowed citizens to, 'find multiple points of entry into varieties of political action.' (p. 144).

Working off of this early research, and then building upon later work (e.g. Bennett & Segerberg, 2011; Bennett, et al., 2011), Bennett & Segerberg (2012) developed the theoretical framework of 'connective action' in contrast to the common concept of 'collective action' to explain how digital media in general (and, in recent years, social media in particular) have contributed to the formation of loosely (and occasionally not-so-loosely) configured activist networks. Via connective action, individuals are able to participate (in vary degrees) in activism via social networking systems; and, in this form of action, 'taking public action or contributing to a common good becomes an act of personal expression or recognition or self-validation achieved by sharing ideas and actions in trusted relationships' (pp. 752-3). Thus, while traditional collective action is rooted in significant levels of centralised organisation, the creation of a collective identity and a significant investment of time and energy on the part of participants, connective action is found in, 'personalized content sharing across media networks' (p. 739). For Bennett & Segerberg, two factors are key within rationalised connective action: (1) a message or political statement which is easily transformed/personalised, and (2) the use of technologies such as social media which allow for these themes to be shared and further personalised.

Bennett & Segerberg's research opened up a series of questions regarding social media, networks and political communication: particularly in relation to issues such as weak and strong ties and the role of central nodes and opinion leaders. In relation to the second issue (central nodes and opinion leaders), an important strand of work within the study of social media has been on that of 'media ecology' used in order to discuss the interplay between ICT/social and legacy media, as well as the integration of the two (e.g., Scolari, 2012, 2013; Alexander & Aouragh, 2014; Cottle, 2011; Robertson, 2013; Tufekci & Wilson, 2012). In their study on the motivations to participate in the Tahrir Square protests, Tufekci & Wilson noted the need for a more complex understanding of political communication systems:

> Social media are just one portion of a new system of political communication that has evolved in North Africa and the Middle East (…) the connectivity infrastructure should be analyzed as a complex ecology rather than in terms of any specific platform or device. This new system involves three broad, interrelated components. First, satellite TV channels such as Al-Jazeera contributed to the formation of a new kind of public sphere in the Arab world (Howard, 2010, Lynch, 2006; Nisbet & Myers, 2010). Second, the rapid diffusion of the Internet and the rise of dedicated platforms such as Facebook and Twitter dramatically changed the infrastructure of social connectivity (Khamis & Vaughn, 2011; Radsch, 2008). Third, the falling costs and expanding capabilities of mobile phones have enriched dispersed communication with picture and video capabilities. In the span of a decade, societies in which it had long been difficult to access information were transformed into massive social experiments fuelled by an explosion in channels of information (Bailard, 2009; Howard, 2010) (p.365).

This view was reflected in the work of Alexander & Aouragh (2014) - also writing about Egypt's 'unfinished Revolution' - who note that instead of defining social media use or a given platform as either positive or negative, and instead of utilising a 'deterministic' approach to addressing online and offline media, it is far more productive to consider how different activist practices can be connected to a 'larger media ecology.' (p. 891). Thus, the focus should not be on a comparison of the affordances of particular platforms, or their relative efficacy in the spread of pro- or anti-democratic messages, but rather to what extent and how the media technologies that existed in particular places and particular times interacted, as species do within an ecosystem.

In terms of network analysis and an understanding of the relationship between social media platforms and established media (what we might call “pre-social media media”), the notion of media ecology makes a theoretical appeal for an increased understanding of the extent to which social media networks serve to either reinforce or undermine traditional authority. This is an issue addressed by Aday, et al. (2013) in their discussion of the concept of “disintermediation”, within which elite gatekeeping is considered to be in the process of collapsing, ushering in a new age where horizontal sharing and peer production will erode traditional media power. Those who argue against the concept, on the other hand, consider large media corporations to have maintained their capital, with citizens simply picking material from the mainstream flow—this reinforcing mainstream agenda setting power—while simply attaching their own interpretations and biases to that information.

In order to get at these nuances within Twitter (and other social media), studies of networks have shown to be useful. Rainie (2014; in Getchell, 2015), for example, made note of six types of Twitter “conversations:” (1) divided, (2) unified, (3) fragmented, (4) clustered, (5) in-hub & spoke, and (6) outhub & spoke. In their classification of Twitter networks in relation to politics, Smith et al. (2014) went into further detail by clarifying the types of conversations that take place within these network types—what they described as “conversational archetypes.” The following are the most relevant to the current study:

- **Polarized Crowd:** two big and dense groups that have little connection between them. Topics discussed are often highly divisive and heated political subjects. Usually little conversation between these groups despite the fact that they are focused on the same topic. Not arguing, they are ignoring one another while pointing to different web resources and using different hashtags. Shows that partisan Twitter users rely on different information sources: liberals link to many mainstream news sources, conservatives link to a different set of websites.
- **Tight Crowd:** highly interconnected people with few isolated participants. These structures show how networked learning communities function and how sharing and mutual support can be facilitated by social media.
- **Community Clusters:** Popular topics may develop multiple smaller groups, which often form around a few hubs each with its own audience, influencers, and sources of information. Global news stories often attract coverage from many

news outlets, each with its own following. That creates a collection of medium-sized groups—and a fair number of isolates. These can illustrate diverse angles on a subject based on its relevance to different audiences, revealing a diversity of opinion and perspective on a social media topic.

- **Broadcast Network:** Twitter commentary around breaking news stories and output of well-known media outlets and pundits has distinctive hub and spoke structure in which many people repeat what prominent news and media organisations tweet. Members of the Broadcast Network audience often connected only to the hub news source, without connecting to one another. There are still powerful agenda setters and conversation starters in the new social media world: enterprises and personalities with loyal followings can still have a large impact on the conversation.

Clearly, these conversational archetypes—the Polarized Crowd and Broadcast Network groupings in particular—serve as useful models for considering the networks that could emerge from an analysis of Twitter following terrorist attacks in Kenya. Getchell (2015) notes that during times of crisis or conflict, an argument could be made based on the Smith et al. (2014) model for a combination of Broadcast and Community clusters:

> Government agencies as well as highly recognized and credible media organizations often provide consistent and influential information during crises. By contrast, Twitter conversations in Community Clusters reflect "diverse angles on a subject based on its relevance to different audiences, revealing a diversity of opinion and perspective on a social media topic" (Smith, et al., p. 3). In communicating before, during, and after a crisis event, it could be argued that different types/forms of networks would be most effective. (p. 600)

In relation to what we might classify as the "ideal type" communication discussed by Smith et al. (2012), Theocharis (2012) notes that Social Network Analysis indicates that, "the more ties an account has, the better connected it is. A better-connected account on Twitter may be able to more effectively influence the network through the messages it tweets because it can make many others aware of the valuable information it potentially holds, or widely and instantly communicate its views" (p. 43). Thus, with these network figures holding a position of "centrality" we return to core media and communications theory, with influential actors at the core of nodes influencing both the tone and direction of platform-based discussions (e.g. de Fresno Garcia, 2016 pp. 30-31).

An understanding of how these networks and nodes will be identified will be discussed in the next section.

**Methodology**

Traditionally, studies on the use of Twitter and conflict start with a hypothesis on how it was used during a particular conflict and then generate empirical data to test the validity of that very hypothesis. This study however, takes a different approach by using the grounded theory method to collect empirical data without any perceived hypothesis or assumptions, and then try to identify patterns that lead to findings, which in turn, could be developed into a better understanding of the use of technology in a time of conflict. The aim is to understand what the structural features of Twitter communication were and how the various actors on Twitter leveraged the technology.

Using the Mecodify[1] open-source tool, we collected Twitter data based on a search query with hashtags related to Garissa attack, which was a terrorist attack that took place on 2 April 2015 when gunmen stormed the Garissa University College in the city of Garissa, which led to the killing of 148 people and the injury of at least 79. The militant group and Al-Qaeda offshoot, Al-Shabaab, which the gunmen claimed to be from, took responsibility for the attack. The hashtags used for the search were #Garissa and #GarissaAttack.

We chose this case since it had substantial activity on Twitter at the time. The aim is to examine, using social network analysis (SNA), if it is possible to identify how the Twitter network around the case was formed over time and who were the main actors involved in the network. As Borgatti (2009) notes:

> A key task of social network analysis has been to invent graph-theoretic properties that characterize structures, positions, and dyadic properties (such as the cohesion or connectedness of the structure) and the overall "shape" (i.e., distribution) of ties. At the node level of analysis, the most widely studied concept is centrality—a family of node level properties relating to the structural importance or prominence of a node in the network. (p. 894)

Concretely, SNA, "(1) conceptualizes social structure as a network with ties connecting members and channelling resources, (2) focuses on the characteristics of ties rather than on the characteristics of the individual members, and (3) views communities as 'personal communities', that is, as networks of individual relations that people foster, maintain, and use in the course of their daily lives" "Wetherell, et al., 1994: 22). Jörgens (2016, pp.984-5; citing Wasserman and Faust 1994, p.5) notes, '[T]he unit of analysis in network analysis is not the

[1] Read more about Mecodify here: http://mecodem.eu/mecodify

individual, but an entity consisting of a collection of individuals and the linkages among them." Thus, by focusing 'on dyads (two actors and their ties), triads (three actors and their ties), or larger systems (subgroups of individuals, or entire networks)' (ibid.), SNA infers influence from an actor's relational position in policy networks rather than their individual preferences or capacities." As a note on limitations, Bosch (2016, p.226) points out that while SNA can show relationships in communities, it is limited by the fact that it provides "static snapshots while neglecting the network's dynamics," thus not revealing the quality of the tweets, but only the frequency." Bosch does note, however, that SNA provides a "useful sense of relationship clusters and influence" (Ibid.).

### Data collection

Mecodify has a built-in script that crawls twitter's search page and extracts the tweet IDs that emerge from search queries. It then feeds the tweet IDs to Twitter's Application Program Interfaces (APIs), which then fetch the Twitter messages and all relevant information about the tweeter[2].

As shown in Table 1, the size of the corpus for each of the two cases was quite substantial.

| **Country and conflict case** | **Tweets total** | **Users total** | **Period** |
|---|---|---|---|
| Garissa terrorist Attack | 68,892 | 28,418 | 2-8 Apr 2015 |

**Table 1: number of tweets and users and the sampling period for the two cases**

The period chosen was one full week starting on the day of the attack. Twitter data was extracted using a search query with the hashtags #Garissa and #GarissaAttack. While it is not possible to collect all relevant tweets using hashtags, they are useful to identify the actors that wish to signify their interest in taking advantage of the hashtag to contribute to the public discussion. Among the limitations of using hashtags is their inability to cover follow-up replies and other related messages since such tweets may not necessarily include the hashtag used in the original tweet. Additionally, tweets relevant to the conflict that do not have the hashtag would be missed.

To identify and analyse the network of communication between the various tweeters, which are also called nodes, messages containing mentions (using the @tweeter format) were identified and directional edges were visually drawn between every two connected nodes with an arrow pointing to a node indicating the fact that the source node mentioned the target node. Only one directed edge is drawn per two nodes. However, two nodes could very well have two links indicating a two-way method of communication. This was possible to achieve using one

[2] The term tweeter refers to the Twitter account holder that published a tweet.

of Mecodify's built-in functions that allows exporting the lists of nodes and edges for importing into another networking platform called Kumu, which is a data visualisation platform that helps organise complex information into interactive relationship maps[3].

### Social network analysis

Kumu was used to carry out basic social analysis functions to identify the most actively communicating actors over time. In order to analyse progress during the week, the first day was partitioned to three parts, starting with the first hour after the first tweet about the attack. The second part contains the first six after the attack while the third covers the whole period until the end of the first day. All times used were in GMT, which is the standard time used by the Twitter API.

Since social network analysis requires nodes (tweeters) and edges (tweets connecting two tweeters), it was necessary to define exactly what constitutes an edge. While other studies used followers and retweets, in this study, we decided to use two ways of connecting two nodes:

- **A Twitter username mention:** This is the most common and is triggered when the tweeter includes a Twitter username starting with the '@' sign. Any mention of a particular username usually triggers an alert at the end of the mentioned user. A tweet can include several mentions and a tweeter can even mention his/her own username.
- **A reply tweet:** Twitter allows users to click on a button below any tweet to reply to that particular tweet. Tweets are easily identifiable as replies through the Twitter APIs and Mecodify identifies them as such. Similarly, a reply can also be to a user. Any tweeter could also send a public message directly to the user by clicking on his/her username on Twitter. This is different to a mention given that it is meant exclusively to one user. Every reply to a tweet is also considered as a reply to the user. Hence replies to a particular user could also theoretically contain a subset of replies to one or more of his/her tweets.

Our justification in preferring replies and comments is due to the fact that replying or mentioning another user usually involves more effort than a retweet and signifies a greater deal of engagement. Furthermore, the Twitter API makes access to this information much easier than retweets and followers' data. Since private messages are not public, they were not included in this study.

[3] The process to extract, import and visualise networks was done as per instructions provided on Mecodify's Github manual at https://github.com/wsaqaf/mecodify/blob/master/manual.md

## Analysis & Findings

In this section, we analyse and present findings in two different areas. The first deals with the formation of the network over time while the second is more of a detailed analysis on the characteristics of the actors that formed the network.

The activity on Twitter measured in terms of original tweets –and not retweets- in relation to the Garissa attack took place after 03:30 GMT in the morning of April 2 (07:30 Kenya time) and continued to the end of the day. As Figure 1 shows, the activity subsided in the subsequent days with the tops covering the period during 10.00-22.00 of each of the seven days.

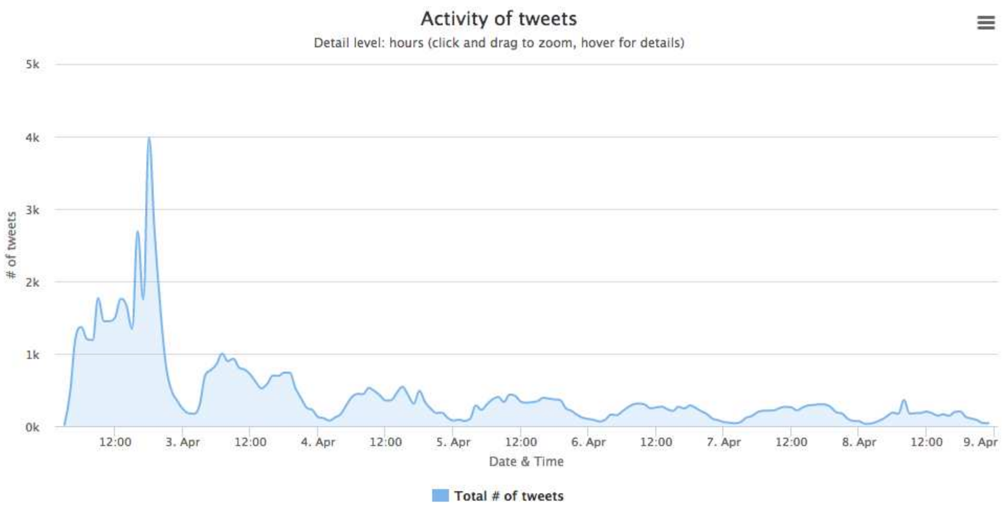


**Figure 1: Garissa attack-related Twitter activity (original tweets) during 1-8 April 2015**

The first replies captured by Mecodify with the #Garissa hashtag emerged as dispersed number of tweets and some replies in relation to the attack. During the first hour, those interactions did not appear to have a central or dominant actor as shown in Figure 2.

**Figure 2: The networks of responses in the first hour after the first tweet about the attack**

Social analysis network metrics such as betweenness[4] and closeness[5] centrality are not useful at this stage since the network was fragmented.

However, over six hours after the first tweet, new networks emerged and some of the old ones started to expand as can be seen in Figure 4. One of those networks, whose central node is marked with a red circle, started forming faster than the others. That central node represented the Twitter account of Robert Talai (@robertalai), who identifies himself as "Kenya's most respected and reliable blogger". With over 400,000 followers, he had several tweets about the Garissa attack that were retweeted and responded to.

[4] In social network analysis, a node's betweenness centrality measures how central its position is in the network. It is calculated by summing the number of shortest paths from all nodes that go through the node.
[5] Closeness centrality is calculated by measuring the distances or hops from the node to all other nodes in the network

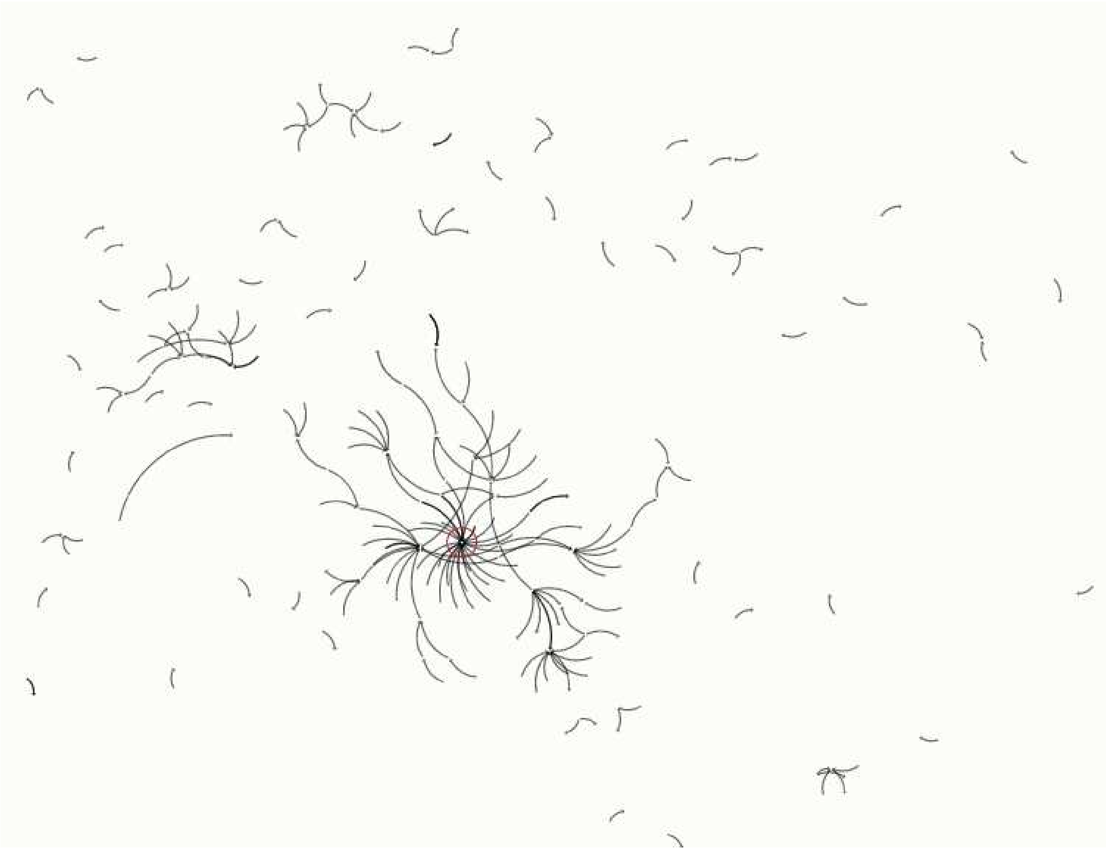

**Figure 3: The networks of responses about 6 hour after the first tweet about the attack**

Furthermore, when calculating the degree centrality[6] for the top nodes, @robertalai got the top spot by far, indicating stronger connectivity in the emerging network. Additionally, he had the highest indegree[7] measure.

At the end of the first day, it becomes quite clear that the network around @robertalai was the most active as can be seen in Figure 5. Additionally, smaller sub-networks connected to the direct network of @robertalai were also strengthened.

[6] Degree centrality is a is calculated by counting the number of connections –when sending or receiving a twitter response - an element has. In general, elements with high degree are the main connectors in the network.

[7] The Indegree metric corresponds to the number of incoming connections for an element. In general, elements with high indegree are the leaders of the network. In the case of the analysis in this study, a high indegree means that the person receives a high number of responses from others.

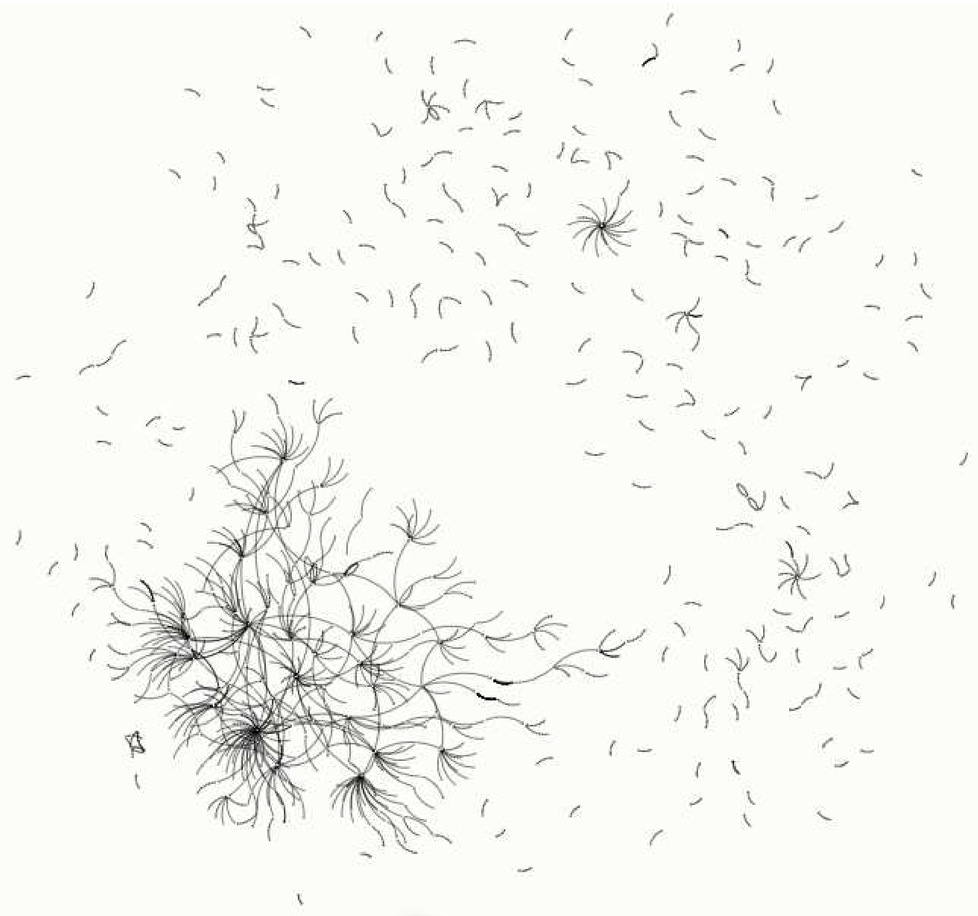

**Figure 4: The networks of responses at the end of the first day on which the attack happened**

Although the network has grown considerably at the end of the day, there were still many fragmented and isolated smaller networks existing in parallel. The leadership of @robertalai in terms of degree centrality remained high. But the margin between the leader and the second and third nodes had started to shrink. In second place a freelance journalist with user name @daudoo succeeded in getting many responses despite his low number of followers.

At this point, mainstream media started to stand out as demonstrated by @BBCBreaking, which is the Twitter account for BBC that specialises in breaking news. With over 22 million followers, it was a mammoth in terms of influence on Twitter compared to all other local Kenyan actors. Nonetheless, the number of responses it received did not match those of @robertalai.

The @BBCBreaking was followed by @juliegichuru, which belongs to Julie Churu, a self-proclaimed "Afro-optimist, wife, mother, change agent, child of God." She had more followers than @robertalai and appeared to form her own sub-network that started rivaling that of @robertalai. All other tweeters were well below them.

By the end of the sampling period of seven days, the network had grown considerably as shown in Figure 6 and the influential actors that have established themselves remained in the same order in terms of degree centrality and indegree metrics. In other words, the tweeters that got the most traction and acted swiftly in covering the developments round the Garissa attack from the beginning were the ones that prevailed and gained the most in terms of interaction based on the social network analysis metrics.

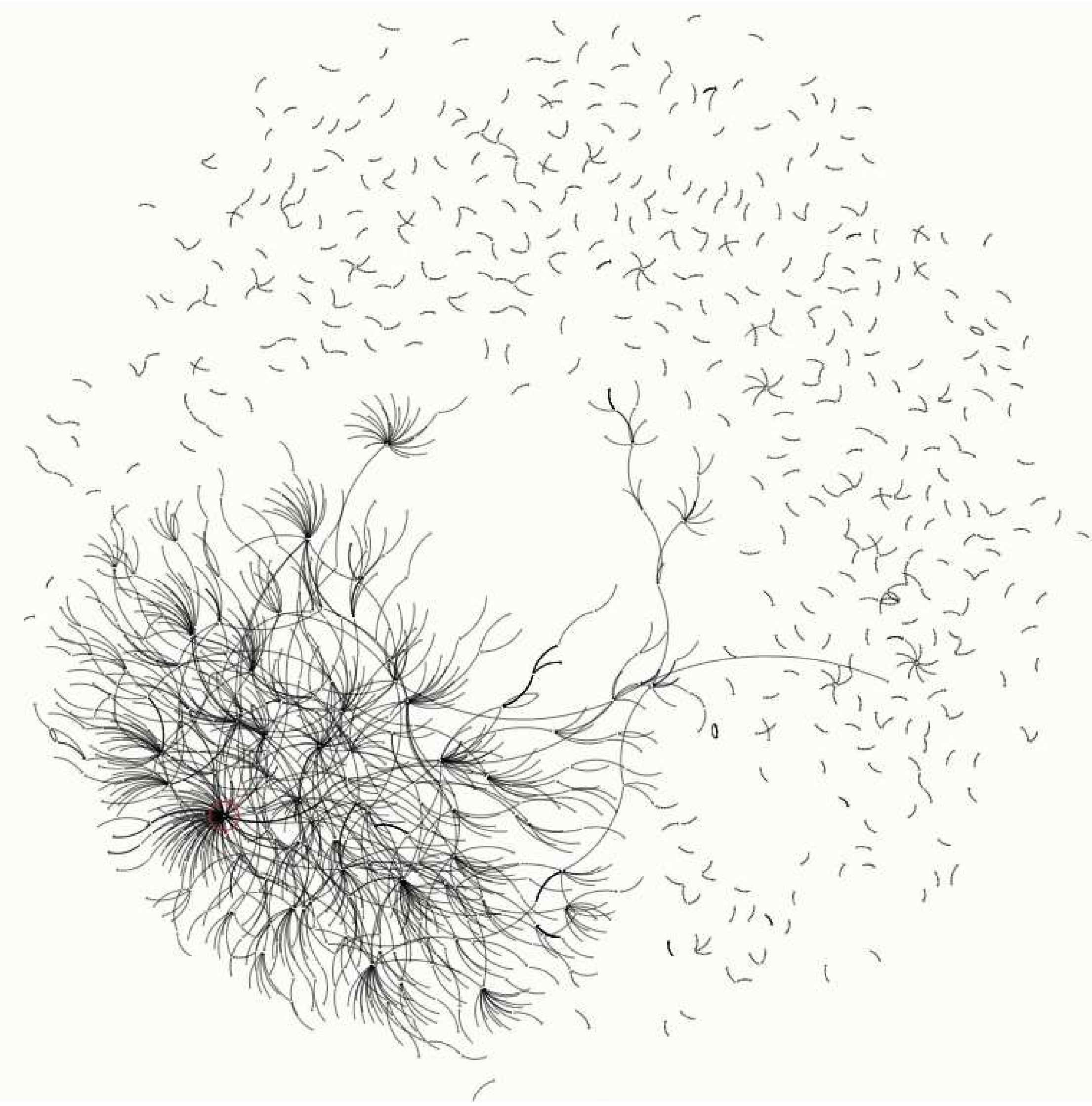

**Figure 5: The networks of responses at the end of the seven-day period**

## Actor groups of the Garissa attack-related Twitter network

While the earlier analysis focused on how the network formed over time, we took a more comprehensive approach when dealing with the fully formed seven-day-old network by looking into the actual actors that compose it.

The study found that out of 28,418 tweeters, around 42 per cent were involved in some form of a network using one or more of the methods described earlier, i.e., mentions or replies.

Upon delving deeper into the data, it became apparent that the type and level of networking activity did reveal some traits of the tweeters themselves, and hence helped shed light on their role and type of contribution –if any- to the network.

The analysis has unveiled four groups of users that were assessed based on the number of replies (including direct tweet replies) and the number of mentions they got and they sent. The groups are described as follows.

**Group 1: Broadcasters**

This group includes users that received responses and mentions from other tweeters yet did not respond or mention anyone back at all during the sample period. When sorting the list by the amount of mentions and responses they got, it was possible to identify some common traits, at least in the main actors of this group.

The highest on the list was the account of Joseph K Boinnet, the Second Inspector General of Police in Kenya. Despite the fact that he only posted a single tweet[8], he got 279 mentions and replies sent from other tweeters. Since the incident involved a terrorist attack, it was not surprising that his account would be among the highest mentioned. However, it was clear that the account was used for one-way announcing a statement or broadcasting rather than as part of a social network to engage and interact with other users. The next four most mentioned tweeters in this group were well-established mainstream media accounts, namely @CNN, @Reuters, @StandardKenya and @cnni (CNN International). Unlike the rest, @StandardKenya, which represents The Standard Newspaper, is a national actor. It represents one of the largest broadsheets in Kenya and is owned by The Standard Group, a media conglomerate that also owns the Kenyan Television Network, which was also active on Twitter.

The group can be characterised by being led by popular traditional or establishment-type accounts that have held the Verified by Twitter label[9]. They also have a high median value of followers[10] exceeding two thousand. They seem to use Twitter as a means of broadcasting their messages and not social interaction despite the significant number of mentions they get.

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[8] It is note-worthy that a second tweet was posted on February 9th, which is not included in this sample, simply stating that the "Government is responsible for police officers' funeral expenses (vide #Garissa) but friends and family are free to raise funds."

[9] Verified Twitter accounts are supposedly genuine since legal documentation proving the owners' identities is required to get that status.

[10] Median was used to assess followers due to the high standard deviation this variable. If the average is to be used, it would create a substantial bias for the few users who have millions of followers.

In total, this group had 1,499 tweeters representing five per cent of the total in the dataset as shown in Table 1, which also shows the top five accounts in that group.

**Table 1: Top 5 tweeter in Group 1 (sorted by number of replies+mentions received)**

| **Top five accounts ->** | **@JBoinnet** | **@CNN** | **@Reuters** | **@StandardKenya** | **@cnni** | **For whole group (N=1,499)** |
|---|---|---|---|---|---|---|
| Is the account verified? | No[11] | Yes | Yes | Yes | Yes | 7% verified |
| Number of followers | 56176 | 24,958,313 | 12,996,254 | 594,353 | 5,025,672 | 2,105 (median) |
| Tweets on the conflict | 1 | 1 | 7 | 9 | 11 | 2,98 (average) |
| Retweets of those tweets | 24 | 311 | 2015 | 74 | 2,217 | 57,17 (average) |
| | | | | | | |
| Replies received | 44 | 35 | 48 | 25 | 21 | 1,02 (average) |
| Mentions received | 235 | 231 | 198 | 120 | 118 | 3,46 (average) |
| | | | | | | |
| Replies sent | 0 | 0 | 0 | 0 | 0 | 0 |
| Mentions sent | 0 | 0 | 0 | 0 | 0 | 0 |

**Group 2: Trolls**

This group constitutes of tweeters that send responses and mentions to others but do not get any response. They are part of the network because they impose themselves using the reply and mentioning techniques. However, their efforts to gain attention seem to go nowhere based on the lack of reaction to their frantic tweets. The list of the top most active in replying and mentioning others includes personal individuals, whose accounts are hidden for privacy concerns. However, among the top 5 are accounts that appear to possibly be spam or bot accounts that keep on sending repetitive tweets but to different usernames, which is a good reason to ignore.

Several of the top accounts in terms of tweeting to others were detected by a bot-detecting app called BotorNot to have a high probability of being a bot. A Pearson linear correlation test between the number of tweets and the number of times those accounts sent or mentioned others resulted in a significant coefficient value (R=0.64) and is statistically significant since p value was quite small. In other words, many of those accounts appear to have taken advantage of the conflict's hashtag to add mentions of other users perhaps in an attempt to gain traction. The more active those users are, the more likely that they will be

[11] As of December 1, 2016, is verified but the data used in this study was extracted several months back when the account was not yet verified.

spamming someone instead of contributing to a debate. This part of the network is apparently the one perceived the most harmful or at least most annoying.

Despite constituting over 8,000 usernames or 28 per cent of the total sample, the average number of retweets and median value of followers is much lower compared to Group 1. Additionally, only two per cent have verified accounts, out of whom none are in among the most active spammers as shown in Table 2.

**Table 2: Top 5 tweeter in Group 2 (sorted by number of replies+mentions sent)**

| **Top five accounts ->** | **@<user1>** | **@<user2>** | **@<user3>** | **@<user4>** | **@<user5>** | **For whole group (N=8,006)** |
|---|---|---|---|---|---|---|
| Is the account verified? | No | No | No | No | No | 2% verified |
| Number of followers | 779 | 24 | 10,518 | 3,068 | 8,57 | 587 (median) |
| Tweets on the conflict | 35 | 36 | 50 | 28 | 27 | 2.35 (average) |
| Retweets of those tweets | 27 | 13 | 17 | 2 | 7 | 1.94 (average) |
| | | | | | | |
| Replies received | 0 | 0 | 0 | 0 | 0 | 0 |
| Mentions received | 0 | 0 | 0 | 0 | 0 | 0 |
| | | | | | | |
| Replies sent | 30 | 33 | 4 | 26 | 19 | 0.59 (average) |
| Mentions sent | 63 | 34 | 54 | 32 | 38 | 2.07 (average) |

It is worth noting that it is not enough to assess the number of mentions and replies sent to others to determine whether such accounts are used for spamming. What is also important is to take into consideration the number of nodes that those accounts send to. If they were many, this would appear to be a form of spamming. But if it is, for example, many replies but persistently to the same account, this may indicate an intentional target. In this study, we use the ratio of edges to nodes to eliminate the extremes.

**Group 3: Orphans**

This group includes those tweeters that are not connected to any of the networks since they neither receive from nor send to other tweeters. Members of this group surprisingly exceeded 16,000 accounts, which constituted 58 per cent of the sample. It meant that the majority of the users are in fact practically not connected to any network. It is difficult to identify a common characteristic for all members of this group. But there may be several reasons why they have not interacted with any other tweeter. While no interaction for less frequent tweeters is plausible, it would be interesting to examine the reasons why high frequency tweeters opted to not interact.

When sorting the list by number of tweets in descending order, we find that the top four are accounts for services or platforms and not individual. The top account @AyotzinapaFeed for example is a service that sends feeds in Spanish probably in the form of automated retweets. Such uses do not require utilising social networking since they are mostly automated. The other three accounts seem to also offer services while the fifth is of an individual whose username is kept anonymous in Table 3.

Like Group 2, this group had a low percentage of verified accounts (2 per cent) and low average median number of followers. They were considerably less active and have fewer retweets on average. Table 3: Top five tweeter in Group 3 (sorted by number of tweets)

| **Top five accounts ->** | **@AyotzinapaFeed** | **@Tupashe** | **@TTMobile_gh** | **@Rondera** | **@<user5>** | **For whole group (N=16,362)** |
|---|---|---|---|---|---|---|
| Is the account verified? | No | No | No | No | No | 2% verified |
| Number of followers | 6,630 | 9,054 | 1,241 | 1,980 | 1,511 | 411 (median) |
| Tweets on the conflict | 105 | 66 | 54 | 46 | 46 | 1.42 (average) |
| Retweets of those tweets | 27 | 0 | 24 | 0 | 3 | 1.42 (average) |
| | | | | | | |
| Replies received | 0 | 0 | 0 | 0 | 0 | 0 |
| Mentions received | 0 | 0 | 0 | 0 | 0 | 0 |
| | | | | | | |
| Replies sent | 0 | 0 | 0 | 0 | 0 | 0 |
| Mentions sent | 0 | 0 | 0 | 0 | 0 | 0 |

**Group 4: Networkers**

The last group is perhaps the true engine of the network since it includes tweeters that engage in two-way interactions through replies and/or mentions. While they constitute about nine per cent of the sample (2,551 tweeters), they have the highest engagement with an average of about nine received mentions/responses and seven sent mentions/responses. There was a clear positive correlation (R=0.76) between the level of interaction and the number of retweets those users get.

When sorting the tweeters in this group by total number of connections, i.e., incoming replies and mentions plus outgoing replies and mentions, one cannot but notice the dominance of BBC accounts (@BBCBreaking, @BBCWorld and @BBCAfrica), which have taken an approach different than that of @CNN and @Reuters of Group 1 and used mentions and replies in their tweets. Despite having fewer followers than the media accounts in Group 1, the leaders of this group approached the Garissa attack with more tweets and more interaction with other active tweeters. This seems to have succeeded in strengthening their network by using social media in more strategic ways compared to the broadcasting approach of Group 1.

Among the top in this networking group was no other than @RobertAlai, who as described in an earlier section, was the most active node at the beginning of the Twitter discussions around the Garissa attack. While he came in as a close second after @BBCBreaking in terms of tweets, he outperformed the BBC accounts by more than two to one as Table 4 shows.

**Table 4: Top five tweeter in Group 4 (sorted by total number of connections)**

| **Top five accounts ->** | **BBCBreaking** | **RobertAlai** | **BBCWorld** | **BBCAfrica** | **bonifacemwangi** | **For whole group (N=2,551)** |
|---|---|---|---|---|---|---|
| Is the account verified? | Yes | No[12] | Yes | Yes | No[13] | 5% verified |
| Number of followers | 22,470,284 | 401,811 | 14,218,601 | 1,259,935 | 372,653 | 2,105 (median) |
| Tweets on the conflict | 16 | 137 | 17 | 50 | 49 | 8.8 (average) |
| Retweets of those tweets | 9,361 | 8,165 | 6,546 | 4,206 | 3,728 | 65.5 (average) |
| | | | | | | |
| Replies received | 149 | 298 | 89 | 101 | 84 | 2,2 (average) |
| Mentions received | 359 | 1034 | 333 | 362 | 283 | 6,9 (average) |
| | | | | | | |
| Replies sent | 7 | 12 | 2 | 1 | 10 | 1,6 (average) |
| Mentions sent | 6 | 28 | 2 | 8 | 25 | 5,7 (average) |

[12] As of December 1, 2016, is verified but the data used in this study was extracted several months back when the account was not yet verified.

[13] As of December 1, 2016, is verified but the data used in this study was extracted several months back when the account was not yet verified.

It is noteworthy that the Twitter account of human rights activist and photojournalist Boniface Mwangi @bonifacemwangi had also performed well and came in fifth place in terms of retweets. The fact that his account had tweeted actively and interacted with other tweeters may have bolstered his role in the network significantly.

While not shown in Table 4, other active nodes in the network included Kenya-based media such as Kenya Television Network Kenya (@KTNKenya), which took a more interactive approach to tweeting compared to its sister company @StandardKenya despite the fact that the two companies are managed by the same media group.

Finally, it is also worth noting that the Kenya Red Cross account @KenyaRedCross was among the most active in receiving mentions and responses as well as engaging with others. Given the high number of casualties caused by the attack, this was expected. By actively responding to a couple of other tweets directly, it had taken advantage of what Twitter's social networking capabilities.

The emergence and expansion of the Garissa attack Twitter network as described in the earlier section was mainly the outcome of the active members of this networking group since they had a two-way mode of communication that social media in general are suitable for. The power of such networks reveals their potential more clearly when dealing with time-sensitive news and information about emergencies such as terrorist attacks and other forms of sudden violent conflicts.

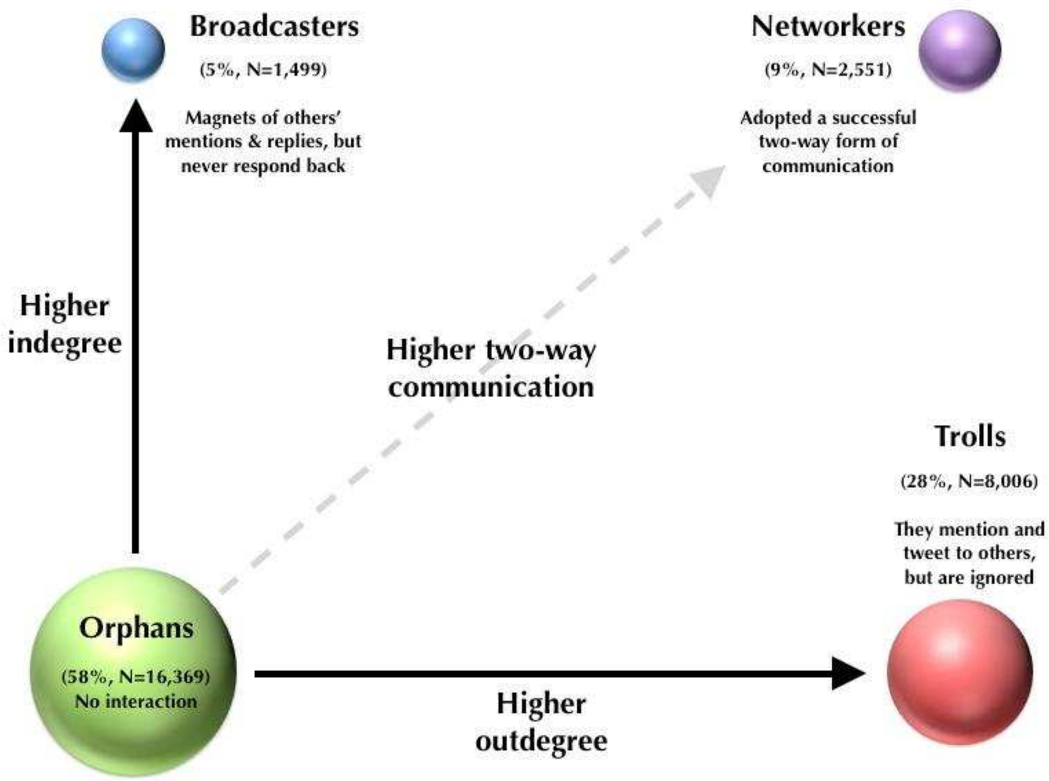


**Figure 6: Comparison between the four groups**

Figure 6 summarises the findings concerning those groups that formed the Garissa's Twitter network. It is important to warn however that simple comparison in terms of size may not always be valid since not all networkers succeed in striking the balance between the level of outgoing and incoming messages on Twitter. There is a range on that diagonal line shown in the illustration where each twitter account could potentially be. So a networker that is 99 per cent of the time tweeting others and just getting 1 per cent response to his/her tweet may be closer to a spammer than a networker. The same applies to those who rarely respond back despite a high number of mentions.

The bottom line is that while anyone can be a Twitter user and talk about a conflict, those who truly engage and interact could be influential in their own network and settings. Moving along fixed horizontal or vertical lines like spammers and broadcasters do not appear to foster and grow Twitter networks. True networkers are the only ones who could fill the void by effectively implementing two-way conversations, especially when the subject matter is about a conflict.

## Conclusions

The results of this study of the Garissa attacks provide a wealth of valuable information, but three issues in particular stick out as important implications of the study: (1) the relationship to disintermediation and media ecology; (2) the implications of the results for the relationship between journalism and the use of ICT; and (3) the reach and influence of a relatively small number of users (the opinion leaders) the primacy of what are defined as ‘Orphans’ and ‘Trolls’.

As discussed previously, the notion of ‘disintermediation’ is one within which elite gatekeeping is in the process of collapsing, with horizontal sharing and peer production eroding ‘traditional’ media power. As also noted, those who argue against the concept see large media corporations maintaining their power to both provide information and set the agenda, with citizens often selecting material from a mainstream flow, and the simply attaching their own interpretations and biases to that information. The results of the study show, at least in terms of the use of Twitter during the Garissa case study, that mainstream news organisations maintain a significant portion of their historical currency when it comes to both providing information and having information forwarded from their accounts. In particular, the BBC, CNN and Reuters emerged as key actors and network nodes.

Interestingly, however, other actors emerged as important, particularly local bloggers and activists such as Robert Alai and Boniface Mwangi. As networkers in particular, these two managed to generate a significant number of retweets for their material despite far lower follower numbers than their large, mainstream media counterparts. These results also point to the role of local social media ‘celebrities’ and activists in media ecologies, as well as how large, multinational news organisations retain their power: an issue in the case of African nations that points to the role of the media of former colonial powers (such as Britain’s BBC) in shaping coverage. What is clear from this case study is that during this particular crisis, users went to large-scale sources, or sources of their region that were well-known.

Related to the issues of disintermediation and ecology is the broader question of the relationship between journalism and ICT/social media during a democratisation conflict such as the Garissa terror attack. Part of the disintermediation argument is that, by virtue of the ability of “ordinary citizens” and small-scale organisations to produce, publish, promote and share their material, mainstream media lose a small or large portion of their gatekeeping and storytelling power. Evidence of the broader challenge of self-published user-generated content (either in the form of single tweets and/or more formal publication) to ‘established’ journalism did not materialise in the data analysed in this study, with the our defined ‘Broadcasters’ and ‘Networkers’ still dominated by established journalistic organisations. At least in terms of spread and sharing, this form of journalism was paramount, with the noted exceptions of Robert Alai and Boniface Mwangi. Thus, Twitter proved to be an important vehicle for mainstream journalism to both spread information and promote their brands during this particular event.

The results of the study, and the identification of the key network nodes also points to an issue raised in both popular and scholarly literature: the rather narrow levels of use of the platform, and the elite-centric nature of Twitter users. Unlike Facebook, which has much broader user base but tends to be used for fewer, or in-depth postings and comments, Twitter is a platform that lends itself well to 'live', on-the-spot updates (including videos and image but has a much smaller number of users, many of whom are journalists, politicians, celebrities, activists. This is borne out in the fact that the total number of tweets from the 'Networkers' and 'Broadcasters' (roughly 4,000) was outnumbered by those from 'Trolls' and 'Orphans' (roughly 24,000). This fact leads to an important methodological and theoretical issue in relation to the study of Twitter in connection with democratisation conflicts: that many of the tweets and comments regarding these issues disappear into the digital soup that is the Twitterverse. The study of the 'Broadcasters' and 'Networkers' tells us what influencers are saying on Twitter, and how they might use the platform, but the practical problems of researching thousands of individual 'orphan' tweets mean that the totality of the opinions expressed on Twitter – often by users with very few followers and very little interaction – are missed. Thus, in turn, primacy is given to 'influence' rather than breadth of voice and opinion. While influence is important, of course, further studies should attempt to map the totality of the political opinion expressed by 'Orphans' thus providing a much more nuanced (and likely complex) map of the use of Twitter.

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