Examining Convergence Behaviour During Crisis Situations in Social Media - A Case Study on the Manchester Bombing 2017

Milad Mirbabaie[1], Deborah Bunker[2], Annika Deubel[1], and Stefan Stieglitz[1]

[1]University of Duisburg-Essen, Duisburg, Germany
{milad.mirbabaie, annika.deubel, stefan.stieglitz}@uni-due.de

[2]The University of Sydney, Sydney, Australia
{deborah.bunker}@sydney.edu.au

Convergence Behaviour Archetypes (CBA) describe the many different ways that individuals spontaneously and collectively move towards an emergency situation. If this movement is not managed effectively, crisis management issues and problems can emerge and lead to an exacerbation of the crisis situation e.g. panic, convergence of people and resources towards danger, convergence of excess and unrequired people and resources etc. Users of social media platforms express different motivations and behaviours while converging on a crisis. While this behaviour has been analysed in previous research, an understanding of convergence behaviour facilitated by social media platforms to an effective level of control, is yet to be achieved. This paper examines how Twitter users, converged on the Manchester Bombing 2017. We identified the most impactful convergence behaviour archetypes, including those with the highest perceived legitimacy of convergence i.e. those deemed by the Twitter network, to have a necessary and meaningful role in the crisis. Manual content and social network analyses were conducted on our data by identifying three roles that determine the Twitter users with the highest impact regarding their retweet behaviour. We determined that Helpers, Mourners and Detectives had the highest impact on crisis communication in this event.

Keywords: Convergence Behaviour, Crisis Communication, Social Media, Social Network Analysis, Information Systems

1 Introduction

Nowadays, man-made disasters caused by acts of terrorism are occurring with an increasing prevalence [11, 41]. With the development of Web 2.0, the use of *Information and Communication Technologies* (ICT), such as social media like Twitter or Facebook, have emerged as an important technological trend [18, 39]. These easily accessible Internet-based applications enable users to create and share content-based information and opinions while seemingly having unlimited reach within a communications network in real-time with no cost [14]. Recent studies consider social media to be one of the most popular sources of receiving and collecting essential crisis information [22, 25] so, therefore, these social networks have various benefits for crisis communication and crisis management.

On the one hand, people can use social media to make sense of what has happened and gather information more quickly while responding collectively [35, 40]. On the other hand, these social networks are not only used for collecting critical news, but also for delivering emotional support to people affected by the crisis [26].

In addition, research has revealed that social media users exhibit different intended behaviours to converge on a crisis, that is reflected in their crisis communication on social networking sites. This specific behaviour is called *Convergence Behaviour (CB*). It describes the movement of individuals or resources towards the crisis event [10] and can be categorised into a specific *Convergence Behaviour Archetype (CBA)*. While these CBA and their legitimacy in crisis situations, have been examined in crisis behaviour research, there is a substantial gap in our knowledge of how CBA are facilitated and legitimized by social media use during crises.

For instance, the legitimacy of Convergence Behaviour has been questioned by various researchers, as "Convergence, at its heart, presents a conflict of legitimacy" [21, p. 103]. People have different intentions when converging on a crisis claiming that their reasons are valid, and their requirement to participate in crisis communications is necessary. As all CBA present certain difficulties and challenges to emergency officials, the legitimacy of these different behaviour types is hard to determine. Researchers have specified that in social media, CBA assume a certain kind of legitimacy through a "wider sphere of influence" [45, p.4]. Thus, if users deem a social media post to be legitimate and trustworthy, its influence increases and the author might emerge as an opinion leader [48] and a reliable information source during a crisis. Opinion leadership is mainly characterised as the social media users' influence on others' behaviours and even their attitudes. Until now, we have yet to understand which CBA exert the biggest influence on crisis communication in social media. In developing this understanding, further knowledge on which CBA have the highest potential for perceived legitimacy on social networks during a crisis, can be developed.

In this paper, we will therefore aim to answer the following research question:

RQ: What Convergence Behaviour Archetypes have the biggest impact (influence and legitimacy) on social media crisis communication?

In order to answer the question, we analysed the communication network on the social media platform Twitter, during the terror attack in Manchester on 22 May 2017. This study provides a new approach to filtering and analysing Twitter data to highlight and identify CBA on social media by conducting a social network analysis (SNA). Distinctive roles were initially identified that were introduced in previous research studies [38]. Through this analysis, we were able to determine the top users and influencers of the platform that lead the Twitter communication (retweetability) during the Manchester Bombing. This gave us a different perspective on this crisis incident when compared to previous crisis incident research, which has mainly relied on text mining analysis

approaches. We were then able to identify the CBA for every tweet through applying a manual content analysis (MCA) to the dataset.
Thereafter, the role measures of each Twitter user were added to a total value for the CBA in order to determine the Impact Measure (IM) of the archetype and therefore identify the most impactful CBA that emerged during the Manchester Bombing.

The remainder of this paper is structured as follows. In section 2 we describe the status quo of the literature. In section 3 we introduce our applied research methods. We then describe the results and develop our discussion. Lastly, we summarise our findings, point out the study limitations and highlight possible future directions.

2 Literature Review

2.1 Crisis Communication on Social Media

Crisis communication represents a domain that describes the "process of creating a shared meaning" [9, p.2] among all individuals that are involved or affected by a crisis. Effective crisis communication is a fundamental principal to successful crisis management and disaster relief [15, 18]. In recent years, the use of social media for crisis communication has increased substantially and emerged as a rapidly growing trend [1, 23]. As a new source of information for the general public, social networking sites are used for information exchange about emergency situations on both a global and local level and have actually changed how crisis information is created and distributed to individuals both directly impacted by a crisis and those merely observing [7, 9, 46].

Understanding this rapid widespread diffusion of social media adoption, and assessing what and how information is spreading, as well as identifying emerging crisis communication problems and issues, is critical for crisis management so as to initiate an effective crisis response by professionals [12]. As a result, research in crisis communication on social media has gained momentum in recent times. For example, research has emerged during the last few years that helps explain the process of *Sensemaking* during crises. Researchers [29] investigated what kinds of information were communicated through social media in order for users to make sense of the situation. They used a relatively new approach of identifying different roles that represent the users with the highest *Information Diffusion Impact (IDI)* regarding their retweetability [38]. In fact, identifying social media users with the highest impact, has been a large field in many disciplines researching social media, such as politics or social media marketing, but has only occasionally been applied in crisis communication.

Previous research indicates that three influence measures exist to understand what different roles users play in social media. Firstly, the indegree, a metric that describes all incoming relations of a user in a Social Network Graph, represents the *Popularity* of an individual. Secondly, the number of retweets serve as the *Perceived Content Value* of a users' post. Lastly, the mentions represent the *Name Value* of a person [8].

Previous researchers based their study of IDI on the act of retweeting, indicating it to be "the principal factor" [38, p.2] of *Information Diffusion (ID)*. They applied a self-introduced user classification to three roles on the Twitter datasets of the Great Eastern Japan Earthquake in 2011 and the Boston Marathon Bombing in 2013. Identifying emerging leaders or impactful users in crisis communication might also be an effective way of identifying posts that ensure a higher probability of reliability and truthfulness [27, 28], although this is not guaranteed. In the last few years, there has been an increasing concern about false information propagation on social media. As stated earlier, the sheer mass of information on social networking platforms provides valuable insight and news for officials, emergency managers and first responders, as well as traditional media sources [7, 33]. Social media platforms, however, also enable false and unreliable information to be spread throughout the network [2, 15]. Since social media platforms generate massive amounts of information that is already hard to manage, the monitoring, identification and analysis of reliable and truthful social media data continue to be one of the main challenges for crisis and emergency managers.

2.2 Convergence Behaviour

It would seem that the overall belief of emergency managers is that people who are affected by a crisis respond in a socially disorganised and disoriented manner [4, 37]. However, research highlights that people actually form a collective intelligence and act in a rational way instead of exhibiting disorganised behaviour [4, 47].

In general, *convergence* means "*the movement or inclination and approach towards a particular point*" [10, p.3]. Contrary to the general image of behaviour in emergency situations, people, resources and information spontaneously converge *toward* a disaster area instead of moving away [6, 10, 21]. This behaviour causes many officials and emergency managers to grapple with the impact of *Convergence Behaviour (CB)* [4]. Instead of losing control and fleeing the crisis area in fear, people try to gather as much information as possible about the situation and, based on this information, make quick decisions in order to save their lives and often to aid others in need of help [19]. Thus, in many instances, officials can be caught "off guard" when an unanticipated number of people turn up to an event, or a large amount of information is generated by reaction to an event, which can, if uncontrolled and unmanaged, complicate crisis management. Understanding the different motives people may have while converging on a crisis, must be better understood to control mass movement of people towards a crisis [45] . With the increased use of digital media as well as ICT, CB can be exhibited not only in the physical but also virtual environment. The use of social networking platforms enables CB to adopt new forms of interaction between actors responding to a crisis [20, 30]. CB in the era of social media is therefore no longer limited by geographical or physical boundaries, but creates a possibility of event participation and convergence for people all over the world through social networks [34, 45]. Through the forming of a collective intelligence during disaster situations, many people start to volunteer in order to support officials or help those affected by the crisis [21]. CB encompasses major negative aspects as well, indicating that it should be controlled to some degree [4, 45]. In general, digital *Convergence Behaviour Archetypes (CBA)* might flood social networks with messages, making it hard to find important and required information, causing poor crisis response or misuse of resources [45]. This especially concerns crisis volunteers, who digitally converge on a crisis to support and aid official emergency managers [42].

In order to control and predict CB, it is inevitable that we must also increase our overall understanding and knowledge of it. Depending on the individual or group's intention and the reason behind converging on a crisis situation, each individual reveals a prominent behaviour [5] through their actions. Based on this range of behaviour, researchers [10] identified five different CBA, which are: *the Returnees, the Anxious, the Helpers, the Curious* and *the Exploiters* [10]. Additionally, other researchers [21] were able to find two new types of Convergence Behaviour which were *the Fans* or *Supporters* and *the Mourners*. The transformation of CB in social media enabled the emergence of new types such as *the Detectives* [45] or *the Manipulators* [6]. Another recent analysis of bystanders CB, [5] uncovered the emergence of *the Furious* and *the Impassive*.

Each CBA attributes to itself a high degree of legitimacy in participation in crisis communication [21], however, not every CBA has a useful role to play in crisis management. This issue has been explored [21, 45] but is yet to be examined in detail.

The CBA reveal the motivation of individuals who converge on a crisis and can also provide an answer as to why CB occurs in crisis situations. Table 1 presents all CBA in evidence so far.

Table 1. Convergence Behaviour Archetypes.

Behaviour	**Characteristics of Social Media Communications Activities**	**Examples**
The Returnees [10]	Enquire about properties they left behind and status updates about crises	*'Back at my house. Whole area looks devastated.'*
The Anxious [10]	Information seeking about missing persons, shelter and medical aid or general expression of fear	*'Please, if anyone has seen my friend let me know. We need to know she's okay!'*
The Helpers [10]	Help in identifying false crisis information, create and share posts about possible shelters	*'If anybody needs a place to stay, message me. I live nearby.'*
The Curious [10]	Ask questions about what happened and crisis conditions	*'What happened? Anybody know?'*
The Exploiters [10]	Scamming or spreading of false information, use crisis to promote own organisation/products	Misuse of the crisis hashtag for own products, e.g. *'#ManchesterBombing try out our new product!'*
The Fans or Supporters [21]	Supportive and grateful social media posts regarding disaster relief and official rescuers	*Staff underpaid and overworked, but there when we truly need them. Thank you.'*
The Mourners [21]	Paying tribute to victims or people affected by the crisis	*'Simply heartbroken by the news. Rest in peace.'*
The Detectives [45]	Surveillance activities, sharing news and information to increase information management	*'Police operation after **unconfirmed** gunshots and explosion.'*
The Manipulators [6]	Attention seeking and manipulative behaviour	*'That proves I was right all along. They should all be banned!*
The Furious [5]	Expression of anger and resentment about the crisis situation	*'What a cowardly act of terror. This is unbelievable!'*
The Impassive [5]	Don't actively take part in crisis communication, "reportage" function	e.g. passively sharing their own location

3 Method

3.1 Case Study

In order to address the research question, we conducted an analysis of a Twitter communication dataset centred on the terror attack that occurred in Manchester, United Kingdom, on 22 May 2017 21:31 (UTC). The attacker detonated a bomb after a concert by the American singer Ariana Grande. Twenty-three people were killed by the bombing, including the attacker and 250 more were injured. The Manchester Bombing was examined due to the nature of the event (terrorist attack) as well its international impact. We focussed on Twitter, which is currently the most popular microblogging service with over 313 million users [5, 38], because of its 140-character communication structure which has recently been expanded to 280 characters, Twitter allows users to make short and public statements [49] with fast and spontaneous information diffusion while reaching a large group of users [17, 32, 47]. These characteristics have been found to be very useful in crisis response.

3.2 Data Collection

For our purpose, we considered a social media analytics framework proposed by researchers [43], which acts as a guideline for social media analytics tools and methods. While originally based on the analysis of political communication on social media, it has been previously extended and the possibility of applying it in other research fields, such as crisis communication, was recently noted [44].

For data selection purposes, we chose a keyword-based tracking approach by focusing on the hashtags #Manchester and #ManchesterBombing, as these were the most prominent hashtags that were used on Twitter during the terror attack. Moreover, only English tweets were examined due to the crisis location, which is an English-speaking city. The nature of the event (terrorist attack) also ensures the internationality applicability of and interest in, this research project. The tracking method targeted the Twitter API[1], which is an interface, enabling us to receive data from Twitter. For analysis, a self-developed Java crawler was used to collect the data through the Search API, by using the library Twitter4J[2]. Subsequently, we saved the data in a MySQL database. In total, 3,265,007 tweets were collected from 22 May 21:31:00 to 24 May 23:59:59 (UTC). We chose to examine this specific timeframe to not only analyse the actual crisis, but also consider the post-crisis communication.

3.3 Data Analysis

In order to answer our research question, we firstly filtered the dataset by identifying the top central users that participated in the crisis communication on Twitter during the

[1] https://developer.twitter.com/en.html, last access 2018/02/05

[2] http://twitter4j.org, last access 2018/02/05

event. This was done by identifying the social network roles using a previous framework [38], which contains the roles of *Information starters*, *Amplifiers* and *Transmitters* [38]. The top 300 users of each role were identified to highlight the occurrence of influential users in every stage of the event. To meet this objective, we conducted a *Social Network Analysis (SNA)* using the tool *Gephi*[3], which is an open-source software tool for analysis as well as visualisation of networks and complex datasets [31]. In conducting a SNA, the data was visualised by a network consisting of nodes and edges, in which the nodes represent the users and the edges represent the different relations between the users [29]. A SNA allowed us to study the structures of the relationships between the users during a certain time span through different techniques and measures.

The *degree centrality (DC)* measures the influence of the different actors on the network by the number of relationships that are established with other members, or in other words, it describes the total number of edges connected to the users [13, 24]. In direct graphs, there exists two kinds of DC. While the *in-degree* represents the number of edges coming into a node and therefore portrays all incoming relations (here: being retweeted), the *out-degree* describes the edges going out of a node, thus representing all outcoming relations (here: retweeting other users). The *betweenness centralit*y *(BC)* represents the importance of a node to the shortest path lengths through the network. Users with a high betweenness centrality enable the flow of information from one network cluster to another [13], as they represent the nodes with the shortest path length.

- *Information Starters*: Information Starters are the most frequently retweeted users and are measured by the in-degree centrality. By being retweeted the most, the Information Starters contain the highest perceived content value.
- *Amplifiers*: The Amplifiers are identified by the amount of retweeting. While they do not tweet interesting content by themselves, they have the potential to diffuse information. The Amplifiers are measured by the out-degree centrality.
- *Transmitters*: Transmitters act as bridges between several Twitter communities that are built in a network through the interaction of the users with each other. They are necessary to reach other communities, which results in a broader information transmission. The community clusters can be detected by conducting a Modularity calculation in Gephi. Transmitters are measured the by betweenness centrality.

Next, we coded the 900 filtered tweets of all three role categories with a *Manual Content Analysis* using the characteristics of the CBA definitions given in Table 1 as a coding scheme. Thus, the number of occurrences of each Convergence Behaviour type was identified. Subsequently to reviewing this analysis, an additional method needed to be applied to the dataset. As the assignment of roles represents an approach for identifying the most impactful users but not whole user groups, this method alone is not sufficient in determining the most impactful CBA, since they vary in how frequently they occur. For example, one CBA might have the highest average in-degree, but only 5 tweets of this type might have appeared in the dataset. In contrast, another CBA might have a slightly smaller average in-degree, however, over 100 tweets of this type might have appeared in the dataset and therefore their impact might actually be higher, since

[3] https://gephi.org/, last access 2018/02/05

the average measure does not contain any information frequencies. To identify the CBA with the most impact in crisis communication during the Manchester Bombing, the measures of each CBA of the respective roles were tallied to an overall measure of each CBA. Hence, this case study proposes an extended method to identify the most impactful user groups, by CBA. Figure 1 represents this formula to determine the measure, which we labelled as *Impact Measure.*

$$\sum IM(I,O,B) = m(I,O,B)_1 + \cdots + m(I,O,B)_\mathrm{n}$$

Figure 1. Formula to determine the Impact Measure.

This formula was applied to every CBA occurring in the three roles (Information Starters (I), Amplifiers (O) and Transmitters (B)). The CBA that contains the highest value of the calculated Impact Measure (IM), is considered to have the highest impact.

4 Findings

4.1 Manual Content Analysis

The Manual Content Analysis revealed the number of CBA in each role, which are displayed in Figure 2.

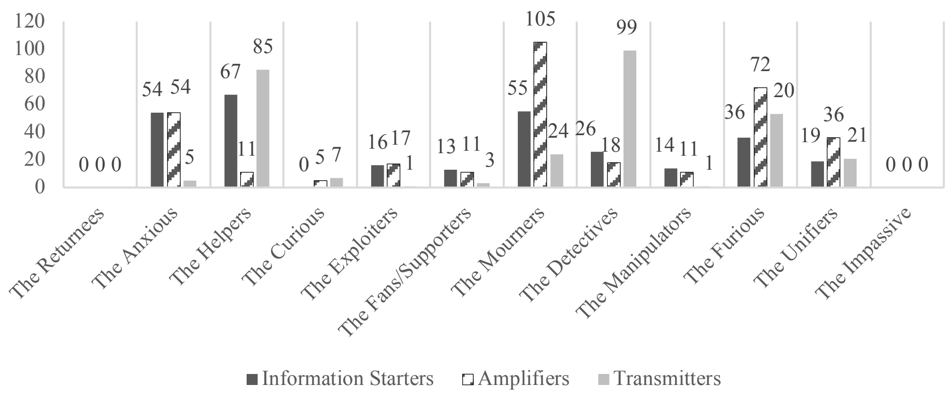

Figure 2. The occurrence of CBA in each role.

4.2 Social Network Analysis

When importing the data in Gephi, the unfiltered Network consists of 1,358,404 nodes and 2,838,008 edges. By filtering the data for the top 300 of each of the roles (Information Starters, Amplifiers and Transmitters), we identified the most influential users in terms of retweet behaviour, so the network then consists of 847 nodes and 8,286 edges. In addition, a Modularity calculation with a Resolution of 1.0 resulted in 3 main community clusters.

Some intersections between roles were also detected. While the Information Starters shared 9 users with the Amplifiers and 98 users with the Transmitters, the Amplifiers and the Transmitters intersected with 21 users. Thus, a total number of 228 intersections occurred in this dataset. Figure 3 visualises the social network graph that was analysed in this study, whereby the medium grey nodes represent the Information Starters, the light grey nodes the Amplifiers and the dark grey nodes the Transmitters.

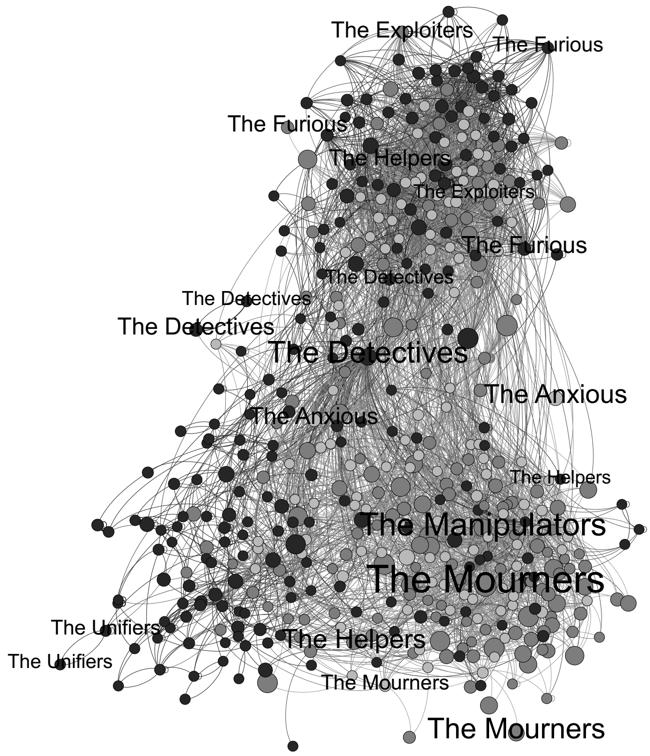

Figure 3. Social Network Graph.

Information Starters
The Information Starters alone consisted of 276 nodes and 394 edges. Their in-degree value ranged from 1,669 (lowest) to 7,6564 (highest) whereby their network analysis shows that nodes with a higher in-degree have more relations with each other, while nodes with a lower in-degree did not have any interaction with the other nodes. The Information Starters had an average follower count of 936,026.38 and were averagely retweeted 51,384 times, while they retweeted other posts 3 times on average. Along with the Amplifiers, the Information Starters consist of 3,958 edges, while with the Transmitters have 959 edges. Hence, their network consists of 5,311 edges in total.

Amplifiers

The network of the Amplifiers consists of 279 nodes and 34 edges. Their out-degree value ranges from 39 (lowest) and 475 (highest). The users have an average follower count of 9,600.79 and are retweeted 89 posts on average, whereas their own tweets were averagely retweeted 8 times. While they barely have edges with themselves, the Amplifiers contain of 3,958 edges with the Information Starters and 3,336 edges with the Transmitters. In total, their network comprises of 7,328 edges.

Transmitters

The network of the Transmitters contains 292 nodes and 1,027 edges. The betweenness centrality ranges from 301,013,002 (lowest) to 278,139,622,76 (highest) with an average of 3,717,157,952. In contrast to the average path length of 5.162 of the whole dataset, the Transmitters comprise an average path length of 7.017 and an average follower count of 137,706.53. Their tweets were averagely shared 1629 times, while the Transmitters themselves retweeted posts 18 times on an average basis. The Transmitter consist of 959 edges with the Information Starters and of 2,209 edges with the Amplifiers. Thus, their network contains 4,195 edges in total.

4.3 Computational Analysis

The Impact Measure, i.e. the sum of all the measures for each CBA has been determined using the proposed formula from Figure 1. As the numbers are in some cases high and hard to grasp, the percentage of the Impact Measure (p (I, O, B)) was additionally calculated. The results are displayed in the table below.

Table 2. Results of the Impact Measure calculation.

CBA	$\boldsymbol{\Sigma IM}$**(I)**	$\boldsymbol{p(I)}$	$\boldsymbol{\Sigma IM(O)}$	$\boldsymbol{p(O)}$	$\boldsymbol{\Sigma IM(B)}$	$\boldsymbol{p(B)}$
Returnees	-	-	-	-	-	-
Anxious	234,574	15.27	927	3.44	27,444,902,321	2.57
Helpers	426,045	27.73	1,965	7.29	274,745,984,251	25.75
Curious	-	-	585	2.17	37,389,355	0.00
Exploiters	44,992	2.92	1,720	6.38	2,366,080,254	0.22
Supporters	56,259	3.66	952	3.54	4,067,205,681	0.38
Mourners	309,209	20.13	9,222	34.26	311,761,760,731	29.22
Detectives	182,625	11.89	1,384	5.14	358,407,938,140	33.59
Manipulators	41,606	2.71	1,338	4.97	1,979,825,464	0.19
Furious	174,774	11.38	6,123	22.74	58,703,065,797	5.50
Unifiers	66,260	4.31	2,713	10.07	27,552,920,068	2.58
Impassive	-	-	-	-	-	-

5 Discussion

By conducting a manual content analysis, we were able to reveal a new Convergence Behaviour type that manifests in crisis communication. *The Unifiers* developed a strong motivation of social cohesion by bringing people in the Twitter network together as well as showing strength and solidarity in times of crises. The emergence of *the Unifiers* also matches with current research findings, as it has been indicated that users who provide emotional support and express solidarity by tweeting posts with a positive sentiment, are noted as having a central role on social media communication networks like Twitter, during crisis situations [3, 16]. An emerging sense of community can, therefore, help social media users to feel better about what is occurring in the crisis situation and also better cope with their emotions. As these characteristics do not fit with current knowledge and characteristics of existing CBA, this study therefore proposes to introduce the new and distinctive CBA category of *the Unifiers*. In contrast to other CBA, *the Unifiers* use the crisis to express positive thoughts and attempt to bring the people together.

The Unifiers	Expression of solidarity, emotional support and the motivation to strengthen the cohesion of social media users in times of crises and to create a sense of community among the social network. *We will not give in to this cowardice. I stand in solidarity with the brave people of #Manchester. (@khalid4PB, 2017).* [Tweet, Content Analysis].

The goal of this study was to identify the most impactful CBA based on three roles, by conducting a Social Network Analysis. In contrast to [29], which determined large intersections between the roles, i.e. mainly between the Information Starters and the Amplifiers, almost no intersections of these two roles could be detected in our study. It is therefore suggested that, in contrast to their previous assumption, these two roles need to be better differentiated. Also, larger intersections between the Information Starters and the Transmitters were identified, suggesting that in this case study, many users who were retweeted the most, could also disseminate their tweets into different communities of the network. Furthermore, we revealed that, the Information Starters have, in contrast to the Amplifiers and the Transmitters, the most followers with an average follower count of 936,026.38.

As opposed to [5], who identified a high occurrence of *the Impassive*, this study could not detect this CBA. We conclude that, while many users assume the role of this type, it does not have an overall high impact on crisis communication.

The results have shown that, based on the three roles that determine the most impactful users based on their retweet behaviour, different CBA can be considered as the most impactful depending on the assigned role.

As for the Information Starters, our analysis has revealed that, based on the developed Impact Measure (IM), *the Helpers* represent the CBA with the highest impact. This means that, overall, the tweets of *the Helpers* were retweeted the most. We were therefore able to confirm previous research that highlights the problematic abundance of volunteers on social media, which can cause unwanted noise of this CBA [42, 45] during a crisis event. As previously stated, the Information Starters can be accredited with high perceived legitimacy, since these users are the most frequently retweeted by other individuals. Thus, our results suggest that social media users accredit *the Helpers* for being the most legitimate CBA. Next to *the Helpers*, *the Mourners* are also evaluated as having a high IM. Additionally, *the Anxious* have the third highest IM(I), proving that social media users assign individuals who search for missing loved ones and seek help on Twitter, as having a high legitimacy.

Regarding the Amplifiers, *the Mourners* emerged to have the highest IM(O) and therefore can be considered to have the highest overall impact by retweeting posts the most. Consequently, *the Mourners* contain not only a high perceived content value as they represent the second most impactful Information Starters, but they also have an important role in amplifying content on Twitter. The second most impactful Amplifier was *the Furious*. The results show that the retweet function was therefore mostly used by the CBA who express their emotions through their tweets, as grief and anger are considered to have a high sentiment [11, 36].

Focussing on Transmitters, the results of the IM(B) calculation implies *the Detectives* to be the most impactful CBA thus being the users who transform and disseminate tweets and knowledge into different communities the most. The *Mourners,* however, only had a slightly lower IM(B). Further, *the Helpers* represent the CBA with the third highest impact. Besides these three archetypes, all others had a surprisingly low measure, indicating that *the Detectives*, *the Mourners* and *the Helpers* are the main CBA who disseminate content through different communities. This strengthens the occurrence of their own content and we can assume that this ensures that many users from different networks are informed about the latest news and possibilities to get help.

The fact that *the Mourners* are at least the second most impactful CBA in all three roles is rather unforeseen, since previous research has never isolated or discovered a high occurrence or impact of this CBA. Their high impact on crisis communication can therefore be perceived as problematic, as it is to be assumed that their tweets create a high level of noise which can aggravate crisis management efforts.

Figure 4 outlines the three CBA with the highest impact on crisis communication of each role, whereas the Information Starters simultaneously represent the CBA with the highest perceived legitimacy.

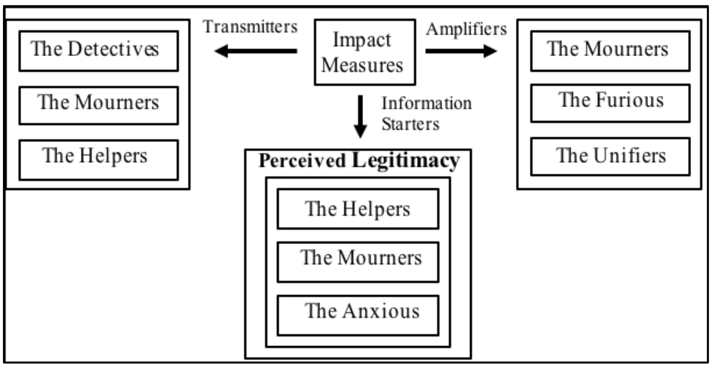

Figure 4. The top three most impactful CBA of each role.

6 Conclusion

Our study extends existing literature on Convergence Behaviour (CB) on social media during crisis situations. It serves as a very first step in the identification of the Convergence Behaviour Archetypes (CBA) that have the biggest impact on crisis communication and thereby the highest perceived legitimacy. This work was able to identify *the Helpers* to be the CBA that was most retweeted throughout the crisis and therefore consisting of the highest perceived legitimacy. Moreover, *the Mourners* had the highest impact by retweeting the most. This would seem to indicate that those social media users who create content based on their emotional state tend to retweet the most. Lastly, *the Detectives* were able to disseminate information into different communities the most. With *the Unifiers*, the study was able to detect a new CBA. We were thus not only able to extend the knowledge on how users converge on social networks during crisis situations, our results can also help crisis managers to gain more insight into users' behaviour. Knowing which behaviour on social media has the biggest impact, might aid them in controlling the sheer mass of information that is generated during a crisis event.

One should be mindful of the limitations of this work. Firstly, only one crisis event looking at 900 Twitter users was analysed. Consequently, it is neither representative of all users who take part in crisis communication on Twitter, nor does it represent other social networks, studies, crises or general social media behaviour. Thus, the results and contributions cannot be generalised and need further confirmation by additional research. Moreover, it must be noted that this study analyses a terror attack that took place at a concert of an American singer with mainly under-aged fans and listeners. The possibility that the social media users might have been significantly younger than users in other case studies of this kind, could have had a big influence on the overall crisis communication and therefore on the resulting CBA that were detected.

By applying the roles, it was possible to reveal the social media users and CBA that had the most impact regarding their retweet behaviour. One question that could additionally be answered in further research, is if these CBA change their role during the crisis communication *do they get affected or impacted by communication with other users*? Further, other approaches (than the application of the three roles) could be used in an analysis to identify CBA impact, such as the follower count.

This work has detected a strong emotional impact during the Manchester Bombing. While this might not be surprising due to the crisis type, it can further be assumed that CBA not only differ in their intent on converging on a crisis, but also in their emotional states. Further research could therefore explore this finding in more detail and examine the emotional impact of CBA with a sentiment analysis.

To enhance our findings, which focus on the issue of legitimacy, the approach applied by this work could be extended by comparing the perceived legitimacy of the social media users with those CBA that emergency management agencies see as having legitimate roles to play in a crisis. What archetypes are the most useful for emergency services agencies to enlist for crisis communications purposes on social media? Qualitative surveys in cooperation with emergency organisations might serve to shed light on these questions.

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