Social Media for Disaster Management:

Operational Value of the Social Conversation

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Abstract

Disaster relief organizations increasingly engage in social conversations to inform social media users about activities such as evacuation routes and aid distribution. Concurrently, users share information such as the demand for aid, willingness to donate and availability to volunteer through social conversations with relief organizations. We investigate the effect of this information exchange on social engagement during disaster preparedness, response and recovery. We propose that the effect of information on social engagement increases from preparedness to response and decreases from response to recovery. Some of the information exchanged in social conversations is actionable as well. We propose, however, that the effect of actionable information reaches its lowest point during disaster response. To test our theory, we use Facebook data from five benchmark organizations that responded to Hurricane Sandy in 2012. We analyze all of the organizations' posts and users' comments during a three-week period before, during and after Hurricane Sandy. Our findings support our theory. Furthermore, we identify an opportunity for relief organizations to improve their use of social media for disaster management. While relief organizations focus on informing disaster victims about aid distribution, most users are asking about how they as individuals can donate or volunteer. Thus, besides posting information directed to victims, organizations should post more information targeting potential donors and volunteers.

Keywords: Disaster Management, Social Media, Humanitarian Operations, Data Analytics

1 Introduction

Nowadays social media is no longer a choice; it is a must for organizations across all sectors. Disaster relief organizations including the Federal Emergency Management Agency (FEMA) are increasingly using social media platforms such as Facebook, Twitter and Instagram to engage users (FEMA 2018). In fact, Facebook had over 2.2 billion monthly active users in 2018, up from 1 billion in 2012 (Statista.com 2018), and offered relief organizations the opportunity to exchange information with the public through social conversations.

Social conversations provide two-way communication between relief organizations and the public, potentially exceeding the benefits of one-way communication, which only "pushes" information from relief organizations to the public (Holdeman 2018). These conversations facilitate the exchange of information, emotions and other types of social support. Social support, which can be informational or not informational, is formally defined as assistance and protection given to others (Shumaker and Brownell 1984). While informing users about the course of a hurricane is an example of informational social support, sending users messages of hope around the time of a disaster exemplifies non-informational social support.

We study the informational social support (henceforth informational support) embedded in the social conversations between relief organizations and users. We choose this topic—over non-informational support—because it carries operational insights for disaster management efforts. In fact, we would expect users' informational support needs to change during disaster preparedness, response and recovery, which are different phases of the disaster management cycle (DMC) (Altay and Green 2006, Tomasini and Van Wassenhove 2009). For example, potential victims need information about evacuation routes during preparedness, and aid distribution times and sheltering areas during response as well as recovery. Moreover, potential donors may need information about what to donate and potential volunteers may need information about what skills are needed during all the phases. We do not study mitigation, the DMC phase that relates to long-term recovery to reduce the potential severity a future disaster, because it occurs later in the DMC when the disaster is no longer the focus of the social conversation.

In order to study the informational support embedded in the social conversation between relief organizations and users during the DMC, we further classify informational support as actionable or non-actionable. We pay special attention to actionable information, i.e. information of practical value (Parker et al 2016). We investigate whether the social conversation between organizations and users facilitates the communication of actionable informational support such as where to receive aid, what to donate and how to volunteer. In particular, we investigate the following research questions: (i) *How does organizations' informational support engage users during different DMC phases?* Likewise, (ii) *How does organizations' actionable informational support engage users during different DMC phases?* and (iii) *How can organizations improve the social conversation with users throughout the DMC?*

In an effort to answer these three research questions, our conceptual framework is grounded in theories of disaster management and social support. We test this framework empirically using the case of Hurricane Sandy, 2012, which is one of the largest disasters in recent years in the U.S., and the U.S. is one the largest consumers of social media in the world. Hurricane Sandy received considerable social media attention from organizations as well as the general public. The disaster impacted more than ten states on the East Coast of the U.S. and affected millions of social media users (CNN Library 2014). The timeline of Hurricane Sandy allows us to compare the social conversation in disaster preparedness (October 22-28), response (October 29-November 4) and short-term recovery (November 5-11) using same-duration disaster phases. We set the period of study based on real actions and reactions by affected areas. The response period is one week because it was the peak of the emergency as indicated by the closing of NYC public schools. The Schools opened again on November 5, which signaled the beginning of the recovery phase.

We study Facebook because it was the most popular social media application in the U.S. at the time of Hurricane Sandy and was instrumental to disaster management (Miller and Tucker 2013). We focus on the social conversations of five benchmark organizations that had active Facebook presences and participated in the Sandy operations: the National Hurricane Center (NHC), FEMA, American Red Cross (ARC), the National Guard (NG) and the City of New York (NYC). Google Trends (GT) data complements the Facebook data as GT is a proxy for the public's attention on Hurricane Sandy and different organizations during the period of study.

Our unit of analysis is the incoming comments from users responding to an organization's post, which are an active form of social conversation, and increase user generated content (UGC). The more comments there are, the greater the volume of UGC. We conduct content analysis on informational support and actionable information contained in each post from the organizations and in each user's comment. While doing so, we create a novel data dictionary to classify actionable information (e.g. information related to aid distribution, donations and volunteering). It is worth noting that our analysis is not at the user level because users may have different characteristics (e.g. number of posts, number of friends) when they make comments at different times. Studying users instead of comments would ignore these dynamics.

We collect and analyze 305 posts generated across five organizations and 18,511 Facebook users' comments on these posts. We estimate the probability that an incoming comment contains informational support or actionable information. We use econometrics to analyze the effects of the social conversation, organizations' Facebook page characteristics, and users' characteristics on such probability. The model captures time-varying effects associated with dynamic social conversations.

We find that informational support organizations provide is most effective during the response phase of the DMC. Strikingly, we find the opposite effect when it comes to actionable informational support. Moreover, our empirical results suggest that the social conversation is led by non-victims that want to help instead of victims asking for help or providing information about the disaster. This finding creates an opportunity for relief organizations to match their social media content to users' needs better during disaster operations. While organizations focus on informing users as to how the organizations are helping, most users are asking about how they, as individuals, can help. Thus, besides posting actionable information directed at victims, organizations should post more actionable information targeting potential donors and volunteers. Our findings are robust to different model specifications.

The contribution of this research is threefold. First, we study the effect of social media on the DMC and characterize users' social informational support needs at different DMC phases. Second, we provide insights on how organizations can improve their social conversations with users. In particular, organizations need to use social media platforms to talk not only to disaster victims but also to potential donors and volunteers. Organizations can prioritize answering comments from users located near the disaster area because those people are more likely to donate or volunteer. Third, in order to analyze actionable information, we create a data dictionary that is suitable for operations management research beyond the humanitarian context. The data dictionary is available as an online appendix to this article. Our contributions are relevant as relief organizations engage millions of social media users in social conversations during disaster operations, such as the Hurricane Harvey in 2017 and Hurricane Florence in 2018. Even though understanding the operational implications of social conversations is important for practitioners, it has been neglected by extant humanitarian operations management literature to date.

2 Conceptual Framework and Hypotheses Development

This research draws on multiple disciplines including operations management, information systems and social psychology. It combines concepts from disaster management and social support to examine the actionable information embedded in the social conversation during disasters. In the following, we review theories that are relevant to this study. Then, we propose hypotheses based on the interface of disaster management and social support.

2.1 Disaster Management Cycle (DMC) and Information Management

DMC comprises four phases: preparedness, response, recovery and mitigation (Altay and Green 2006, Tomasini and Van Wassenhove 2009, Van Wassenhove and Pedraza-Martinez 2012, Stauffer et al 2016, Besiou et al 2018). We study the preparedness, response and short-term recovery, henceforth referred to simply as recovery, phases of the DMC. Preparedness relates to the actions the community takes before a potential disaster strikes, which include the pre-positioning of relief items such as water, medicine and food to facilitate a fast response. Response relates to urgent actions taken during the disaster and in the immediate aftermath, which include search and rescue, first aid provision, food distribution and other emergency services. Recovery relates to the actions taken after an initial response. Recovery can be divided in two sub-phases: short-term recovery and long-term recovery. Short-term recovery is the transition between response and long-term recovery, and includes conducting damage assessments, building temporary shelter and cleaning debris (Holguin-Veras et al 2012a). Short-term recovery in the U.S. and other developed countries typically has short duration (JHU and IFRC 2008) because they have more resources and trained personnel than developing countries.

Information management affects all DMC phases (Tomasini and Van Wassenhove 2009). The act of providing information to others is known in the literature as informational support (House 1981, Barrera

1986, Tilden and Weinert 1987). Moreover, information can be actionable or non-actionable (Tushman and Nadler 1978, Gardner et al 2015). In particular, the word "actionable" is defined as "relating to or being information that allows a decision to be made or action to be taken (AHD 2019)." Thus, actionable information can be acted on (Feng and Shanthikumar 2018) as it relates directly to disaster management operations. We define the term "actionable informational support" as informational support with practical value for organizations and users. Examples of this type of support during the DMC include communicating aid distribution and funding requests (cash or in-kind) for disaster response to potential donors (Aflaki and Pedraza-Martinez 2016). Examples of non-actionable informational support include describing the course of the disastrous event and the damage it has caused.

The study of the role of social media in the DMC can help organizations to improve their response operations by interacting with victims as well as potential donors and volunteers. Better management of actionable informational support could potentially contribute to decreasing the volume of unsolicited in-kind donations. This is a critical problem during the DMC because up to 60% of unsolicited donations are not needed in the disaster area (Holguin-Veras et al 2012b). These donations often create bottlenecks in field operations and slow down the entire response (Holguin-Veras et al 2012a). Moreover, donors located closer to the disaster area tend to send more in-kind donations than donors from far away (Destro and Holguin-Veras 2011). Similarly, actionable information can improve volunteer management as it allows organizations to communicate what skills are required at any point in the DMC to the public. Otherwise, poorly-managed unskilled volunteers may cause bottlenecks and delays to the response operation (Lodree and Davis 2016).

We study the DMC through the lens of social media to investigate the effects of informational support and actionable information on the social conversation. Our study is different from extant literature in multiple ways. First, there is a nascent stream of literature about how disaster-related information spreads on social media platforms. For instance, Yoo et al (2016) study information diffusion (cascades) during the response to Hurricane Sandy using Twitter. They focus on the dynamics of information cascades but do not analyze the content embedded in social conversations. In other words, they assume that there is a match of social support and analyze Twitter diffusion patterns. We unpack this assumption and investigate the effect of actionable information on users' comments. Moreover, extant literature has not studied the match between the actionable information provided by organizations and the information wanted by users. This match has clear, practical implications for organizations such as the possibility of learning the dynamic needs of their audience. Second, there is a stream of literature focused on algorithms to categorize disaster-related data as well as mapping needs and requests (e.g. Nguyen et al 2017, Purohit et al 2013). Although those algorithm-based studies can improve the accuracy of classification, more relevant to operations management is how to use classified data (informational, actionable informational) to improve disaster response, which is the focus of our study. Our findings contribute to the generation of actionable strategies and policies to facilitate the social conversation between organizations and the general public during the DMC.

2.2 Social Support Theories

Organizations use social media to provide social support and engage in social conversations with the general public during the DMC. As an important and widely studied concept, social support can be categorized into four collectively exhaustive types: informational, emotional, instrumental and appraisal support (House 1981, Barrera 1986, Tilden and Weinert 1987). Informational support involves providing information to another person. Emotional support includes the provision of care, empathy, love and trust (House 1981, Cronenwett 1985) and is transmitted through the communication that one (i) is taken care of and loved, (ii) is valued and (iii) is not alone and belongs to a network (Cobb 1976). Instrumental support is defined as providing tangible goods, aid and services (House 1981, Tilden and Weinert 1987). Appraisal support refers to affirmational support, which is comprised with expressions to affirm the appropriateness of acts or statements made by another (Kahn and Antonucci 1980).

Social media is well known for providing informational support and emotional support (Yan and Tan 2014). The most attractive feature of social media for organizations is the opportunity to distribute information to a large population at low cost, in a timely manner and without geographic boundaries. Extant literature suggests that users are more inclined to provide informational support than emotional support through the web. Many organizations such as non-profits consider social media platforms an important data source and utilize them as efficient information dissemination means. During the DMC, disaster relief organizations collect information to assess the situation and coordinate actions as well as disseminate information to their donors and beneficiaries (Van Wassenhove and Pedraza-Martinez 2012).

Social media platforms are effective means for both organizations and users to have a social conversation. These platforms allow users to share information with organizations and other users. Engagement in the social conversation is understood as users' actions of joining the social conversation with organizations by leaving comments on the organizations' social media applications (Ma et al. 2015). Users' social engagement increases the power of these media social platforms (Ransbotham et al. 2012).

Because of our interest in social media as an operational tool during the DMC, we focus on the intangible social support that we divide into two categories: informational support and non-informational support. The latter includes emotional support and other text that cannot be classified as informational. We further classify content as actionable or non-actionable to obtain operational insights on information management during the DMC. Figure 1 illustrates our classification of content as informational support and actionable informational support in a hierarchical structure.

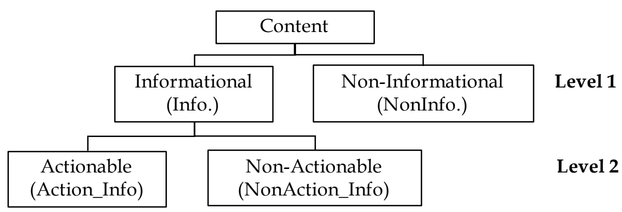


Figure 1: Social Conversation Analysis

In the following, we first focus on the effect of informational support embedded in the social conversation between organizations and users during each phase of the DMC and then introduce the actionable aspect of informational support. Our analysis excludes multimedia content such as photos and videos that are displayed without text because we could not estimate the social support they provided accurately.

2.2.1 Informational Support and DMC

It is conceivable that each DMC phase requires different types of social support to engage users effectively. The *Stages of Change Model*, which emphasizes that the effectiveness of social support may vary across time periods (Verheijdent et al. 2005), supports the existence of these differences. Thus, during stressful events like disasters, it is critical for organizations to deliver the right support for the dynamic needs of social media users.

In line with the dynamic needs of information across the different DMC phases, it is also worth noting that such benefits depend on specific situations, albeit positive effect of social support on various outcomes that have been documented in prior literature. First, social support is an exchange process including at least two parties, i.e., providers and recipients (Shumaker and Brownell 1984). Hence, the outcome of supportive actions is tied to the intention of both parties. Whereas there is demand for support and there is a supply of support, the actual effects of supportive actions depend on whether support recipients receive the help they need. As such, the optimal matching theory generally concludes that certain types of support are more beneficial than others for a given stressful situation. Specifically, matching the social support offered by providers to the unique needs of support recipients makes exchanges most effective and beneficial (Brock and Lawrence 2009).

We conjecture that informational support is most effective during the disaster response phase compared to other phases as people's lives may depend on it. For example, organizations disseminate information about search and rescue as well as available emergency relief services (Holguin-Veras et al 2012a). On the other hand, the informational support organizations offer during preparedness includes evacuation routes (Regnier 2008). Informational support during recovery comprises further actions such as debris collection (Celik et al 2015) that will help users to go back to their normal life routine (Van Wassenhove and Pedraza-Martinez 2012). Although important, informational support during preparedness and recovery has less urgency than informational support during response.

HYPOTHESIS 1. *The effect of organizations' informational support on social engagement varies during different DMC phases:*

a. *The effect of informational support on social engagement is weaker during disaster preparedness than it is during disaster response.*
b. *The effect of informational support on social engagement is stronger during disaster response than it is during disaster recovery.*

It is worth noting that we do not compare the effects of social support and actionable information on social engagement between the phases of preparedness and recovery. The comparison would have limited theoretical value because these two phases are not adjacent in the DMC.

2.2.2 Actionable Informational Support

As the DMC phases shift, one would expect actionable informational support to change as well. During preparedness, organizations provide actionable informational support about what items to store (food, water, medicine). Users are concerned about the risk of the event and how to prepare for it. Thus, they are likely to engage with organizations to find out more actionable guidance about preparing. Second, during response, organizations provide actionable informational support about evacuation, aid distribution and location of provisional shelters. However, it may be easier for users to gather information through information diffusion from people around them (Kadushin 2012) or directly from field relief staff and volunteers. Therefore, they are less likely to engage with organizations via social media. Finally, during disaster recovery, organizations provide actionable informational support about sheltering, aid distribution, debris clearing and what to donate. Users begin to resume their daily routines and rely on the actionable information provided by organizations for this purpose. Hence, users are more likely to engage in social conversation with organizations.

HYPOTHESIS 2. *The effect of organizations' actionable informational support on social engagement varies during different DMC phases:*

a. *The effect of actionable informational support on social engagement is stronger during disaster preparedness than it is during disaster response.*
b. *The effect of actionable informational support on social engagement is weaker during disaster response than it is during disaster recovery.*

To test our hypotheses and get insights about the role of social media for disaster management, we use the case of Hurricane Sandy. We acknowledge that Hurricane Sandy took place in 2012, so it could be seen as an "old" event already. However, Hurricane Sandy does not have any fundamental differences from more recent hurricanes such as Harvey in 2017 or Florence in 2018. All hurricanes are rapid-onset natural disasters that allow several days for disaster preparedness and take several days for response and recovery in the affected area. The operational activities around Hurricane Sandy reflect the typical operational deployment following a major hurricane in the U.S. Thus, we believe our choice of case study is sufficient to investigate our research questions. Moreover, our focus is on the social conversation *between* organizations *and* users instead of information diffusion *from* organizations *to* users. Therefore, the social media platform we use in this study is Facebook rather than Twitter. Finally, the validity of our research depends on whether there have been substantial: (i) material changes in technologies that run social media applications and (ii) changes in human behavior towards the use of social media. Because these two aspects have not changed substantially since 2012, our findings and theoretical contributions remain valid regardless of the data's age. Next, we give a brief background on the case of study and describe our data.

3 Case Study, Organizations and Data

Tropical Storm Sandy first developed in the Caribbean Sea on October 22, 2012. On October 26, North Carolina, Maryland, Washington D.C., Pennsylvania and New York declared a state of emergency—i.e. a public emergency that threatens the life of the citizens (United Nations 2001). On October 27, New Jersey, Connecticut and Massachusetts declared a state of emergency, and the first evacuations in New Jersey were ordered. On October 28, President Obama declared a state of emergency in Washington D.C., Maryland, Delaware, New York, Rhode Island, Connecticut and Massachusetts. The Governor of New York directed the NG to mobilize, and New York City suspended subway and public bus services (CNN Library 2014). On Monday, October 29, one week after it developed, Sandy's center made landfall around 8 p.m. near Atlantic City, New Jersey. On October 30, Sandy began to move towards Canada, where it caused minor damage. Although technically Sandy was a post-tropical cyclone when it made landfall on October 29, we refer to it as Hurricane Sandy because that is how it was referred to on social media at the time. Ultimately, its path of destruction extended from Jamaica to Canada. The damage Hurricane Sandy caused in the U.S. approached $62 billion (USD) and created major disruptions to public transportation, electricity, maritime logistics and many other services. The death toll was over 200 including 147 deaths in the United States (NOAA 2013).

The physical response operation to Hurricane Sandy was large, fast and effective. Within 48 hours FEMA had 1,200 field staff in NYC alone. In coordination with ARC, NG, NYC local responders and other organizations, they distributed 1.9 million meals and 1.3 million liters of water during the three days after the storm. More than 11,000 volunteers helped to clear debris and distribute meals (NYC 2013). The public received information about Hurricane Sandy through television, radio, internet news outlets, Facebook and Twitter (NYC 2013). However, Sandy left more than 2 million people without electricity. A task force from the Army Corps of Engineers installed 211 generators mostly in hospitals and other critical points in NYC (Byrne 2013). Brightbox, a NYC based firm, provided mobile phone charging stations to the public starting October 30. By November 5, one week after Sandy's landfall, most public schools resumed classes with the exception of severely hit areas such as Red Hook, New York (Mead 2012). The distribution of food, water and fuel was handed to the states of New York and New Jersey, which used predetermined points of distribution for last mile delivery (FEMA 2012). By November 11, the floodwaters had receded and most subway lines were running again (Mead 2012).

Then NYC Mayor Michael Bloomberg asked the general public to donate cash to support the operation. However, the response operation was not free of unsolicited in-kind donations that created operational bottlenecks. Unrequested clothing that accumulated in neighborhoods became a sanitary concern (NYC 2013). In January 2013, relief groups in NYC were still figuring out what to do with piles of clothes and other unsolicited items that were sent to the disaster area after Sandy (Fessler 2013).

3.1 Selection of Organizations in Facebook

This exploratory study uses a purposive sample (Yin 2014) to get managerial insights from organizations that operate across the different phases of the DMC. The sample focuses on organizations that were heavily involved in the operation and had a social media presence, but it is not intended to get a significant representation of all the organizations that participated in Sandy response operations. It is composed of five organizations and includes federal (NHC, FEMA), nonprofit (ARC), military (NG), and local government organizations (NYC) engaged in DMC.

NHC is part of the National Oceanic and Atmospheric Administration. NHC's mission is "*to save lives, mitigate property loss, and improve economic efficiency by issuing the best watches, warnings, forecasts, and analyses of hazardous tropical weather and by increasing understanding of these hazards.*" (nhc.noaa.gov). Social media was an effective means for NHC to reach the public during Hurricane Sandy.

FEMA is the main disaster coordinator at the federal level in the U.S. FEMA's mission is "*to support our citizens and first responders to ensure that as a nation we work together to build, sustain and improve* *our capability to prepare for, protect against, respond to, recover from and mitigate all hazards.*" (fema.gov).

ARC is one of the largest disaster relief organizations in the U.S. According to its mission, ARC "*... prevents and alleviates human suffering in the face of emergencies by mobilizing the power of volunteers and the generosity of donors*" (redcross.org). More than 20 trained digital volunteers at ARC donated hundreds of hours to provide actionable information on preparedness and safety before Hurricane Sandy as well as the location of emergency response vehicles, shelters and fixed feeding sites after the hurricane hit.

NG is the primary reserve U.S. military force. NG's mission is "*to maintain well-trained, well-equipped units available for prompt mobilization during war and provide assistance during national emergencies (such as natural disasters or civil disturbances)*" (nationalguard.com). NG participated actively in responding to the Hurricane Sandy and used social media to inform the public about its operations (Greenhill and Soucy 2012).

NYC is the public administration of the largest U.S. city. In 2011 Mayor Bloomberg named the first chief digital officer to make New York "*the world's leading digital city*" (Huffington Post 2012). NYC's digital vision in 2012 included an increase in the social conversation and a strong presence on Facebook.

3.2 Data

It has been discussed that the three key problems in studying humanitarian operations are "data, data and data" (Starr and Van Wassenhove 2014). As such, data collection on disaster management is challenging. We endeavored to overcome this challenge by collecting our own data from Facebook and combining two sets of data: Facebook and Google Trends. We collected daily data from October 22 to November 11 corresponding to the phases of preparedness, response and recovery, and aggregated data by week (one week per DMC phase).

3.2.1 Facebook Data

The official Facebook account of each organization displays a blue icon with a check mark next to the organization's name. The page includes the official identification for the Facebook account, henceforth referred to as Page. Similar to other social media platforms (e.g., Twitter and Yelp), Facebook has a category that describes the general type of activity for every organization such as non-profit, charity and education.

The Facebook data include 305 organizations' posts and 18,511 users' comments. The focal variables of interest are defined as follows. Info_P/C measures the informational support embedded in posts/comments of a Page. NonInfo_P/C measures the non-informational support embedded in posts/comments of a Page. It includes emotional support and other types of support. Action_Info_P/C measures the actionable information embedded in posts/comments of a Page. Finally, NonAction_Info_P/C measures the non-actionable information embedded in posts/comments of a Page. These four variables are not accumulative but constructed for each DMC phase. The corresponding notation used from now on is included in Table 1.

Variable	Type	Description
Disaster management cycle (DMC):		
t		DMC index. $t = 1, 2, 3$ for preparedness, response and recovery, respectively.
Social conversation:		
X		Vector that includes the social support exchange in posts and comments. In the analysis on informational support, X includes Info_P and Info_C. In the analysis on actionable informational support, it includes Action_Info_P, NonAction_Info_P, Action_Info_C and NonAction_Info_C.
Info_P/C	In-period	Informational support embedded in posts/comments of a Page.
NonInfo_P/C	In-period	Non-informational support embedded in posts/comments of a Page. It includes emotional support and other types of support.
Action_Info_P/C	In-period	Actionable Information embedded in posts/comments of a Page.
NonAction_Info_P/C	In-period	Non-actionable information embedded in posts/comments of a Page.
Organization's characteristics :		
i		Organization's ID. $i \in I$, where $I = \{$NHC, FEMA, ARC, National Guard, NYC$\}$.
s		Index for posts.
Page		Vector of organization's characteristics: UGC, Likes, Shares, Posts and Comments.
UGC	In-period	User's generated content: Facebook metric of "Number of people talking about this" Page.
Likes	Accumulative	Total number of likes for an organization's Page.
Shares	In-period	Total number of shares for activities that have been done by a particular organization.
Posts	Accumulative	Total number of posts of an organization on its Page.
Comments	Accumulative	Total number of comments made by users on a Page.
Control for public attention:		
GT		Google Trends index. Proxy for public attention on each organization.
User's characteristics at the individual level:		
j		Index for the comments generated in the social conversation. $j = 1, 2, \ldots$
k		Index for the comments that were written on a Page before comment j. For user $j = 3$, $k = 1, 2$.
User		Vector of user's characteristics. It includes: Friends, User_P, NYC and East.
Friends		User's number of friends.
User_P	Accumulative	User's generated content (UGC) to date.
NYC		New York area. NYC=1 if the user is from the New York area; NYC=0 otherwise. NYC is composed of: include Manhattan, Brooklyn, Queens, The Bronx, and Staten Island.
East		East Coast area. East=1 if the user is in the East Coast; East=0 otherwise. This area is composed of 14 states: Maine, New Hampshire, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, Delaware, Maryland, Virginia, North Carolina, South Carolina, Georgia, and Florida.
Dependent variable:		
$\Pr(\text{C\_Type}_j^{is} = 1 \mid t)$		Probability that comment j is of a particular type: informational, non-informational, actionable information or non-actionable information for a post s contributed by organization i at a given disaster phase t.

Table 1: Model Variables and Descriptions

We classify textual data embedded in the social conversation between organizations and Facebook users as informational and actionable. The detail of this classification will be discussed in Section 4. The user's social engagement depends on the organization's characteristics on Facebook. The basic metrics of each Page include the total Page "Likes" (Table 2), which activates a link that displays the profiles of all the users that like the Page. "UGC" is the user-generated content, which corresponds to the "number of people talking about this" metric of Facebook that counts the number of people sharing stories about the Page. These stories include liking the Page, posting on the Page's timeline, commenting on or sharing the Page's posts, mentioning the Page, and so forth. Besides the basic metrics, the social conversation generates data such as "Posts" that measures the number of posts displayed by the organization and users' "Comments" that can be disaggregated per post and per user.

Org.		NHC			FEMA			ARC	
t	Prep.	Resp.	Reco.	Prep.	Resp.	Reco.	Prep.	Resp.	Reco.
Likes	145,543	147,581	149,263	38,075	38,311	38,824	367,667	371,344	376,246
UGC	53,330	6,761	3,054	5,741	6,822	3,913	20,831	29,652	11,264
Posts	50	66	79	26	53	78	7	29	43
Comments	6,508	7,181	7,431	3,145	4,061	4,641	679	1,864	2,551
Shares	21,658	3,289	1,200	10,167	7,114	3,940	3,297	10,103	6,772
GT	9	4	-	-	13	8	-	11	7
Org.		NG			NYC		All Organizations (average)		
t	Prep.	Resp.	Reco.	Prep.	Resp.	Reco.	Prep.	Resp.	Reco.
Likes	1,056,576	1,072,002	1,082,936	105,422	106,666	107,562	342,656.6	347,180.8	350,966.2
UGC	15,019	30,705	12,951	20,424	12,616	9,445	23,069	17,311.2	8,125.4
Posts	22	34	45	28	45	60	26.6	45.4	61.0
Comments	519	2,077	2,907	364	763	981	2,243	3,189.2	3702.0
Shares	1,600	4,106	2,065	2,199	1,312	799	7,784.2	5,184.8	2,955.2
GT	-	-	-	192	341	191			

Table 2: Statistics on Organization's Characteristics

The social conversation also depends on individual users' characteristics at the moment of commenting such as number of "Friends," "User_P" that captures the total number of posts a user has contributed on Facebook, and user's location, which we label as "NYC" and the "East" (as in the East Coast) in Table 3. Our sample comprises all social conversations on Facebook for the five organizations during the three-week long window of study. The Facebook data were collected using an application programming interface (API) provided by Facebook.com.

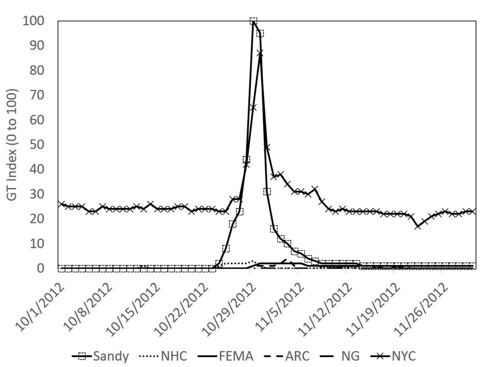
Variable	Mean	Std. Dev.	Min	Max
Friends	255.52	148.08	1	512
User_P	256.67	148.12	1	512
NYC	0.5	0.5	0	1
East	0.74	0.44	0	1

Table 3: Statistics on Users' Characteristics

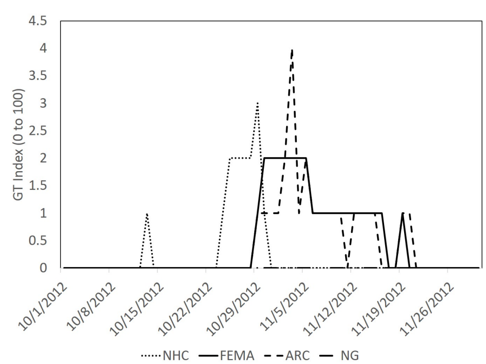
3.2.2 Google Trends (GT) Data

Prior studies use GT data to control for general interests in different contexts. For example, Moe and Schweidel (2012) use it to proxy category-level interest among the public; Varian and Choi (2009) link it to short-term economic trends; Carneiro and Mylonakis (2009) use it to control for disease outbreaks; Luo et al. (2013) use it as a proxy for conventional online behavior metrics. GT data provides an index that shows the relative frequency of a search term compared to the total number of searches conducted using Google during a period of time. The GT index is displayed on a scale of 0 to 100 indicating to what extent the search term is currently attracting the general public's attention. The search terms included keywords like "Hurricane Sandy," "NHC," "FEMA," "American Red Cross," "National Guard" and "NYC." Later we use GT as a control variable that serves as a proxy for public interest.

The public awareness of Hurricane Sandy began to increase substantially on October 25 (Figure 2a). The peak of searches occurred on October 29, when the search term "Hurricane Sandy" dominated GT. Although overall public concerns about Sandy dropped quickly after October 31, there were still many searches on Hurricane Sandy until November 11, which is the end of our period of study. During this period we also observed a peak for the search term "New York City" that follows a similar pattern as Hurricane Sandy.



(a) GT including Hurricane Sandy and NYC



(b) GT for NHC, FEMA, ARC and NG

Figure 2: Control for Public Attention: Google Trends (GT) Data, October 22 to November 11, 2012

During Hurricane Sandy, organizations' GT follows an interesting pattern. NHC, which provides real time updates on possible hurricane patterns, dominated Google searches in the preparedness phase (Figure 2b). Even though the other organizations in the sample were also active during the preparedness phase, they received less attention than the NHC. However, ARC and FEMA dominated Google searches during the response and recovery phases. Those organizations implemented disaster response programs and deployed staff to the disaster area. Although the NHC and the NG also participated in response and recovery activities, they received less attention from the general public.

4 Content Analysis and Models

Our research approach includes content analysis (text mining) and empirical models. First, we apply text mining techniques on all the posts and comments organizations and users generated during the period of study and classify content into two categories: informational and non-informational (Yan and Tan 2014, Yan 2018). Second, we create a novel data dictionary of actionable information, which helps label information with practical value. Actionable information is particularly important for operations management because it captures the exchange of information about aid distribution, sheltering, donating and volunteering. Third, we use the results of content analysis and actionable information as inputs for social conversation analysis. Finally, to understand how social conversations develop, we construct an econometric model that explores the social conversation at two different levels: informational and actionable-informational.

4.1 Content Analysis on Informational Support

Our content analysis approach combines both unsupervised and supervised learning. Regarding supervised learning, we classify organizations' posts and users' comments into informational and non-informational categories (sample content shown in Table 4). This is a text categorization—or text classification—problem in which text is assigned to predefined categories according to their content. Since there are two predefined categories, we use LingPipe (Alias-i 2008), a software package for text mining, to classify the data. To incorporate the content-specific characteristics of this study, our content analysis process is different from prior studies in two ways. First, we specially label the terms "hurricane," "Hurricane Sandy" and "Sandy" as phrases that are associated with information category. One might think that such terms would appear in a vast majority of posts. However, in our data set we only have 154 counts of "Hurricane," "Hurricane Sandy" and "Sandy" in organizations' posts. This may be because Hurricane Sandy was a large disaster that became common knowledge, therefore, many organizations omitted its name when publishing posts.

Second, we consider the mixed nature of online content that goes beyond evaluating a textual input in a binary manner (yes or no). It is common that a post may have different types of information embedded in it. A number between 0 and 1 returned for each post or comment indicates the probability that the content belongs to a particular type (informational or non-informational). We assign these probabilities to each post and comment, corresponding to the particular type of content (Table 4).

ID	Sample Content	Info. Support	NonInfo. Support	Action	Non Action
1	We are focusing on getting comfort and aid to thousands of people, putting plans to reach affected neighborhoods as soon as we hear needs. Keep up with the latest relief info by following our updates at newsroom.redcross.org.	0.67	0.33	1.00	0.00
2	"If I could hug you right now, I would." That's how we feel about all of you. Thank you for your incredible support.	0.33	0.67	0.00	1.00
3	Take care of yourself and your neighbors as the Nor'easter comes in today. We've sent in thousands of blankets and hand warmers. Get to a red Cross shelter or NYC warming center if you need a safe place to stay.	0.67	0.33	0.67	0.33
4	Hurricane Sandy is moving northwest across the northwest Bahamas, centered this morning about 15 miles east-southeast of Great Abaco Island.	1.00	0.00	0.00	1.00

Table 4: Sample Texts in the Data Set

Using sample content in Table 4 as an illustration, suppose that an organization has displayed four posts and the probabilities of offering informational support are 0.67, 0.33, 0.67 and 1 (Column Info. Support). The total value for informational support is 0.67+0.33+0.67+1 = 2.67 (Sum of Column Info. Support). The value for non-informational support is 0.33+0.67+0.33+0=1.33 (Sum of Column NonInfo. Support).

The values in Table 5 represent the sum of the probabilities of a post being either informational or non-informational for the entire data set. We further classify content into posts, labeled as "_P", e.g. "Info_P" and comments, labeled as "_C", e.g. "Info_C".

Variable	Mean	Std. Dev.	Min	Max
Classification based on Content Analysis				
Info_P	13.08	7.35	3.61	27.59
NonInfo_P	9.56	5.87	2.99	22.41
Info_C	1063.48	804.42	1.07	2362.23
NonInfo_C	1711.77	1504.30	1.81	4623.97
Classification based on Actionable Content				
Action_P	17.711	11.353	4.99	42.25
NonAction_P	4.934	1.645	2.01	8.76
Action_C	1874.290	1553.796	1.68	5192
NonAction_C	900.963	779.499	0.61	2921.64
Classification of Actionable Information				
Action_Info_P	10.292	6.60	2.57	23.31
NonAction_Info_P	2.789	0.859	1.037	6.060
Action_Info_C	718.093	551.50	0.60	1867.98
NonAction_Info_C	345.389	278.45	0.22	1046.49

Table 5: Data Analysis Descriptive Statistics

4.2 Content Analysis on Actionable Informational Support

In contrast to the previous section, we could not find a data dictionary for actionable information analysis. Thus, we used both supervised and unsupervised learning approaches. First, we created a coding scheme that includes rater classification and a data dictionary (Bambina 2007) for text classification. To do this, we followed the general procedure for text classification. In general, text classification is a supervised learning method in which there are pre-defined categories used in a training set. Each document in the training set is used as a positive instance for the category labels associated with it and a negative instance for all other categories. A classification model is built by extracting word features from each document, and the feature vectors are used as inputs to a scheme that learns how to classify documents (Witten 2005). In our study, each document refers to either an organization's post or a user's comment on Facebook.

Following this procedure, we first created two categories: actionable and non-actionable. Then we randomly selected 50 posts and 320 comments in the dataset, and two operations management researchers (raters) classified each of the instances in the sample set as "actionable" or "non-actionable." Inter-rater reliability based on simple agreement (Bambina 2007) on actionable information was 85.9% for the entire set, 86.0% for posts and 85.6% for comments. The disagreement was discussed and reclassified accordingly. Following the typical 80-20 rule, we "hold out" 20% of the examples with known classifications by not allowing the learning program to train on those examples to evaluate the accuracy of our classification model. The text classifier obtained an accuracy of 86.39%.

Regarding the unsupervised learning approach, we created a data dictionary to classify posts and comments as actionable or non-actionable (Appendix 1). The basis for the dictionary was lists of action verbs published by Harvard University (Harvard.edu), Yale University (Yale.edu) and the University of California, Berkeley (Berkeley.edu). We searched for the three closest synonyms of each verb from the lists on the Oxford Dictionary website. We repeated this procedure until we reached a circular reference or the third level search, whichever came first. As a result of this process, we obtained 399 words.

We included DMC terms through the list of emergency items of the ARC and IFRC lists. This process added 769 words/phrases to the data dictionary. These keywords belong to categories such as food, inventory, logistics, packaging, personnel security, power supply, shelter, vehicles and warehousing.

We added the data dictionary to the text classifier and re-trained the model. The last two columns in Table 4 illustrate examples for this classification. Including the "actionable" data dictionary to the text classifier increased accuracy to 90.58%. Finally, we applied the enriched text classifier to the entire data set and classified all the posts and comments as either actionable or non-actionable (Table 5). The increase in accuracy (from 86.39% to 90.58%) confirms the effectiveness of the new data dictionary on actionable information, which is one of the contributions of this research.

4.3 Models on Social Conversation

Recall that the more users participate in the social conversation, the greater the UGC and the greater the value generated. Therefore, we explicitly model comments during the social conversation between organizations and users. Our objective is to examine the factors that encourage users to contribute particular types of social support in their conversations with organizations. We capture three aspects of this participating behavior. First and central to this research, the decision on how to contribute is contingent on the evolution of the social conversation at the time of communication. Second, users may hold different attitudes toward the organization and its original post, which motivates some of them to participate. Third, users' intention to participate in online activities may also depend on individual characteristics such as number of friends and geographic location. Moreover, individuals may differ in their preference to utilize social network or to share information, which may impact their decision to write a comment.

We formally develop the model as follows. We consider a group of users who participate in social conversations on Facebook. For every post that an organization displays, users write comments, which are displayed in sequential order. Let

$$\Pr(\mathrm{C\_Type}_j^{is} = 1 | t) \tag{1}$$

be the probability that comment j is of a particular type (informational, non-informational, actionable information or non-actionable information) for a post s contributed by organization i at a given disaster phase t.

Our main interest lies in the way that commenting may vary across individuals and the factors that encourage users' social engagement in a dynamic social conversation. Therefore, we need further controls for: (i) the variation of effect that previous comments have on individuals and (ii) the factors that encourage users' social engagement, which may have a dynamic effect on the probability of a particular type of comment because of how the conversation evolves (time-varying effect). For instance, a user may read an ARC post but might not be interested in responding to the organization's initial post. As more individuals participate in the conversation, comments written by other users motivate the user, who decides to join the conversation by writing a comment. It is also possible that a user may not be inspired by a single message expressed in the post or comment. Instead, the user decides to write a comment because of multiple messages exchanged for a particular post. As a result, other than the type of social support embedded in the organization's initial post (e.g. informational, actionable information), the reactions of others might be an important factor influencing a user's decision to comment.

Let j and k indicate the j^{th} and k^{th} comments for organization i's post s respectively, where $k < j$. Then, the contribution of the evolution of the social conversation to the j^{th} comment is captured by two components: the content embedded in the post s and the content embedded in comments k prior to the j^{th} comment. We model the type of comment (e.g. informational, actionable information) by including factors that affect the social conversation, which come from three aspects: (i) the features of the organization's Page, (ii) the characteristics of the post itself and (iii) the user characteristics as follows,

$$\Pr(\text{C\_Type}_j^{is} = 1|t) = \frac{\exp(\omega_0 + \sum_{k<j} \beta \times X^{ist} + \theta \times \text{Page}^{it} + \alpha \times \text{GT}^{it} + \gamma \times \text{User}_j^t + \epsilon_j^t)}{1 + \exp(\omega_0 + \sum_{k<j} \beta \times X^{ist} + \theta \times \text{Page}^{it} + \alpha \times \text{GT}^{it} + \gamma \times \text{User}_j^t + \epsilon_j^t)}. \quad (2)$$

Expression (2) captures the probability that content belongs to informational support for a given DMC phase.

4.3.1 Model on Informational Support

The model focuses on the extent that informational support encourages the social conversation. Expression (1) becomes the probability of comment j being information-oriented for organization i's s post at time t, $\Pr(\text{C\_Info}_j^{is} = 1|t)$. The term $\beta \times X^{ist}$ in (2) captures the effect that informational support embedded in prior posts and comments have on the incoming comment j. It is also possible that users may read the first few comments and make their contribution to the social conversation based on those few comments. To capture the diminishing effect of later comments on the social conversation, we discount the weight of later comments on the discussion. The expression in parentheses in the numerator of (2) can be rewritten as

$$\begin{aligned}
&\omega_0 + \sum_{k<j} \beta \times X^{ist} + \theta \times \text{Page}^{it} + \alpha \times \text{GT}^{it} + \gamma \times \text{User}_j^t + \epsilon_j^t = \omega_0 \\
&+ \beta_0 + \beta_1 \times \text{Info_P}^{ist} + \sum_{k<j} \frac{1}{k}\Big(\beta_2 \times \text{Info_C}_k^{ist}\Big) \\
&+ \theta_1 \times \text{UGC}^{it} + \theta_2 \times \text{Likes}^{it} + \theta_3 \times \text{Shares}^{it} + \theta_4 \times \text{Posts}^{it} + \theta_5 \times \text{Comments}^{it} \\
&+ \alpha \times \text{GT}^{it} \\
&+ \gamma_1 \times \text{Friends}_j^t + \gamma_2 \times \text{User_P}_j^t + \gamma_3 \times \text{NYC}_j + \gamma_4 \times \text{East}_j + \epsilon_j^t.
\end{aligned} \tag{3}$$

The post characteristics in (3) include two parts: (i) the informational support embedded in the post and (ii) other users' content included in prior comments. We assume that users who made comments would read the organization's post and other users' comments before making their own contribution. The intuition is that a user who makes a comment may be encouraged by either the post itself or other users' comments or the aggregated support expressed in the conversation. Therefore, the model contains the recursive component to capture these possibilities. In the expression $\sum_{k<j} \frac{1}{k}(\beta_2 \times \text{Info\_C}_k^{ist})$, β_1, β_2 are the associated coefficients to be estimated. We are aware that a particular user may not read all of the prior comments and relax the assumption in section 5.4. Individual user heterogeneity is captured by β_0, where the random intercept captures users' preferences in the social conversation. We specifically control for an organization's characteristics, a user's characteristics at the individual level and public attention.

4.3.2 Model on Actionable Informational Support

Building on the previous model, we add a level of analysis by identifying the actionable information embedded in the posts and comments. Specifically we are interested in identifying the effect of "Actionable_Info_P," "NonAction_Info_P," "Actionable_Info_C" and "NonAction_Info_C". Expression (2) becomes

$$
\begin{aligned}
&\omega_0 + \sum_{k<j} \beta \times X^{ist} + \theta \times \text{Page}^{it} + \alpha \times \text{GT}^{it} + \gamma \times \text{User}_j^t + \epsilon_j^t = \omega_0 \\
&\quad + \beta_0 + \beta_1 \times \text{Action\_Info\_P}^{ist} + \beta_2 \times \text{NonAction\_Info\_P}^{ist} \\
&\quad + \sum_{k<j} \frac{1}{k}\Big(\beta_3 \times \text{Action\_Info\_C}_k^{ist} + \beta_4 \times \text{NonAction\_Info\_C}_k^{ist}\Big) \\
&\quad + \theta_1 \times \text{UGC}^{it} + \theta_2 \times \text{Likes}^{it} + \theta_3 \times \text{Shares}^{it} + \theta_4 \times \text{Posts}^{it} + \theta_5 \times \text{Comments}^{it} \\
&\quad + \alpha \times \text{GT}^{it} \\
&\quad + \gamma_1 \times \text{Friends}_j^t + \gamma_2 \times \text{User\_P}_j^t + \gamma_3 \times \text{NYC}_j + \gamma_4 \times \text{East}_j + \epsilon_j^t. \qquad (4)
\end{aligned}
$$

Expression (4) captures the probability that content belongs to actionable informational support for a given DMC phase. Note that the above models follow a hierarchical structure (Figure 1) such that we restrict our attention to information-oriented posts and associated comments in the analysis on actionable informational support.

5 Discussion of Results

We use a maximum likelihood (MLE) approach to estimate the coefficients for informational support embedded in preparedness, response, and recovery as well as their variances. This model specification allows us to compare the magnitudes of the β coefficients of interest within and between phases of the DMC. These comparisons are the basis for discussing the results. We slightly abuse the notation introduced previously to keep the discussion simple. For example, the coefficient of informational support embedded in organizations' posts during disaster response is referred to as $\beta_1[\text{Info\_P}|\text{Response}]$. In the following, we report and discuss analysis results based on a 0.5 threshold for the dependent variable. We also estimate the model using different thresholds in Section 5.4.

5.1 Results on Informational Support

The discussion of results begins with organizations' posts during the DMC phases and continues with a discussion of users' comments. Finally, it compares posts and comments for each DMC phase. Each subsection discusses the β coefficients as well as possible explanations for the findings.

	Preparedness		Response		Recovery	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
Constant						
ω_0	2.454***	0.2066	1.8264***	0.4789	0.3623	0.2906
Social Conversation						
β_0	0.5238***	0.0869	0.4916**	0.2265	0.1003***	0.0217
β_1[Info_P]	0.2211***	0.0148	0.3406***	0.0234	0.178***	0.0117
β_2[Info_C]	0.6248***	0.0501	0.393***	0.0451	0.5956***	0.0407
Organization Characteristics						
θ_1[UGC]	0.0126***	0.0001	0.0047***	0.0001	0.013***	0.0003
θ_2[Likes]	0.0282***	0.0008	0.03***	0.0005	0.0189***	0.0004
θ_3[Shares]	0.0158***	0.0003	0.0243***	0.0002	0.0172***	0.0002
θ_4[Posts]	0.4421*	0.2596	1.6297*	0.8666	0.5285***	0.1516
θ_5[Comments]	0.0064***	0.0002	0.007***	0.0002	0.0105***	0.0003
Control for Public Attention						
α[GT]	0.7521***	0.1394	0.1422	0.1284	0.3787***	0.0757
User's Characteristics						
γ_1[Friends]	1.5902***	0.5463	-0.3914*	-0.2005	1.421***	0.2461
γ_2[User_P]	1.4498***	0.0485	0.4194***	0.1217	0.7511***	0.0678
γ_3[NYC]	1.036***	0.1553	0.4351***	0.1679	0.4938***	0.0366
γ_4[East]	0.7689*	0.4145	0.1773***	0.0487	0.5882***	0.0587
No. of Observations	12,784		17,515		20,080	
Log Likelihood	-14,763.8					

To avoid multi-collinearity, Shares, Posts, Comments are log-transformed and Comments are further de-meaned. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6: Estimation Results on Informational Support

The social conversation coefficients are β_1[Info_P|Preparedness] = 0.2211 (Table 6), β_1[Info_P|Response] = 0.3406 and β_1[Info_P|Recovery] = 0.178, all of which are significant at 0.01 level. The β values for Info_P suggest an increase in the effect of informational support as a driver of users' social engagement on informational content. The change in the effect of informational support between preparedness and response is significant (at 0.01 level), which supports Hypothesis 1a. Moreover, there is a significant decrease (at 0.01 level) in this effect from response to recovery, which provides supporting evidence for Hypothesis 1b.

The positive and significant coefficient estimates of Info_P imply that users are more likely to participate in the social conversation when the posts contain more informational support. This encouraging effect is not static as it first increases from preparedness to response and then decreases from response to recovery, which suggests that informational support during the response phase is critical and attracts users' attention.

It is also possible that users' habits regarding information searches about the weather impact how they get information from different channels. For instance, East Coast residents primarily relied upon mass media such as television and radio to seek weather information (NOAA 2013). NYC released a "Post Sandy Survey of Zone A Residents" (NYC 2013) that asked the question "*where did you turn to for information about*

Hurricane Sandy?" The answers—that do not add to 100% because each respondent could choose multiple answers—included television (70%), radio (34%), internet news (22%), Facebook (3%), Notify NYC (2%) and Twitter (1%). However, electricity shortages that follow disasters affect users' access to mass media during disaster response. Although electricity cannot be restored immediately after a hurricane, organizations can install power stations to charge personal electronic devices. This was the case with Hurricane Sandy. As mentioned above, Brightbox provided free mobile phone charging stations beginning on October 30 (CNN 2012). "*As whole neighborhoods went dark, mobile phones stayed online, allowing us to exchange internet telegrams while chaos howled outside*" (Maly 2012). As a result, users were able to switch from mass media to social media in the search for informational support. Hence, the effect of informational support on the social conversation during response is stronger than it is during preparedness. During the recovery phase basic services such as electricity are reestablished in most of the affected areas. Users' attention turns back to mass media as before the disaster, which helps to explain the decrease in the effect of informational posts compared to the response phase.

5.2 Results on Actionable Informational Support

This section presents a deeper analysis of the actionable information, i.e. information of practical value embedded in the social conversation. We use the same format as in Section 5.1 to present results.

The coefficients are β_1[Action_Info_P|Preparedness] = 0.0571, β_1[Action_Info_P|Response] = 0.0105 and β_1[Action_Info_P|Recovery] = 0.035, all of which are significant at 0.01 level (Table 7). The effect of Action_Info_P decreases from preparedness to response. This change is significant (at 0.01 level), which supports Hypothesis 2a. Furthermore, there is a significant decrease (at 0.01 level) in the effect of actionable informational support between response and recovery, which provides support for Hypothesis 2b.

The effect of Action_Info_P|Preparedness is relatively strong because organizations post information of practical value for users to face the threat of the disaster during preparedness. Users seem very responsive to such information during the preparedness phase. However, this effect decreases during the response phase, when organizations post mostly about their own response operations. The actionable information in the response phase includes the location of shelters, distribution points and the state of the achievements when it comes to demand fulfillment. During the response phase organizations do not post much actionable

	Preparedness		Response		Recovery	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
Constant						
ω_0	0.0594	0.0527	0.1224***	0.0323	0.0552	0.0415
Social Conversation						
β_0	0.0268	0.0169	0.1891***	0.0062	0.0468***	0.0076
β_1[Action_Info_P]	0.0571***	0.0039	0.0105***	0.0024	0.035***	0.0032
β_2[NonAction_Info_P]	0.0259***	0.0037	0.0328***	0.0045	0.0283***	0.0029
β_3[Action_Info_C]	0.0026***	0.0002	0.0029***	0.0002	0.0009***	0.0001
β_4[NonAction_Info_C]	0.0043***	0.0001	0.0023***	0.0001	0.0014***	0.0001
Organization Characteristics						
θ_1[UGC]	0.0014***	0.0005	0.0025***	0.0009	0.0013***	0.0001
θ_2[Likes]	0.0105***	0.0007	0.0039***	0.0001	0.0046***	0.0001
θ_3[Shares]	0.0008***	0.0003	0.0005***	0.0001	0.0008***	0.0002
θ_4[Posts]	0.444***	0.1711	0.491*	0.2579	0.0209***	0.004
θ_5[Comments]	0.0015***	0.0003	0.0006***	0.0002	0.0012***	0.0004
Control for Public Attention						
α[GT]	0.0919***	0.0357	0.1561***	0.0276	0.0467*	0.0283
User's Characteristics						
γ_1[Friends]	-0.1616**	0.0798	-0.1814*	0.0996	-0.0785**	0.0374
γ_2[User_P]	0.071***	0.0173	0.0469**	0.0184	0.125***	0.0019
γ_3[NYC]	0.077***	0.0279	0.1605***	0.0165	0.072***	0.0238
γ_4[East]	0.0634	0.0488	0.1697***	0.0177	0.126***	0.0203
No. of Observations	8,309		10,384		14,082	
Log Likelihood	-13,528.7					

To avoid multi-collinearity, Shares, Posts, Comments are log-transformed and Comments are further de-meaned. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: Estimation Results Level 2. Actionable Information

information about how to donate or volunteer directed at users that want to help. Instead, they focus on information of practical value for the disaster victims, which is their top priority. However, victims can obtain that information through other information diffusion channels. Finally, the effect of Action_Info_P|Recovery is relatively strong because organizations keep posting actionable information about aid distribution. They also begin to tell users how to donate cash to support their operations. This trend reveals important insights for organizations.

We find, through our case study, that organizations post actionable information about the activities they are performing to help victims during the response phase (e.g. food delivery), but most engaged users may be eager to know how they can help. Therefore, not knowing how they can help decreases the likelihood that users engaging in the social conversation will contribute actionable information. Thus, there may be an opportunity for organizations to improve social conversations with users by sharing how users can help, resources users can provide or responses to call to action. In other words, while organizations focus on informing how they are helping, engaged users may be providing actionable information about the resources they have to help the victims. We investigate this opportunity further in the following section.

5.3 Additional Insights

Users' behaviors are difficult to predict during the different DMC phases as disasters affect users differently. For example, victims may ask for relief while donors may offer help and digital volunteers may provide information about aid delivery. Our empirical model allows us to provide some insights on user comments and the effectiveness of the social conversation between organizations and users.

5.3.1 Actionable Information in Users' Comments

Users share information about (i) how to prepare for the disaster, e.g.: "*Download their smartphone #hurricane app to prepare and stay alerted with updates. #Sandy. Droid and iPhone,*" (ii) donating and volunteering during response, e.g.: "*how can we donate goods - clothing, toiletries, blankets etc? '*" " *My sister and I are in NYC. We want to volunteer. Where do we go or who do we contact?.*" Users' comments also contain actionable information about (iii) demand for aid, e.g.: "*I do know that there are people in need of help; in the areas of Brighton Beach, and Sea Gate. This areas are in Brooklyn, NY*" as well as (iv) donating and volunteering during recovery, e.g.: "*We are doing a dance for the Red Cross on November* 17^{th} *in Coeur d'Alene, ID to raise funds for Hurricane Sandy victims. Could you please put me in touch with the person that would be able to give us permission?*"

The coefficients are β_3[Action_Info_C|Preparedness] = 0.0026, β_3[Action_Info_C|Response] = 0.0029 and β_3[Action_Info_C|Recovery] = 0.0009, all of which are significant at 0.01 level (Table 7). The effect of Action_Info_C increases from preparedness to response and decreases from response to recovery. The increase is significant at the 0.05 level, and the decrease is significant at the 0.01 level.

The effect of actionable information in users' comments during preparedness is relatively weak. The information of practical value that users contribute about how to prepare for the disaster does not seem to influence other users to contribute actionable information. Interestingly, the effect of Action_Info_C|Response increases. As we discussed above, users are eager to help. During the response phase they are not only providing emotional support for the victims, they are also willing to provide actionable information on how they can donate or volunteer.

The willingness of users to help the victims is further supported by the coefficients of users' location in

Table 7 (NYC and East Coast). Note that the effect of NYC and East Coast locations on incoming actionable information comments is the strongest during response. This suggests users that are close by are willing to help, and their location has a strong effect on incoming comments. Disaster response from users located close to the disaster area is consistent with extant literature on disaster management that identifies local response as the first layer of disaster response (Besiou et al 2014). However, actionable information provided by organizations is not tailored to users' willingness to help. The gap of official actionable information is filled by users as their own actionable information comments encourage more users to join the social conversation (Mason et al 2007).

Finally, the effect of actionable information in users' comments during recovery is relatively low. Comments on how to help do not have as strong of an effect as during the response phase. This may be because organizations are already contributing actionable information on how to help during the recovery phase. Moreover, users may be already helping people they know or know how they can help at this stage, thanks to information channels such as mass media.

5.3.2 Actionable Information Comparison between Posts and Comments

When we compare the actionable information coefficients of posts and comments we find that the effect of Action_Info_P dominates the one of Action_Info_C for all the DMC phases (Figure 3). These differences are significant at the 0.01 level.

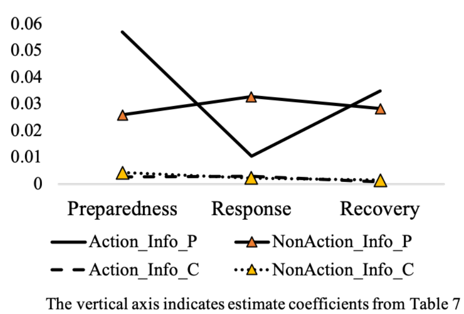


Figure 3: Summary of insights

The credibility of the source of actionable information could explain this result. The actionable information or guidance needs to come from a trusted source to ensure its legitimacy. This is particularly important in the case of instructions about how to donate or where to go to volunteer. Using their personal accounts, digital volunteers and staff wrote comments in response to users such as "*I'm a digital volunteer with the Red Cross and I have a lot of information that might help.*" However, users did not seem to respond to these comments as well as they respond to the official post from the organization. The federal government encouraged users to communicate with official sources rather than unofficial ones. In the aftermath of Hurricane Sandy, the Homeland Security and Emergency Services of New York State warned the public about internet scams "*As disaster relief efforts continue for the victims of Hurricane Sandy, many individuals feel moved to contribute to assistance programs and while doing so, may fall prey to phishing scams.*" This explains why the effect of actionable information posted by organizations is valued more than the one contained in users' comments. The dominance of Action_Info_P on Action_Info_C provides strong evidence that organizations should use their official page to respond to users' comments about how to donate or volunteer. In other words, well-intentioned digital volunteers and staff that participate in the social conversation as individuals do not have the same effect official organizations' posts have on incoming users' comments.

5.4 Robustness Checks

We conducted multiple robustness checks on our findings (details reported in Appendix 2, online). First, in our main analysis we pooled the five organizations to find the average effects of actionable and non-actionable information across different DMC phases. It is possible, however, that these effects could be different among these organizations since each plays a different role during the DMC. We apply the proposed Level 1 and Level 2 models to each organization and conduct analysis separately. We find, from our empirical results, that the patterns we identified in the main analysis are consistent with the ones for single organizations.

In addition, to classify the type of comment, i.e. the dependent variable, we used and reported the results based on a threshold of 0.5. One may argue that this classification threshold is too low, raising the concern of binary outcome. Hence, we increase the thresholds for the dependent variable to be 0.55 and 0.6. Based on these new criteria, we re-classify the dependent variable and run again Level 1 and Level 2 analyses. Our findings remain consistent, albeit some changes in the magnitude of the estimates.

Moreover, there might exist a concern on the social support included in prior comments. In both equations (3) and (4), we assume that users would read all prior comments before making their own. We have used a discount factor in the recursive component to account for the possible different weights associated with comments. However, it is possible that user might only read the first few comments before making a new contribution. Hence, instead of considering all prior comments, we consider the first m comments and their social support in the recursive component. On the one hand, if $j \leq m$, then all k prior comments will be included. On the other hand, if $j > m$, then only up to m comments will be used when calculating the social support embedded in users' content. For this m, we further consider cases that include (i) m equals the average number of comments, (ii) m is the mean minus one standard deviation of comments, and (iii) m is the mean plus one standard deviation of comments. These model estimates provide consistent results supporting our main findings for both Level 1 and Level 2 analyses.

6 Discussion of Operational Implications

Our analysis suggests that organizations can improve the social conversation with users by posting more (official) actionable information for those willing to help disaster victims. We clarify that actionable information for potential donors and volunteers is not a substitute but a complement to actionable information organizations post for disaster victims. There may be victims that read actionable informational posts and benefit from them but do not engage in the conversation because they lack the time to comment as the disaster directly affected them.

Our analysis also suggests that it is more likely for individuals located near the disaster to contribute actionable information in their comments. These findings have important operational implications for donations and volunteer management as well as for how to prioritize the time and effort of organizations' digital volunteers and staff.

6.1 Unsolicited donations and volunteering

The users that contribute actionable information on items they can donate and time they can volunteer are most likely not affiliated with the organizations. Otherwise, they would already know the procedures to help in response operations. If these potential donors and volunteers do not receive official guidance on how to help, they will either find their own way to make a donation, volunteer or not help at all. If the donor follows official instructions from organizations and donates cash, her donation will help the operation. At the other extreme, if the donor gives an unsolicited in-kind donation, her contribution will create operational bottlenecks that result in the "disaster within the disaster" (Holguin-Veras et al 2012a, Pedraza-Martinez and Van Wassenhove 2016). In the case of Hurricane Sandy, the disaster within the disaster is exacerbated by the fact that: (i) the volume of in-kind donations increases with proximity to the disaster area, (ii) the volume of in-kind donations increases with population density (Destro and Holguin-Veras 2011) and (iii) organizations do not seem to provide actionable information through the social conversation about what in-kind donations are needed.

Likewise, operational problems may occur if unskilled volunteers arrive at the disaster area looking for ways to help. In the process of creating the data dictionary on actionable information, we learned that a number of users are offering to donate in-kind and others are offering to volunteer. Unfortunately, during the Hurricane Sandy operations, donor and volunteer requests through Facebook were either not answered at all or answered by digital volunteers and staff that did not use the organization's official page to identify themselves. Thus, the effect of these unofficial answers on users' actionable information was weak. It is likely that some of these users sent unsolicited in-kind donations or decided to go to the disaster area. Perhaps, if the organizations had provided tailored, official answers to users' questions about how to donate and volunteer, some unsolicited donations could have been avoided.

6.2 Prioritization of official responses to users' comments

This research identifies the issue of how users are more favorable to official responses from organizations than they are to ad-hoc responses from digital volunteers and staff. Thus, the social conversation would benefit from official responses from organizations' Facebook pages to users' comments. We monitored the Facebook pages of FEMA, ARC and NG following Hurricane Harvey in 2017. For example, in response to Harvey, FEMA, ARC and NG use two social media best practices regarding non-victim users that others can follow. They (i) address potential donors and volunteers directly in their Facebook posts and (ii) provide official responses to the question "how can I help?" These best practices help organizations channel help and mitigate unsolicited in-kind donations and unskilled volunteering. What if an organization does not have enough resources to answer all the users' comments? Such an organization could prioritize answering the comments from users that are located close to the disaster area as they are more likely to make in-kind donations or volunteer.

7 Conclusions

Organizations are increasingly using social media platforms to engage with consumers. 73% of organizations were expected to produce more social media content in 2017 than in 2016 (Pulizzi and Handley 2017) and this number was expected to increase to 85% in 2018 (Pulizzi and Handley 2018). Likewise, social media opens tremendous opportunities for organizations to improve disaster management.

We investigate the social conversation between five benchmark organizations that participated in the Hurricane Sandy response operation and Facebook users. Our main purpose is to understand the social support needs (informational and actionable information) of users that participate in the social conversation during the disaster management cycle (DMC). We study the social conversation during the disaster preparedness, response and early recovery phases during a period of three weeks. The data include social conversations between organizations and users on Facebook as well as Google Trends data, used as a control for public attention. We classify text as informational or non-informational using content analysis. Moreover, we create a novel data dictionary for text classification of actionable and non-actionable content. The content from the posts and comments feeds an econometric analysis that involves two levels: informational support and actionable informational support. The dependent variable is the probability that a particular comment is of certain type: informational, non-informational, actionable information or non-actionable information.

Our main results are summarized as follows. Organizations' informational support is most attractive to social media users and actionable informational support is the least attractive during the disaster response. There seems to be an opportunity to match the actionable information that organizations post and the actionable information that users are interested in more effectively. While organizations focus on informing users about aid distribution, most users are asking about how they, as individuals, can either donate or volunteer. These results show that there is potential to improve the organizations' social media activities to match users' informational support needs and encourage participation with the organizations.

Organizations can improve the social conversation by answering users' questions on actionable information directly instead of handing that task to their digital volunteers and staff as individual users. A potential operational effect of better actionable information management would be a decrease in unsolicited in-kind donations and unskilled volunteering, which often create bottlenecks for aid distribution and end up causing a "disaster within the disaster". This is particularly important during the response and recovery phases because the social conversation between organizations and users is most dynamic at that time. Moreover, organizations can prioritize answering users' comments by focusing on users that contribute actionable information and are located close to the disaster area.

Perhaps the most evident limitation of this research is our inability to analyze multimedia content such as photos and videos. Most multimedia content is accompanied by text, which may not capture the richness of the post. We mitigate this issue by including all the comments for each particular post in the sample. Together the text included in the post and users' comments give a good idea of the multimedia content the organizations share. Another limitation of this paper is that we do not observe people's offline activities or people who look at the social conversation but decide not to participate. However, as our focus is analyzing the conversation between organizations and users, this research helps us understand the effectiveness of the social conversation. Our findings can help develop better social media strategies to encourage more users to engage in the conversation. A potential limitation of our research is the age of our case study. While we affirm that our findings are not case-dependent, we acknowledge that there is a need for future research on the evolution of the social conversation between organizations and users. Because our research is a building block to understand the role of social media for disaster management better, we end this paper by offering avenues for future research.

Future research can apply our framework to other social media platforms such as Twitter. We set the pattern for other researchers to expand the research on the opportunities social media brings to disaster management using more up-to-date data. Moreover, our data dictionary can be used to classify content according to different humanitarian logistics activities such as donating, sheltering, warehousing, distributing, volunteering and so forth as well as refine the analysis of users' needs. Future research can also use our data dictionary for text classification in other areas outside of humanitarian operations because the basis for the dictionary is a general list of actionable verbs.

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