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Appealing to the Heart: How Social Media Communication Characteristics Affected Users' Liking Behavior During the Manchester Terrorist Attack

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Social media enable users to exchange information, sympathy, and support in disasters. To understand the communication characteristics leading to users' liking behavior, we examine how social media audiences react during disasters to various message features, including emotional appeals, informal tone, and message frames in textual and visual forms. A content analysis was conducted on a random sample of tweets related to a terrorist bombing in 2017. Our results from multilevel modeling (N = 698) reveal that the number of likes a tweet receives is positively predicted by the presence of emotional appeals, human-interest frames, and inconsistent text-image framing. The results provide a sophisticated understanding of social media audiences' message preferences during disasters. It is recommended that practitioners employ personally relatable messages that accommodate people's emotional needs during disasters.

Keywords: social media, disaster communication, emotional appeals, framing, terrorism

Social media serve as free forums for publics and organizations to share information, co-create meanings, and negotiate relationships (Briones, Kuch, Liu, & Jin, 2011; Zhao, Zhan, & Wong, 2018). During disasters involving high uncertainty and severe consequences, social media users participate in the events by sharing information, sympathy, and support on digital platforms (Fraustino & Liu, 2017; Fraustino, Liu, & Jin, 2017; Zhao, Zhan, & Jie, 2018). Thus, it is crucial to understand social media audiences' message liking patterns so that message producers can deliver disaster communication that protects individuals' safety and facilitates a resilient community.

Few disaster communication theories focus on explaining how disaster communication content affects people's message preferences (cf. the internalization-distribution-explanation-action model of Sellnow, Lane, Sellnow, & Littlefield, 2017). As a result, it is still unknown how and why social media users favor certain types of social media messages during disasters. Given growing concern about the public's

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vulnerability to misinformation and "attention hacking" by ill-intentioned actors (e.g., Huang, Starbird, Orand, Stanek, & Pedersen, 2015; Marwick & Lewis, 2017), it becomes urgent to study how various social media communication characteristics affect audiences' liking behavior in disasters. Only by understanding audiences' message liking patterns can message producers develop messages that foster resilience and help publics cope with disasters.

By examining social media users' liking responses to various disaster communication characteristics, this study features three contributions. First, we aim to understand how and why social media audiences like some disaster messages more than others. Liking a disaster social media post not only promotes the message but also reflects people's affective connections with the community and felt obligations to benefit the society at large (Brandtzaeg & Haugstveit, 2014). Only by understanding the content characteristics explaining audiences' liking behavior can organizations and publics co-create a social media environment with social support and disaster resilience. Second, based on the persuasion, public relations, and mass communication literature, we examine the effectiveness during disasters of a set of communication characteristics on social media, including emotional appeals, informal tone, and message frames. Previous crisis and disaster communication research has explored how social media users build textual frames during crises (e.g., van der Meer, 2016; van der Meer, Verhoeven, Beentjes, & Vliegenthart, 2014). Going beyond textual frames, we examine how the use of textual frames can be complemented by visual frames on social media. Last, effective disaster communication relies on both source and content (Liu, Fraustino, & Jin, 2016). To account for the effects of source and content simultaneously, we employ multilevel modeling that takes into consideration that social media messages are nested within certain sources (Hox & Roberts, 2011). With multilevel modeling, our study tests both source- and message-level predictors of audiences' liking behavior using Twitter data from a significant terrorist disaster in 2017.

In sum, our study examines what types of disaster communication generate social media audiences' liking behavior. We randomly sampled Twitter data of the Manchester terrorist bombing in the United Kingdom, where 22 civilians died and more than 100 people were wounded (BBC, 2017). After performing a content analysis of tweets, we conducted multilevel modeling to test the effects of various message characteristics on audiences' liking behavior (N = 698). Our results can help message producers design social media messages that are both liked and needed by audiences, which in turn can protect people's safety and facilitate resilience in disasters.

Social Media Audiences in Disasters

Understanding the unique characteristics of social media audiences serves as a premise for further inquiries about how and why they respond differently to messages during disasters such as a terrorist attack. Several characteristics of social media audiences can be identified. First, younger users rely on social media platforms more than the general public does. According to the Reuters Institute Digital News Report (Newman, Fletcher, Kalogeropoulos, Levy, & Nielsen, 2017), 33.3% of global users ages 18 to 24 report that social media constitute their main source of news; this compares with 10% of users ages 45 to 54 and 7% of users age 55 and older. Sloan, Morgan, Burnap, and Williams (2015) found that 16- to 22-year-old users accounted for 67.5% of the UK Twitter user population. Social media users also have distinct educational and professional backgrounds compared with the general population. In terms of occupations, Sloan et al. (2015) identified 40.4% of Twitter users as "lower managerial, administrative, and professional occupants" (p. 9). Finally, one-third of social media users have college degrees, and they tend to live in urban areas and have above-average incomes (Smith & Anderson, 2018).

Social Media Audiences' Liking Behavior

A user can like a tweet by selecting the heart icon via the Web interface or other Twitter clients. Despite the abundant research on the antecedents and implications of customers' liking behavior in the social media marketing communication literature (e.g., de Vries, Gensler, & Leeflang, 2012; van Meter, Grisaffe, & Chonko, 2015), little research has examined users' liking behavior during disasters. We argue that social media audiences' liking behavior during disasters is distinct from that studied in the marketing literature and is worth scholarly inquiry, because audiences' liking behavior as a communicative process and outcome plays an essential role in fostering a disaster-resilient community—or the ability of a community to "bounce forward" after a disaster to address the changed reality and face new challenges (Dufty, 2012).

Motivated by prosocial desires and emotional needs (Brandtzaeg & Haugstveit, 2014), social media users interact with the heart icon to express emotions and support in disasters. From a social media affordance perspective, Twitter users' liking behavior plays a proactive role in forging an imagined affordance—or users' expectations about certain social media affordances (Bucher & Helmond, 2018)—rendering Twitter a virtual space for exchanging emotional and social support. As such, social media users' engagement in the imagined affordance helps them cope with the disaster and develops postdisaster resilience. Moreover, those who watch the growing number of likes of disaster-related messages may feel emotionally relieved and develop a sense of belongingness to an empathetic community (Neubaum, Rösner, Rosenthal-von der Pütten, & Krämer, 2014). Thus, users' liking practice offers emotional and social benefits for those involved in disasters (e.g., victims), which nurtures a resilient social media community.

Therefore, it is essential to understand the mechanisms underlying social media audiences' liking behavior during disasters. The following discussion delineates how audiences' message liking is affected by various social media communication characteristics.

Communicative Characteristics Predicting Audiences' Liking Behavior

Emotional Appeal

Emotion plays an essential role in crisis and disaster communication (Kim & Cameron, 2011) by influencing the processing and judgment of messages (Alhabash et al., 2013). Emotional appeals use affective message tones, words, and/or contents to arouse audiences' emotions or feelings (Lee & Hong, 2016; Liu, Li, Ji, North, & Yang, 2017). Communication researchers have found that messages with emotional appeals are more likely to be shared online (Alhabash et al., 2013) and to generate high levels of positive attitudes among audiences (Mattila, 1999).

Social media audiences should prefer disaster communication with affective implications. Literature on disaster communication and mass communication identifies the essential role of emotion among social media audiences in disasters (e.g., Jin, Fraustino, & Liu, 2016; Kyriakidou, 2015). Applying the concept of media witnessing (Pantti, Wahl-Jorgensen, & Cottle, 2012), news audiences often respond to a distant event with intense emotions and develop empathetic identifications with the suffering. Based on the integrated crisis mapping framework (Jin, Pang, & Cameron, 2007), publics experience various negative emotions such as anxiety and fright during disasters (Jin et al., 2016). Thus, social media disaster messages that fulfill audiences' emotional needs should be liked more (DeSteno, Petty, Rucker, Wegener, & Braverman, 2004; Huang et al., 2015; van der Meer & Verhoeven, 2014). For example, Huang et al. (2015) found that individuals prefer disaster information of emotional proximity (i.e., information sharing the emotion of the audiences). Van der Meer and Verhoeven (2014) suggested that a disaster message with an emotional appeal might increase the authenticity of the source and enhance the rapport between the source and its audiences. In sum, we propose the following hypothesis:

H1: Social media disaster messages with emotional appeals generate more likes.

Informal Tone

An informal tone is a common, nonofficial, casual, and colloquial communication style associated with the spoken language (McArthur, 1992). In today's social media environment, more organizations have employed informal styles (e.g., emojis or acronyms) in their communication (Beukeboom, Kerkhof, & de Vries, 2015). An informal tone is conceptually different from the conversational human voice (Kelleher, 2009): An informal tone is a language attribute, whereas the conversational human voice as "an engaging style" (Kelleher, 2009, p. 177) centers on the communication effect (Gretry, Horváth, Belei, & van Riel, 2017).

The communication literature provides inconclusive evidence regarding the effectiveness of an informal tone on social media. On the one hand, several studies support the influence of an informal tone on positive postcrisis outcomes (e.g., Crijns, Cauberghe, Hudders, & Claeys, 2017; Park & Cameron, 2014). For example, Park and Cameron (2014) found that blogs with the first-person human voice (vs. the third-person corporate voice) lead to a higher level of engagement and word-of-mouth communication in an organizational crisis. This is probably because an informal tone of voice can foster consumers' perceptions of the organization as being more real and closer in a mediated scenario (Men & Tsai, 2015; Sung & Kim, 2018).

On the other hand, some studies find only limited or even negative effects of an informal tone on organizational outcomes (e.g., Barcelos, Dantas, & Sénécal, 2018; Gretry et al., 2017; Kerkhof, Beugels, Utz, & Beukeboom, 2011; Steinmann, Mau, & Schramm-Klein, 2015). For example, Steinmann et al. (2015) found that a personal tone reduces consumers' satisfaction with a brand community. One reason for this may be that the effectiveness of informal tones in social media communication is dependent on the context and audiences' perceived appropriateness of an informal tone in a certain context. For example, Gretry et al. (2017) found that consumers show a higher level of brand trust only when a familiar (vs. unfamiliar) brand uses an informal tone.

It is unknown how social media communication with an informal tone affects audiences' liking behavior in disasters. An informal tone brings a message source closer to its audience (Park & Cameron, 2014) and increases an audience's engagement with a source (Men & Tsai, 2015; Sung & Kim, 2018).

Nevertheless, in disaster scenarios, which are saturated with high risk and uncertainty, people tend to seek reliable information from credible sources to keep themselves safe (Anthony, Sellnow, & Millner, 2013). As such, an informal tone may sound inappropriately lighthearted, weaken the credibility of a message source, and in turn lower the number of likes. Thus, we propose the following research question:

RQ1: Do social media disaster messages with an informal tone generate more likes among audiences?

Furthermore, a message that combines emotional appeal and an informal tone may evoke a more humane presence and may positively affect audiences' liking behavior. As such, we propose a second research question:

RQ2: Is there an interaction between emotional appeals and an informal tone?

Message Framing

By manipulating the inclusion, exclusion, and emphasis of issues presented (Hallahan, 1999), framing can make certain aspects of a perceived reality more salient to promote a particular interpretation of an event (Entman, 1993). During disasters, social media users can discuss their own understandings of an issue and thus shape the issue framing (Zhao, Zhan, & Jie, 2018; van der Meer, 2016). Based on their distinct motivations and preferences, social media audiences may prefer certain types of frames to interpret the disaster information and decide on protective actions (van der Meer, 2016; van der Meer et al., 2014). For example, van der Meer et al. (2014) found that, during an organizational crisis, social media users choose distinct frames compared with public relations and media.

In the media effects literature, framing has been found to influence information processing and recall, attitude formation, and behavioral intention (e.g., Powell, Boomgaarden, De Swert, & de Vreese, 2015). In disasters, specific frames created or shared by social media audiences can also affect people's issue interpretations and solution recommendations (van der Meer, 2016). By processing disaster information framed from specific angles, people's different trains of thought are activated, leading to different affective and cognitive evaluations of the disaster-related messages (Price, Tewksbury, & Powers, 1997).

On the one hand, based on the high uncertainty and informational needs in crises (e.g., Zhao, Zhan, & Jie, 2018), social media users need to make sense of the disaster through certain cognitive frames, such as a conflict or responsibility frame. Conflict-framed messages feature conflict among individuals, groups, or institutions and have been found to be effective in capturing and retaining audience interest (Semetko & Valkenburg, 2000). Responsibility-framed messages emphasize attributing responsibility for a problem's cause (Semetko & Valkenburg, 2000). In the context of man-made disasters, responsibility-framed messages involve the attribution of responsibility on a broader level (e.g., a policy perspective). Frames embedded in media messages have been found to shape audiences' understanding of the causes and solutions of social problems (Iyengar, 1987).

On the other hand, driven by the needs to vent emotions and connect to the community (Jin et al., 2016), people may express their emotional needs through human interest frames. Human interest frames "personalize, dramatize, and emotionalize" (Valkenburg, Semetko, & de Vreese, 1999, p. 551) the presentation of issues, which fulfills users' need for social connectedness. In fact, the human interest frame is the most frequently used framing strategy in social media messages during disasters (Brunken, 2006).

Few studies have examined the influence of framing on social media audiences' responses in disasters. We argue that social media audiences will like human interest frames more than conflict or responsibility frames. The reasons are twofold. First, individuals are naturally interested in learning about others' stories (Price et al., 1997). Human interest–framed disaster messages can help remote audiences develop imaginative emotional connections with people in the stories such as victims (Kyriakidou, 2015). By making the events more relatable and relevant for audiences, human interest–framed messages can help audiences experience the disaster in ways similar to the affected individuals and can foster their sympathy and positive emotions. Second, people experience high levels of uncertainty and anxiety during crises. In a highly uncertain and rapidly changing situation, the human interest frame reifies relevant information and facilitates effective cognitive processing of information (Petty & Cacioppo, 2012), which should be appreciated by audiences (Gorrell & Bontcheva, 2016).

Alternative frames, such as conflict or responsibility frames, tend to generate fewer positive responses among social media audiences than human interest frames in disasters. There are several reasons for this. First, unlike the personalized narrative of human interest frames, conflict frames usually feature winners and losers, which may activate cynicism and mistrust among social media audiences (Cappella & Jamieson, 1997). Additionally, the inclusion of multiple, opposing parties in conflict-framed messages (de Vreese, 2004) makes it impossible to express positive evaluations of either party. Second, human interest frames should appeal to a wider audience than the controversial responsibility frame. Human interest frames emphasize social connection and feature individual experiences and stories, whereas the speculated nature of responsibility-framed messages makes it difficult to generate message likability.

Based on this discussion, in disasters, social media messages with human interest frames should generate more likes than messages with conflict or responsibility frames. Thus, we propose the following hypothesis:

H2: Social media disaster messages with human interest frames receive more likes than messages with alternative frames.

Complementing Textual Frames With Visual Frames

In the multimodal social media reality, graphic images typically accompany textual messages (Powell et al., 2015). The unique characteristics of image and text result in differential framing effects. Images reflect reality and grab attention, whereas texts provide clear structures of who did what to whom and why (Entman, 1993). Scholars have found that when texts are accompanied by pictures, the meanings of the pictures are accessed faster than when a message is conveyed by text alone (Barry, 1997). Pictures also affect interpretations of the image-text integration (Gibson & Zillmann, 2000). For example, images featuring a higher level of conflict lead to more negative evaluations of social protests.

Many scholars argue that arbitrarily pairing image and text yields unpredicted effects (e.g., Fahmy, Bock, & Wanta, 2014; Gibson & Zillmann, 2000; Powell et al., 2015). Indeed, the interactive effect of image and text framing is underexplored in social media practices (e.g., Fahmy et al., 2014). The literature offers few insights on how to effectively match images and texts and whether audiences prefer consistent or inconsistent text-image framing.

One may argue that the consistent text-image framing results in higher message favorability. Images can attract attention and enhance message salience (Zillmann, Knobloch, & Yu, 2001). Geise and Baden (2014) indicate that images have an "amplifying effect" that makes the messages more persuasive due to their salience and analogical quality. Matching modalities (e.g., visual and audio) with consistent frames has been found to improve news recall and issue understandings (Graber, 1990). During crises, social media users are attracted by messages with attention-grabbing visuals. Visuals that match the textual framing should ease message processing, enhance issue interpretations, and in turn receive more likes (Alhabash et al., 2013). Furthermore, human emotions are expressed more directly and accurately by images than by text (Bernhard & Scharf, 2008). Consistent text-image framing provides the audience with the opportunity to empathize with the visually represented objects, resulting in higher message favorability (Bernhard & Scharf, 2008).

Alternatively, inconsistent text-image framing may lead to higher message favorability. The dual coding theory (Paivio, 2007) indicates that people's verbal and nonverbal mental systems encode, store, and process information collected from their interaction with the environment. Images, although usually processed by the nonverbal system, might induce belief changes by supplementing new content that is processed by the verbal system (Seo, Dillard, & Shen, 2013). Social media messages (e.g., blogs, tweets) tend to be shorter than other forms of organizational communication, such as press releases. Pairing a social media text with an image of an inconsistent frame supplements disaster information and persuasive appeals, which may lead to more positive message evaluations. Moreover, social media users are younger and have lower levels of preference for consistency (Guadagno & Cialdini, 2010). As such, social media users may be more open to inconsistent text-image framing.

In conclusion, the literature does not offer a prediction for whether consistent or inconsistent framing between texts and images yields more positive responses on social media in disasters. Thus, we ask the following research question:

RQ3: Which type of visual is more effective with text on social media during disasters—one that is consistent or inconsistent with the frame of the text?

Method

We chose to collect data from the social media platform of Twitter because of the prevalence of Twitter in disaster and crisis communication. Publics are often active on Twitter during crises (e.g., Lachlan, Spence, & Lin, 2017; Zhao, Zhan, & Liu, 2018). In addition, with its real-time and interactive features, Twitter allows crisis managers to engage social media users and build relationships with diverse stakeholders.

We examined a significant disaster: the Ariana Grande concert terrorist attack (BBC, 2017). The suicide bombing took place at the singer Ariana Grande's concert in Manchester, United Kingdom, on May 22, 2017. Twenty-two civilians died and more than 100 people were wounded. This was the deadliest terrorist attack in Britain in the recent decade (BBC, 2017). To understand audiences' responses in community-based disasters (e.g., Jin et al., 2016), we investigated this man-made disaster in which UK citizens were highly involved. With Twitter data of people's communication in the disaster, we sought to determine the message features that induce favorable responses on social media.

Data Collection

The time frame was from the first day after the disaster occurred (May 22, 2017) to the last day people still talked about the disaster (July 31, 2017) on Twitter. With a complete set of keywords and hashtags (e.g., #PrayForManchester, Ariana concert attack), we captured a full set of Twitter data in the time frame through our data collection program (Zhao, Zhan, & Liu, 2018).[1] A total of 84,199 tweets with 63,950 unique Twitter accounts were collected.

Most tweets were posted by individual followers who posted one tweet with no response. This could lead to low variance of liking (i.e., nearly no variance to be explained for the dependent variable) and harm the predictive power of our statistical models. To address the data imbalance problem and carry out content analysis of both source- and tweet-level features, we implemented two steps of sampling. First, we focused on tweets that received at least one favorite in the disaster, which led to a subsample of 9,702 tweets with 1,493 users. Second, to acquire a manageable sample size for content analysis, we randomly selected 800 tweets from the subsample. This led to a sample size of 800 tweets from 392 users.

Measures

Content Analysis and Intercoder Reliability

Two independent coders with expertise in public relations and disaster communication were trained to code the type of social media accounts and various message features. After six rounds of training, satisfactory intercoder reliability was achieved on all variables (Krippendorff, 2004). For the source-level variable of type of sources, Krippendorff's α is .80. For message-level variables, including emotional appeals, informal tone, message frames, and visual frames, Krippendorff's α ranges from .85 to .94. The two coders proceeded to code the remaining tweets.

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[1] To capture a full set of crisis-related tweets, we built a data collection pipeline in three steps. First, we developed a complete list of keywords, terms, and hashtags for the crisis. A total of 12 keywords for the Ariana Grande concert bombing was used. Second, within the time frame, we archived all the keyword search results returned by Twitter.com in Web ARChive (WARC) files, using the open-source Web archiving service Webrecorder. WARC is a file format for storing Web crawls with metadata attached to each record. Third, we parsed the WARC files into JavaScript Object Notation format data frames in Python.

Dependent Variable: Liking Behavior

One can indicate a favorable response toward a tweet by clicking the heart icon. Liking behavior can be measured by the total number of likes that a post receives. The median number of liking behaviors was 2 (M = 34.01, SD = 190.60), and the dependent variable ranged from 0 to 3,650. Because the distribution of scores of favorable responses was skewed (skewness = 12.56), we scaled and centered the dependent variable (M = 0, SD = 1) in subsequent statistical analyses.

Message-Level Predictors

Message features, including emotional appeals, informal tone, message frames, and visual frames, can influence the number of likes received by a post.

Emotional Appeal

The emotional appeal of a tweet was measured by the presence of any emotional cue in the post, including emoticons, emojis, and emotional words or terms. For example, if a tweet contains the word *heartbreaking* or *grateful*, the tweet was considered as demonstrating emotional appeal. Emotional appeal was coded in a binary manner, where 1 = *have an emotional appeal*, and 0 = *no emotional appeal*. A total of 180 (22.5%) tweets used emotional appeals.

Informal Tone

Whether a tweet employs an informal tone was evaluated based on several linguistic features adapted from Gretry et al.'s (2017) study of the informal tone on social media. Examples of informal tone include the use of first- and second-person pronouns (e.g., we, you), informal vocabulary (e.g., awesome, awwww), informal punctuation (e.g., !!!), acronyms (e.g., smh), and verb omissions (e.g., taxi offering free rides). Informal tone was coded in a binary manner, where 1 = *show an informal tone*, and 0 = *no informal tone*. A total of 434 (54.3%) tweets demonstrated informal tones.

Message Frame

Message frames were coded into the following categories: human interest, conflict, responsibility, or no frame. A human interest frame "brings a human face or an emotional angle" (An & Gower, 2009, p. 108) to the presentation of the disaster event. The coding of the human interest frame was based on Semetko and Valkenburg's (2000) coding scheme. Conflict frames center on the episodes about terrorists, bombing scenes, or police investigations of the attack (e.g., policemen raided the street to look for the terrorist). Instead of emphasizing details of the attack, the responsibility frame focuses on attributing responsibility for a problem's cause, such as how the disaster was attributed to Europe's immigration policy. The message frame was coded categorically, with 1 = *human interest*, 2 = *conflict*, and 3 = *responsibility*.

It should be noted that the content of several tweets is not directly related to the disaster, despite the use of hashtags such as #PrayForManchester. In addition, some tweets contain too little information to exhibit a frame, or they employ no frame. For example, one tweet reads, "NEW POST in collaboration with @GMMH_NHS #ManchesterAttack." In sum, 110 tweets did not employ a particular frame and thus were coded as not applicable (−9). Of the 690 tweets with a message frame, 341 (49.4%) had a human interest frame, 141 (20.4%) had a conflict frame, and 216 (31.3%) used a responsibility frame.

Visual Frame

In the sample, 440 (55%) tweets contain only text (coded as 0), 296 (37%) tweets have pictures (coded as 1), and 64 (8%) have videos (coded as 2). In the 360 (45%) tweets that contain pictures or videos, if the visual frame is consistent with the message frame (e.g., a human interest frame), then the variable was coded 1 (visual frame congruent with message frame). Otherwise, the variable was coded 0 (visual frame incongruent with message frame). Of the 360 tweets, the visual frames of 178 (49.9%) tweets were congruent with their message frames.

Source-Level Predictors

Source-level characteristics include source type, number of followers, and number of friends.

Source Type

A source (i.e., Twitter account) was coded as an individual, traditional media, online-only media (including blogs and information aggregation accounts), corporation, or nonprofit organization/independent group based on the screen name, profile description, and profile picture. In the sample, 408 (50.1%) tweets were posted by individuals, 238 (29.8%) were from traditional media, 108 (13.5%) were from online-only media, six (0.8%) were from corporations, and 40 (5%) were from nonprofit organizations.

Number of Followers

The number of followers measures how many people follow a source. The median number of followers was 4,704 (M = 313,341, SD = 986,976), and the variable ranged from 0 to 6,157,582. We scaled and centered the number of followers in subsequent analyses.

Number of Friends

The number of friends measures how many friends a source has. The median number of followers was 1,299 (M = 4,051, SD = 12,216), and the variable ranged from 1 to 167,836. We scaled and centered the number of friends in subsequent analyses.

Analytical Strategies

To examine the effects of both source- and message-level predictors on the dependent variable of liking behavior, we constructed multilevel models using the R "lme4" package (Bates et al., 2014). The 800 tweets were nested within different types of Twitter accounts. Multilevel models take this multilevel data structure into consideration by modeling the random effects of the hierarchically nested structure. The descriptive statistics and correlation matrix of variables are reported in Table 1.

Table 1. Descriptive Statistics and Correlation Matrix of All Variables.

			Pearson correlations							
	M	*SD*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Liking behavior	34.01	190.60	1.0							
(2) Source type	1.79	1.04	0.02	1.0						
(3) No. followers	313,341	986,977	0.15**	0.20**	1.0					
(4) No. friends	4,051	12,216	0.01	0.02	−0.02	1.0				
(5) Emotional appeal	0.22	0.42	0.03	−0.08*	−0.09*	0.08*	1.0			
(6) Informal tone	0.54	0.50	0	−0.06	−0.09*	−0.02	0.27**	1.0		
(7) Message frame	1.82	0.88	0.09*	0.15**	−0.02	0.10**	0.20**	0.07	1.0	
(8) Visual frame	1.50	0.50	−0.09	−0.02	0.08	0.02	0.02	0.05	0.10	1.0

Note. *N* = 698. All the strategy predictors are binary variables, where 0 = *no*, and 1 = yes. The original summary statistics of liking behaviors, number of followers, and number of friends are reported. Subsequent analyses employed the scaled and centered values of these variables.
* $p < .05$. ** $p < .01$.

Considering source type as the level, we specified an intercept-only model. To test whether our nesting data structure necessitates multilevel models, we computed the intraclass correlations, which reflect the degree of clustering within groups (Newsom, 2017). Computed by dividing the random intercept variance of the level by the total variance, the intraclass correlation for the two-level model is 0.7%.

We proceeded by specifying a random intercept model with some message-level predictors, including emotional appeals (H1), informal tone (RQ1), the interaction term of emotional appeal and informal tone (RQ2), and message frames (H2). Source-level predictors (number of followers, number of friends) were used as control variables. *P* values were computed through the Satterthwaite approximation in the R "lmerTest" package (Kuznetsova, Brockhoff, & Christensen, 2015). Next, we specified a second random intercept model with the additional message feature of visual frame (RQ3). Since less than half of the tweets had visuals, the limited sample size could harm the statistical power of statistical tests and bias the results. As such, we evaluated the hypotheses and research questions based on results from the two random intercept models.

Results

H1. Emotional Appeals

H1 predicted that social media messages with emotional appeals will generate more likes during crises. Based on the results of the multilevel models, a tweet's emotional appeal significantly predicted the number of likes it received (b = 0.25, SE = 0.10, $p < .01$ in random intercept model 1; b = 0.37, SE = 0.18, $p < .05$ in random intercept model 2). As such, H1 is supported. The results are shown in Table 2.

Table 2. Multilevel Models Predicting Message Favorability From Source- and Message-Level Communication Characteristics.

	Random intercept model 1 (listwise *N* = 698)		Random intercept model 2 (listwise *N* = 317)	
Predictors	*B*	*SE*	*B*	*SE*
Source-level predictors				
No. followers	0.19***	0.02	0.21***	0.05
No. friends	0.01	0.02	0.05	0.05
Message-level predictors				
Emotional appeal	0.25**	0.10	0.37*	0.18
Informal tone	0.03	0.06	0.02	0.10
Interaction term (emotional appeal × informal tone)	−0.30**	0.12	−0.42*	0.22
Human interest frame (reference: policy frame)	0.12*	0.05	0.23*	0.10
Terrorism frame (reference: policy frame)	−0.06	0.07	0.04	0.13
Text (reference: video)	−0.24**	0.09		
Pictures (reference: video)	−0.22*	0.09	−0.27*	0.12
Visual frame			−0.15*	0.08

Note. We conducted two-level multilevel models with random effects for the source type with maximum likelihood estimation. In random intercept model 2, the sample size of text-only tweets was 0, so no estimates were provided. Emotional appeal, informal tone, and visual frame were binary variables, where 0 = *no use*, and 1 = *use.* The *no use* group is used as the reference group. The number of likes, number of followers, and number of friends were scaled and centered for analysis.
* $p < .05$. ** $p < .01$. *** $p < .001$.

RQ1. Informal Tone

RQ1 asked whether social media messages with an informal tone generated more likes during the crisis. A tweet's informal tone did not significantly predict the number of likes it received.

RQ2. Interaction Between Emotional Appeal and Informal Tone

RQ2 asked whether there is an interaction between emotional appeal and informal tone. Based on the results, the interaction between emotional appeal and informal tone on liking behavior was significant ($b = −0.30$, $SE = 0.12$, $p < .01$ in random intercept model 1; $b = −0.42$, $SE = 0.22$, $p < .05$ in random intercept model 2). However, the direction of the interaction was unexpected. Tweets with an emotional appeal and a formal tone received more likes than tweets with an emotional appeal and an informal tone.

H2. Message Frames

H2 predicted that social media messages with human interest frames will generate more likes during disasters than messages with conflict or responsibility frames. Compared with the reference group of tweets with a responsibility frame, tweets with human interest frames received more likes (b = 0.12, SE = 0.05, p < .05 in random intercept model 1; b = 0.23, SE = 0.10, p < .05 in random intercept model 2). There was no difference between the responsibility frame and the conflict frame in terms of likes.

RQ3. Visuals

RQ3 asked which type of image worked best with text on social media during the crisis. Tweets with visuals that are incongruent with the textual frames received more likes than those with visuals that are congruent with textual frames (b = −0.15, SE = 0.08, p < .05 in random intercept model 2). In addition, tweets with pictures had significantly fewer likes than those with videos (b = −0.22, SE = 0.09, p < .05 in random intercept model 1; b = −0.27, SE = 0.12, p < .05 in random intercept model 2). As such, social media users liked videos more than pictures during the disaster.

Discussion

This study investigates how and why audiences like certain types of social media messages in a terrorist bombing attack. Our study is among the first disaster communication studies to explore how textual frames can be complemented by visual frames on social media. Among the sample of tweets about the disaster, emotional appeals, human interest frames, and inconsistent text-image framing received more likes from social media audiences. Whether a message has an informal tone does not affect the number of likes. This research produces important findings in four areas, detailed in the following paragraphs.

First, disaster messages with emotional appeals receive more likes on social media. This is consistent with the literature on integrated crisis mapping (e.g., Jin et al., 2016) and media witnessing (e.g., Kyriakidou, 2015). In man-made disasters, people are charged with emotions both negative, such as anxiety and anger (Jin et al., 2016), and positive, such as hope and sympathy (Coombs & Holladay, 2005). As such, messages with emotional appeals cater to audiences' emotional needs during a disaster. By revealing the feelings and preferences of the message producer, emotional appeals also help audiences interpret the disaster event and potentially increase message acceptance.

Second, we found no effect of informal tone on audiences' liking behavior, supporting previous studies that found limited effectiveness of using an informal tone on social media (e.g., Barcelos et al., 2018). It seems that an informal tone is a double-edged sword in social media disaster communication. On one hand, an informal tone sounds more personal and real, closing the distance between an organization and its stakeholders (Kim & Cameron, 2011; Sung & Kim, 2018). On the other hand, an informal tone embedded in a disaster message sounds inappropriately playful, reduces the perceived organizational credibility, and decreases audiences' favorability toward the message. Thus, employing an informal tone may not be the best personification strategy for relationship building during disasters. Instead, alternative personification strategies such as using organizational avatars should be employed.

Third, audiences respond more favorably to the human interest frame than to the conflict or responsibility frames. This finding supports the literature on people's informational, social, and emotional needs during crises and disasters (e.g., Heinonen, 2011; Zhao, Zhan, & Jie, 2018). It may be that human interest frames personalize the social messages and make them more relatable. Thus, users like social media messages with a human interest frame that facilitates their capacity to analyze a large amount of incoming information during deadly disasters (Gorrell & Bontcheva, 2016).

Last, pairing the textual frame with visuals of an inconsistent rather than consistent frame increases audiences' favorability toward the message. Research has revealed the importance of using visuals in disaster and crisis communication (e.g., Liu et al., 2017). Our results speak to the significance of choosing specific visuals to accompany texts to increase communication effectiveness. For instance, crisis managers should match human interest–framed texts with visuals containing supplemental information such as disaster background information. We also found that social media audiences like videos more than photos during disasters. Audiences may feel more involved and sympathetic given the richer modality offered by videos. Scholars should further explore visual communication strategies, which are underdeveloped in the area of disaster and crisis communication.

Theoretical Implications

This study extends the literature on crisis and disaster communication in several ways. First, our results reveal that social media audiences interpret crises, especially disasters with significantly negative consequences, in an affective perspective rather than a rational cognitive perspective. This resonates with the literature on media witnessing (Kyriakidou, 2015) and crisis emotions (Jin et al., 2016). During disasters, social media users form a like-minded community by exchanging information, emotions, and support. Affective disaster messages favored by these audiences weave a discursive space where publics empathize with the affected individuals and together build community disaster resilience.

Furthermore, our study is among the first to examine social media audiences' preference for textual and visual framing during disasters. Previous public relations research on framing has overwhelmingly focused on how public relations agencies and media use framing rather than on how social media audiences use framing and their framing preferences (Lim & Jones, 2010). Our results on social media publics' preferences of human interest frames support the literature about the prevalence of human interest frames, especially in disasters (Brunken, 2006). The results of pairing textual and visual frames and the modality of visual frames support the dual coding theory (Paivio, 2007) and reveal the importance of considering visual frames (Seo et al., 2013) in disaster communication.

Another key characteristic of disaster communication is information accuracy and credibility. Given the noisy social media environment, where misinformation and disinformation are rampant (Huang et al., 2015; Mendoza, Poblete, & Castillo, 2010), it is crucial to consider the influence of disinformation and "attention hacking" (Marwick & Lewis, 2017). Scholars should adopt a critical perspective of social media audiences' liking behavior and examine how such behavior can be affected by disinformation in disasters.

Practical Implications

Our study provides valuable insights for social media message producers regarding the message features favored by social media audiences in disasters. Disasters are usually filled with strong emotions (e.g., anger, Jin et al., 2016), and people long for relatable messages that accommodate their emotional needs. Message producers such as organizations can employ disaster messages with emotional appeals and human interest frames to better satisfy social media audiences' needs.

Moreover, although individual users as well as organizations increasingly use an informal tone to communicate on social media, this communication style may not be universally appreciated during disasters. During disasters, what matters may be the content rather than the tone of communication. Social media communication that adopts a formal (rather than informal) tone may sound more credible and appropriate.

Finally, message producers need to not only employ visuals to increase message liking (e.g., Liu et al., 2017) but also consider how to strategically pair texts and visuals. For example, practitioners can complement human interest–framed text with a video offering background information about a crisis. The richer visual modality and complementary information provided by the video should appeal to a wider array of audiences and offer them relatable and useful information.

Limitations and Future Directions

Our study has some limitations. First, only one disaster case was investigated, so researchers should generalize the findings to other disasters with caution. Future studies might examine organizational crises and investigate how message features combine with situational crisis communication strategies to affect audiences' responses in crises. Second, we only examine Twitter data. It is possible that users of other social media platforms have different preferences for crisis communication messages. For example, Instagram relies heavily on visuals, so audiences on that platform may care less about the pairing of visuals with text. Thus, future studies should consider other social media platforms such as Facebook or Instagram. Third, due to the constraints of Twitter data, we have limited measures of user characteristics (e.g., number of followers). Future studies might examine how users' sociopsychological factors interact with the communication features to affect their message favorability. Last, we used users' behavioral traces to measure their message preferences. To strengthen the results, both perceptual and behavioral measures of preference can be adopted.

Despite these limitations, our study offers a comprehensive framework for strategically using message features on social media in disasters and unveils how and why some social media messages are favored by audiences in disasters.

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