A cross-hazard analysis of terse message retransmission on Twitter

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For decades, public warning messages have been relayed via broadcast information channels, including radio and television; more recently, risk communication channels have expanded to include social media sites, where messages can be easily amplified by user retransmission. This research examines the factors that predict the extent of retransmission for official hazard communications disseminated via Twitter. Using data from events involving five different hazards, we identity three types of attributes—local network properties, message content, and message style—that jointly amplify and/or attenuate the retransmission of official communications under imminent threat. We find that the use of an agreed-upon hashtag and the number of users following an official account positively influence message retransmission, as does message content describing hazard impacts or emphasizing cohesion among users. By contrast, messages directed at individuals, expressing gratitude, or including a URL were less widely disseminated than similar messages without these features. Our findings suggest that some measures commonly taken to convey additional information to the public (e.g., URL inclusion) may come at a cost in terms of message amplification; on the other hand, some types of content not traditionally emphasized in guidance on hazard communication may enhance retransmission rates.

disaster | warning | social media | retransmission | communication

Under conditions of imminent threat, rapid communication of warning information to the public is a primary strategy for decreasing loss of life and increasing public safety by eliciting protective actions from those at risk (1). For decades, public warnings have been relayed via mass media channels, including radio, broadcast television, and sirens (2). With the advent of social computing, warnings have begun to be disseminated via online social networks (OSNs), where messages can be more easily propagated and amplified by the user population (3–6). Risk amplification via message retransmission in this setting is important because it enables a message to reach individuals beyond the sender's direct contacts, increasing exposure and potentially leading to lifesaving actions (7). Although such transmission occurs offline as well (8–11), OSNs offer the potential for the rapid retransmission of short messages with higher fidelity—and to more persons—than would typically be feasible via other means.

In addition to enabling message diffusion, the clustered structure of most OSNs (12, 13) allows retransmission to expose individuals to the same message multiple times. Multiple exposures to messages have been linked to greater confidence in message veracity (14, 15), which can lead to further sharing (16, 17). Repeated exposures from multiple network ties are often a prerequisite for the spread of information through networks, and are of particular importance for inducing behavioral change (4, 18–20). Under conditions of imminent threat, exposure to a warning message from a trusted source (such as a neighbor, friend, or family member) strongly affects one's willingness to take protective actions (21, 22). This highlights the need to understand the factors that enhance or suppress the amplification of emergent risk messages within OSNs, with particular attention on the features of the messages themselves. Such an understanding can inform evidence-based strategies to increase message proliferation, thus allowing risk communicators to achieve a higher level of message penetration and/or to increase the number of exposures per person in the impacted population. This research examines message retransmission—commonly referred to as "retweeting"—on Twitter, identifying network, content, and style features that promote the amplification (23) of terse (i.e., content-constrained) messages within five types of hazard events.

Network Features

Considerable attention has been given to the role of traditional media in amplifying risk; until recently, few studies have focused on the online environment, and even fewer have studied the amplification process in real time (5). Past OSN propagation models have focused on local network structures that influence message amplification (24–28) in disaster and nondisaster settings alike. This body of work demonstrates the importance of local network characteristics for propagation. For example, Tyshchuk et al. (27) found that official emergency management accounts quickly became leaders of information diffusion and maintained that position throughout the period of imminent threat during a hurricane. Importantly, the network structures can create "information cascades" where individuals amplify information received by retweeting, and thus further sharing, the information (29). Moreover, these cascades tend to be wide (i.e., composed of a large number of short-length passing chains)

Significance

Online social networks (OSNs) enable time-resolved measurement of communication behavior during disasters, making it possible to probe the mechanisms by which messages are amplified or suppressed with precision unattainable by traditional data sources. To our knowledge, this research provides the first systematic study of the factors predicting the social amplification of risk communication in OSNs by examining the retransmission of official messages across five hazards. Our findings demonstrate the respective impacts of sender characteristics, message content, and message style in determining whether an official message will be passed on during an emergency, as well whether these vary across hazards. These results contribute to the evidence base for policies guiding the delivery by emergency management organizations of lifesaving information to the public.

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rather than long (i.e., composed of a small number of long passing chains), which highlights the importance of initial message exposure for subsequent amplification.

Message Content

An emerging line of research mines the textual content that users generate for online media (27, 28). This development has enabled researchers to examine the message content features associated with higher rates of message retransmission (30, 31). Researchers note the emergence of user conventions when retweeting, such as the inclusion of a RT (indicating a retransmitted message or retweet), # (hashtag), and web link or URL (32). These style conventions are related to retransmission: for instance, Starbird and Palen (33) and Bruns and Burgess (34) tracked retweeted messages across events to identify the content and source of individual messages and found that hashtags are used to form ad hoc discussion channels around a particular event. Additionally, researchers have suggested that including a web link to additional information for terse messaging channels, such as Twitter, can increase message clarity because length-constrained messages may not be able to convey all pertinent information (35).

Under quotidian conditions, the inclusion of URLs and hashtags in a message strongly influences the likelihood that the message is retweeted (4, 31); however, researchers have not found this to be true during disaster settings (6, 36, 37). Collectively, they find that URL inclusion significantly reduces retweet counts, whereas the inclusion of a hashtag significantly increases retweet counts during a wildfire (6); Burnap et al. (36) observed similar results for message retransmission after a terrorist attack in the United Kingdom; and Genes et al. (37) noted that the messages most retweeted during a blizzard or hurricane do not include a URL. As discussed below, our results shed light on these discrepancies.

Message Style

Although previous studies of public message retransmission have examined message content by focusing on trending topics (31), performing sentiment analysis (30), or analyzing word choice through its frequency of use (25, 26), these approaches do not include message style features—that is, how the message is written to improve message clarity. Rhetorical strategies—such as the use of punctuation, the choice of sentence style, or the capitalization of words or phrases—are additional message features that may affect perceptions of message salience among recipients and subsequently influence their likelihood to retransmit a message. For instance, warning messages with clear and specific information (2) or that include instructional information (37) are found to increase message understanding, leading to increased likelihood that message receivers will take protective actions. Similarly, imperative sentences are directive and can instruct message receivers (38). Thus far, analyses on the use of "ALL CAPS" have centered on its function to convey sentiment (39) or as an "intensifier" of information (40); capitalization may also serve to bring attention to key warning elements (41).

In this research, we link these three factors—network properties, message content, and message style—in a combined model of message retransmission. By analyzing these factors' impacts across multiple hazard events, we are able to determine the influence of each on message retransmission net of other factors, and to determine the degree to which these effects are similar, or different, across hazard types. This is a critical first step in generating a normative template for message amplification during hazards, estimating the distinct impact of different message and contextual features on the flow of hazard information through OSNs, and modeling the amplification of risk through message retransmission during imminent threat events.

Materials and Methods

Design, Sample, and Data Collection. We manually coded and analyzed Twitter messages sent from official accounts during five different hazard events, with the goal of identifying features that consistently predict increased or decreased message retransmission under conditions of imminent threat. All data were collected via the Twitter Application Programming Interface (API), and all messages were publicly available; as no human subject research was performed, IRB approval was not required. We selected five events that represent five different hazard types: terrorist attack (TA), wildfire (WF), blizzard (BL), hurricane (H), and flash flood (FL) with differing population sizes and regions impacted. For each event, the time period of imminent threat and warning varied based upon environmental conditions or containment of the hazard agent. These ranged from 48 hours (H) to 5 days in duration (TA). Table 1 below includes information on each event; additional information for each event can be found in Table S1.

Following previous research (6, 23, 42), we identified and enumerated Twitter accounts for each of our five events, obtaining a census of the population of public officials or agencies at the local, state, and federal level posting in response to the respective event (n = 188). Using the Twitter REST API, we collected each account's posting history over the time period of the hazard event. This includes all public-facing messages posted during the period of imminent threat for each event; for each message, we observed the time of posting and message content. We also obtained the number of "Followers" for each account and the number of times that each message was retweeted: we updated this information daily over the period of observation.

For four cases, we identified the accounts that were posting tweets on the primary event hashtags. (In one case, TA, we were already collecting data from the apropos accounts because we had targeted them for the BL, which occurred in the same geographical area.) Subsequently, we scanned each organization's connections and local websites to identify additional relevant accounts and added them to our list of targeted accounts. Although an account may exist that was not discovered by our collection procedure, it is highly unlikely to have been central in the response because such an account did not post any messages with an event hashtag and was not referenced by an active organization. We therefore regarded the accounts used for each case as an effective census of the population of official accounts responding to the event in question. We focused on official emergency management accounts, both because these accounts are central information diffusers during disasters (27) and because the retweeting of messages from official accounts provides a direct probe on the amplification of official messages by members of the public (6, 23, 38).

Content Coding. We used a deductive coding approach developed in prior research (23, 41) to code each tweet for message content and style. All data are available in Dataset S1. We coded for the presence of 11 primary content themes: *advisory*, i.e., actions to take or refrain from; closures/openings (*close/open*) of facilities, events, or roads; *corrections* to previously posted information; evacuation/shelter (*evac./shelter*) information; information on hazard impact (*haz. Impact*) to the environment or population at risk; general *information*, including phone numbers, websites, or help facility locations; information on *reentry* to the affected area; thanks and prayers (*thanks*); information on volunteering (*volunteer*); direct responses to requests for help (*help/dir.*); and emotive/evaluative (*emot./eval.*) content, e.g., cohesion-building statements such as "we will recover." Two additional codes were used for messages with content that was considered undeterminable (*unsure*) or irrelevant to the hazard event (*not on topic*), and these messages were removed from the dataset. Theme code definitions with examples are available in Table S2. This approach enabled us to focus on what the general public views as salient based on what messages content they choose to retransmit and hence amplify.

To assess message style (clarity and specificity), we coded each message for sentence style (declarative, imperative, interrogative, or exclamatory) as well as the inclusion of a word or phrase in ALL CAPS to specify a category signifier (e.g., UPDATE) or to emphasize a word or phrase within the message (e.g., NOW or DO NOT). Additionally, we coded each message's style features including whether the tweet was directed at or responding to another Twitter user, or referencing a third party (i.e., @name), whether it was a retweet (RT), and the inclusion of a hashtag or URL. Content categories and style features are not mutually exclusive (i.e., multiple themes and sentence styles might be included in a single message—see Table S3 for these counts). Fig. 1 below shows the proportion of themes present in the messages (see Fig. S1 for similar depictions of message style). Finally, we measured message exposure as the number of Followers for each targeted account.

Analytic Strategy. For each disaster event, we used a negative binomial regression model for retransmission activity (total retweets per initial message), whose expectation is a function of network features, message style, and message content. This form accounts for unobserved heterogeneity in the underlying retransmission process (manifesting empirically as overdispersion relative to a Poisson process); Poisson and geometric models were also considered but were found to produce inferior models as selected by the corrected Akaike information criterion (AICc). We used the generalized linear

Table 1. Numbers of accounts, tweets, and period of collection for each event

Hazard	Accounts targeted	Tweets collected	Time of data collection
Terrorist attack (TA)	22	698	4/15–4/20/2013
Wildfire (WF)	16	518	6/26–6/27/2012
Blizzard (BL)	52	1,063	2/7–2/9/2013
Hurricane (H)	61	2,354	10/29–10/30/2012
Flood (FL)	37	2,578	9/11–9/16/2013

modeling (glm) functionality within the R statistical computing environment to analyze our data.

Results

Table 2 below displays the negative binomial regression results for each hazard (see Fig. S2 for visual depictions of the results).

Network Features as Predictors of Retransmission. The number of Followers for a given source account at the time of posting is a statistically significant, positive predictor of message retransmission in three events. The effect is most pronounced in TA and WF: every doubling in the number of Followers (e.g., from 10 to 20 or from 100 to 200) increases the predicted number of retweets for an organization's posts by a factor of ~5.7 and 6.7, respectively. For the same proportional increase in number of Followers during TA and WF, we would expect more than a fivefold boost in the number of predicted retweets, and slightly more than double for FL.

Message Content Features as Predictors of Retransmission. Message content describing the "hazard impact" is the most consistent predictor of message retransmission across all five events, and it is significantly positive for all of the cases. The effect size for hazard impact varies from a 25% boost in retweets in FL to a 222% predicted increase in TA. In cases where a long-term cleanup and recovery is involved, such as severe flooding, messages containing information about volunteering are significant (H, FL). In cases where residential areas are at risk for substantial damage, messages containing "evacuation/shelter in place" notices are positive and significant (FL, WF). Messages that contain "emotive/cohesion building" themes are statistically significant, positive predictors of retransmission in three events (TA, BL, H), suggesting the emergence of organizational norms around messaging that are reinforced by the message receiver audience. Messages that target a single recipient, such as messages of gratitude (e.g., thank you) or direct requests for help, are consistently negative predictors of retransmission (thank you: TA, BL, WF, FL; help: BL, H, FL). Fig. 2 illustrates the significant themes for each event.

Message Style Features as Predictors of Retransmission. Message style features impact message retransmission both positively and negatively. The use of an imperative sentence style is significant and positive for three events (WF, H, FL). The inclusion of a hashtag is a positive predictor of retransmission in three events (WF, H, FL), whereas the inclusion of a web link is a statistically significant negative predictor of retransmission in four events (TA, WF, H, FL) and dropped from the fifth model (BL). In all events, messages directed to a single individual (i.e., @username) are a significant, negative predictor of retransmission, and tweets containing a flagged party significantly and negatively predict message retransmission in four events (TA, BL, FL, H). Finally, the use of ALL CAPS for emphasis (e.g., NOW or DO NOT) is a statistically significant, positive predictor of message retransmission in three of the events (BL, H, FL), and the use of ALL CAPS as a signifier (e.g., UPDATE) is a significant, positive predictor for one case (TA).

Discussion

Imminent threat events often require rapid dissemination of emergency risk information designed to increase public protective actions. Understanding how OSNs and other new media channels, such as Twitter, are used to relay, retransmit, and amplify risk information can offer insight into other short messaging channels that are terse, or content constrained. This study develops predictive models of message retransmission incorporating network, textual content, and style features of messages sent by public officials under conditions of threat involving five types of hazards, offering direct insight into risk amplification processes. We observe consistent patterns across five types of hazard events suggesting three things: (*i*) that the public finds particular topics more salient, (*ii*) that the design of a message impacts the degree of a message's passing, and (*iii*) that initial network exposure strongly impacts message amplification.

Prior research demonstrates that hazard impact and protective action guidance information are strong predictors of behavioral outcomes (2). Similarly, we find that messages delivering this same content are also highly salient among the public and are consistently retransmitted. Fig. 3 illustrates the effects of themes on messages' retweet counts; messages using particular theme sets (for each event) are retransmitted at higher rates. This provides a direct behavioral indication of thematic saliency, to the extent that salient content is likely to be judged worthy of passing on to others. These findings align with seminal work on the social amplification of risk (3), which argues that the amplification of messages will be influenced by content attributes via their effect on the perceived significance of the message to the receiver.

Additionally, messages containing features that provide greater specificity, such as using a hashtag to signify a clear information channel, are more likely to be retransmitted; this also aligns with prior research (4). In one of the two events where this finding is not present (TA), there was no agreed-upon hashtag among the public agencies that used social media to communicate to the public (23). This suggests that public officials should coordinate the use of hashtags before an event to facilitate wider dissemination. The use of ALL CAPS significantly enhances retransmission

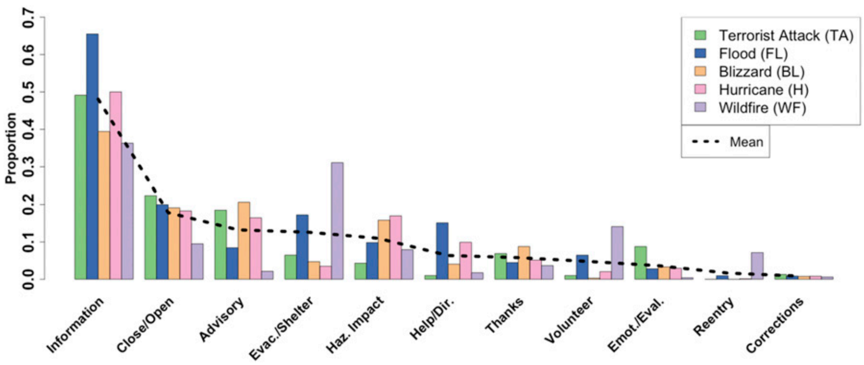

Fig. 1. This figure illustrates the proportion of messages sent by official accounts that contain one of the 11 themes. Although the presence of each theme differs in some events, overall the use of themes across events is quite consistent. This indicates that emergency management organizations send out similar types of messages during different hazardous events.

Table 2. Negative binomial regression predicting retweet counts of disaster-related tweets

Group		Terrorist attack (TA)	Wildfire (WF)	Blizzard (BL)	Hurricane(H)	Flood(FL)
	Intercept	−18.18***	−19.61**	1.63**	2.25***	−7.17**
		(2.63)	(5.99)	(0.56)	(0.57)	(2.63)
Source	Fixed effects†					
	Logged Followers	2.5***	2.75***			0.99**
		(0.30)	(0.73)			(0.35)
Tweet style	Directed tweet	−2.42***	−1.51***	−3.17***	−3.28***	−2.75***
		(0.22)	(0.25)	(0.16)	(0.13)	(0.12)
	Flagged party	−0.6***		−0.21*	−0.31***	−0.33***
		(0.15)		(0.10)	(0.09)	(0.09)
	Includes URL	−0.44***	−0.22*		−0.38***	−0.19***
		(0.12)	(0.10)		(0.07)	(0.06)
	Includes hashtag		0.55***		0.65***	0.53***
			(0.14)		(0.08)	(0.06)
Sentence style	Imperative		0.48***		0.33**	0.18**
			(0.12)		(0.10)	(0.07)
	Interrogative			0.53**	−0.76***	0.5**
				(0.17)	(0.15)	(0.16)
	Exclamatory					0.4***
						(0.11)
	Declarative				0.21	
					(0.11)	
Use of ALL CAPS	EMPHASIS	0.42		0.99***	0.39**	0.34**
		(0.23)		(0.19)	(0.13)	(0.11)
	SIGNIFIER	0.61*	0.25			
		(0.25)	(0.14)			
Theme	Advisory	0.7***	0.52	0.63***		0.18
		(0.15)	(0.34)	(0.09)		(0.10)
	Closures/Openings	−0.53**	−0.44*	0.64***		
		(0.18)	(0.20)	(0.11)		
	Corrections				1.37***	−0.72*
					(0.29)	(0.29)
	Evacuation/Shelter	−0.50*	0.37**	0.30		0.41***
		(0.23)	(0.12)	(0.16)		(0.07)
	Hazard Impact	1.17***	1.08***	0.24*	0.32***	0.23**
		(0.27)	(0.18)	(0.10)	(0.09)	(0.08)
	Information		−0.33**			
			(0.13)			
	Reentry		−0.54*			
			(0.22)			
	Help/Directed Communication			−1.87***	−0.88***	−1.08***
				(0.26)	(0.13)	(0.18)
	Thank You	−0.75***	−1.73***	−0.62***		−0.50**
		(0.23)	(0.35)	(0.18)		(0.17)
	Volunteer				0.53**	0.76***
					(0.19)	(0.10)
	Emotion/Evaluative	1.29***		0.48*	0.94***	
		(0.20)		(0.23)	(0.15)	
Model fit	Null deviance	9,398	3,586	8,307	22,770	16,348
	(DF)	(697)	(517)	(1,062)	(2,353)	(2,577)
	Residual deviance	7,802	3,082	6,041	14,937	12,695
	(DF)	(664)	(488)	(1,000)	(2,280)	(2,525)
	AICc	7,876	3,148	6,178	15,092	12,806

*$P < 0.05$, **$P < 0.01$, ***$P < 0.001$.

†Source accounts (not shown) are included as dummy variables to directly estimate fixed effects. See Table S4 for these effects.

in three out of the five cases (BL, H, FL). An imperative sentence style is also a positive predictor of retransmission in three events (WF, H, FL). Recent research on food safety and public health outbreaks demonstrates that the most effective messages will include instructional communication (43). Therefore, directive messages that use an imperative voice to tell people what to do, coupled with content about the hazard impact, may have the strongest impact for individuals who need to take protective action.

Based on previous research, we also expected that the number of Followers for the sending organization would increase retransmission rates (25). The greater the number of people that may initially view a message, the more likely it becomes that a message will be amplified, or retransmitted, under conditions of threat. Our findings are generally consistent with this expectation, although we do not detect this effect in two events (BL, H).

In line with previous research on message retransmission during disasters (6, 36–38, 43), the inclusion of a web link significantly

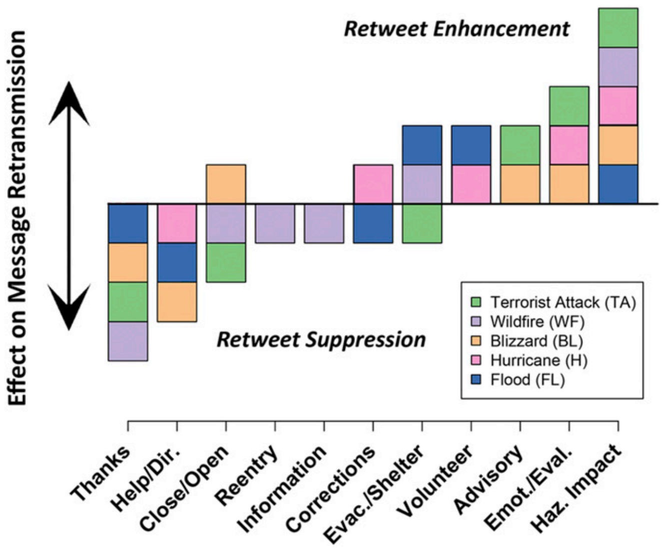

Fig. 2. This figure illustrates the significant coefficients and the direction of their influence on retweet rates for five hazard events. The blocks indicate themes with significant effects on message retransmission, arranged vertically in order of their coefficients' magnitudes (i.e., the hurricane model has the smallest coefficient for "Thanks," and the terrorist attack model has the largest coefficient for "Hazard Impact"). Although there is some heterogeneity regarding themes' effect on message retransmission, overall we see clear trends; e.g., the presence of the themes "Thanks" and "Help/Directed Communication" consistently reduce message retransmission, whereas messages that include "Hazard Impact" or "Emotional/Evaluative" content are consistently retransmitted at higher rates.

decreases predicted message retransmission in four out of five cases and was dropped from the fifth model (BL) when controlling for all of the other message's features. To determine whether this effect was consistent across content categories, we also examined all potential theme/URL interactions over the five events; out of 110 possible interactions, only 1 interaction yielded a net positive URL effect for any content category (see Table S5 for the results and further discussion). Although web links have been suggested as a strategy to provide additional information and clarity (43), under conditions of imminent threat, complete terse messages—messages that do not require additional time and bandwidth to open and view—are more consistently propagated.

This result differs from previous research that finds messages with URLs are retweeted more under normal circumstances (4). The apparent discrepancy is partially explained by noting that if we look only at marginal differences—i.e., not controlling for sender characteristics, thematic content, or other factors—we also find that messages with URLs are often retransmitted more in our data. The mean retransmission counts for messages including a URL are higher in all of the events except the flood, and the difference is only significant for the flood event. However, the difference is significant when pooled across all events; see Table S6 for the values and *t* tests. These findings highlight the importance of controlling for messages' themes to understand message retransmission rates; when doing so, the inclusion of a URL becomes a negative predictor of retransmission. This suggests that organizations seeking to maximize information amplification via OSNs should focus on key thematic features and minimize the use of URLs.

By contrast, we find that messages containing emotive content are more likely to be retransmitted for three of the five events (TA, BL, H). Messages that make statements about personal and societal resilience, such as encouraging the public to "stand strong," are found to be highly salient in events where the warning period produced longer times of heightened awareness—such as the terrorist attack where the effect is largest: this aligns with prior research (36). Messages amplifying cohesion appear to be salient among Twitter users, perhaps due to the fact that social media is used as a personal network as well as a broadcast mechanism under conditions of stress.

Implications and Conclusions

Warning systems, and the messages they deliver, are designed with the intent to relay information that will motivate people to take action under conditions of imminent threat. With the advent of OSNs and social media, new channels are available to transmit information in new ways, resulting in a cacophony of voices

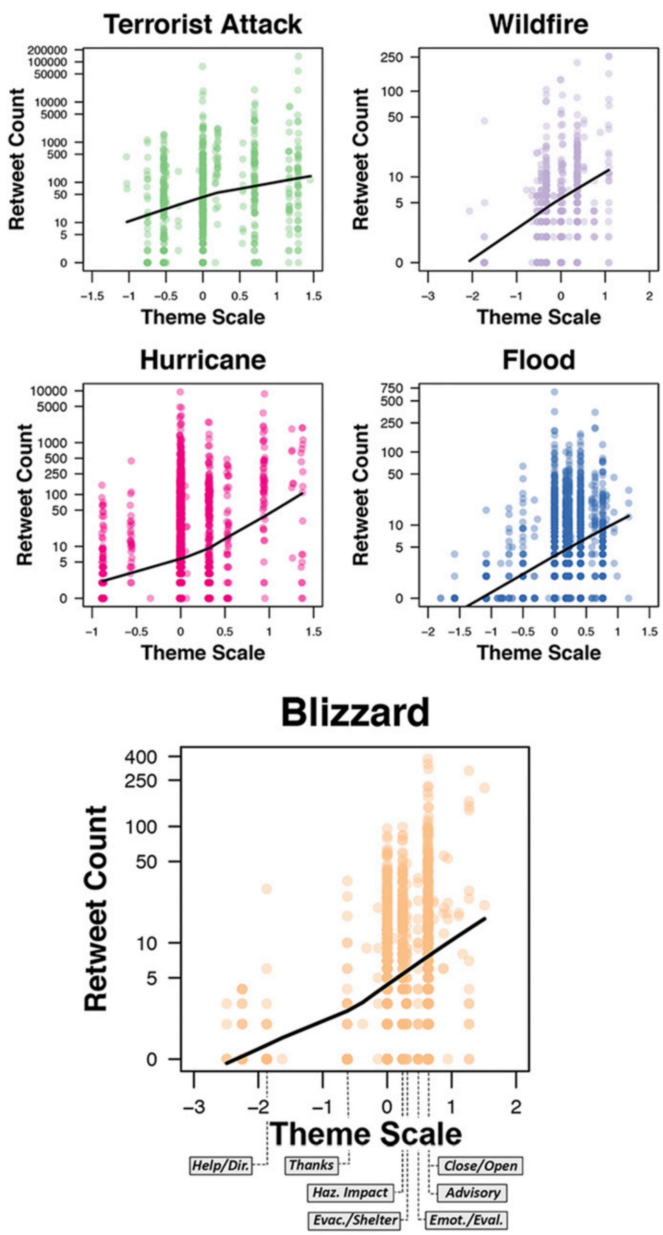

Fig. 3. This figure displays the impact that themes have on message retransmission for each event. The theme scale is derived from coefficient values from the negative binomial regression (Table 2). Each tweet's theme scale value is the sum of the theme coefficients for all themes present in that tweet. Locally weighted scatter plot smoothing (LOWESS) curves displayed in black show retweet trends. The Blizzard scatter plot is enlarged to show how each theme contributes to the theme scale values. Taken together, the five scatter plots demonstrate the importance of themes for message retransmission: messages that incorporate prominent themes (e.g., hazard impact or advisory) are retransmitted at consistently higher rates across all five hazards. Plots with theme boxes shown for all events are in Fig. S3.

competing for attention in a noisy environment. Thus, organizations should use empirically informed strategies to amplify their warning messages. Although design of risk messages is currently governed primarily by "best practices" (44, 45), evidence-based message design has the potential to substantially improve communication to the public. Future preevent warning policy for risk communicators of all types who use terse messaging channels should include the design and adoption of message templates that include highly salient content areas and the use of effective stylistic features, while avoiding features, such as URLs, that reduce retransmission. In the absence of a URL, however, additional clarifying information should be made available through alternative sources. The URL finding also highlights the fact that emergency management organizations may have different goals in providing relevant information to the public. If emergency managers want to disseminate detailed information to the public on Twitter, then the inclusion of a URL to that information is advisable; however, emergency managers should be aware that this could attenuate the amplification of that message. Therefore, emergency managers should use preestablished hashtags, capitalize critical information, and use imperative sentences to increase message amplification.

Our study also shows differences in retransmission patterns across hazards, suggesting the value of a quantitative theory relating hazard characteristics to the social amplification of risk. The development of a database covering a wider range of hazard cases would greatly contribute to this effort and further validate existing frameworks. A systematic theory of cross-hazard message amplification would provide a foundation for the development of "normative principles" that exploit common retransmission patterns across hazard types to enhance the dissemination of official messages. By focusing on message content and style along with network attributes, we are closer to generating templates that can maximize message amplification during imminent threats.

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