Role of Expressed Emotions on the Retransmission of Help-Seeking Messages during Disasters

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ABSTRACT

Emergency managers rely on formal and informal communication channels to identify needs in post-disaster environments. Message retransmission is a critical factor to ensure that help-seekers are identified by disaster responders. This paper uses a novel annotated dataset of Twitter posts from four major disasters that impacted the United States in 2021, to quantify the effect that expressed emotions and support typology have on retransmission. Poisson regression models are estimated, and the results show that messages seeking instrumental support are more likely to be retransmitted. Expressions of anger, fear, and sadness increase overall retweets. Moreover, expressions of anger, anticipation, or sadness increase the likelihood of retransmission for messages that seek instrumental help.

Keywords

Social Amplification, Retweet Prediction, Crisis Informatics

INTRODUCTION

The United States has seen unprecedented natural disasters leading to significant deaths, displacement, and other disturbances (Fang et al. 2019; Palinkas 2020). Online Social Network (OSN) usage shapes how our society responds to these disasters and catastrophes. One such function of OSN during disasters is facilitating and disseminating information (Castillo 2016). With the widespread adoption of OSN to communicate during extreme events, stakeholders are also using these tools to coordinate services. On both sides of the spectrum, emergency responders use OSN to identify needs, and impacted communities use it to seek help. Several tools are available to automate the process of matching the supply and demand of support in the aftermath of disasters (Purohit, Castillo, et al. 2014; Purohit, Hampton, et al. 2014; Basu et al. 2017; Kirac and Milburn 2018).

The COVID-19 pandemic has renewed interest in the study of online help-seeking, with research focusing on individuals seeking help with healthcare (Quinn-Scoggins et al. 2021), mental health (Richardson et al. 2020; She et al. 2021; Ogrodniczuk et al. 2021; Alonzo and Popescu 2021), among other needs (Saud et al. 2020). Research into online help-seeking behaviors has primarily focused on the medical healthcare space (Ybarra and Suman 2006; Pretorius et al. 2020). Other help-seeking behaviors that have been studied include educational support (Chao et al. 2018), family violence relief (Fiolet 2020), financial issues (Lim et al. 2014), gambling (Gainsbury et al. 2014), and mental health (Alonzo and Popescu 2021).

A relevant aspect of the flow of information on OSN, specifically Twitter, is disseminating information through retweets or retransmission. Understanding the factors associated with retransmission may shed light on the controlling mechanisms for facilitating actionable aid to individuals in need. Widely retransmitted help-seeking behavior has a broader audience and is, thus, more likely to produce needed assistance. There are several classifications of help-seeking behaviors; in general, support is classified into two main categories: emotional and instrumental. The former elicits emotional support from others, such as connection, while instrumental support refers to tangible or logistical assistance, such as food or shelter.

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Understanding the factors that impact the retransmission of help-seeking messages on OSN is critical to enhancing the impact that help-seeking messages have, the potential for matching help-seekers with support providers, and leveraging the OSN tools for disaster response. Therefore, there is a need to characterize help-seeking posts during natural disasters, and understand the features of these messages that impact their retransmission.

A critical characteristic of help-seeking messages is their emotional salience. Disasters, particularly natural disasters, are associated with significant psychological distress (Freedy et al. 1994). Individuals seeking help are bound to express these emotions in their messages on OSN. Understanding the role these emotions play in disseminating information is essential, as they might be a crucial factor in determining the reach that help-seeking messages have. Theoretically, negative emotions, particularly anger, can exert a high degree of influence over other individuals' behavior. Specifically, anger motivates action (Van Kleef et al. 2011), and in the context of OSN, individuals may be more likely to comply with a user's request if they are perceived as angry. Another "negative" emotion is sadness, which is conceptualized to elicit sympathy in others (Van Kleef et al. 2011). Overall, negative emotions are expected to be more influential in message dissemination than positive emotions (Fan et al. 2014).

There is a growing interest in understanding the role that expressed emotions have on the retransmission of social media publications. The work by Firdaus et al. 2021 has leveraged emotional displays in Twitter posts to accurately predict their retransmission. The research by Pivecka et al. 2022 found that the display of emotions, particularly high arousal emotions such as anger, anxiety, and joy, are relevant factors to predict the retransmission of political messages. So far, no previous studies have researched the role that expressed emotions have in the retransmission of messages on OSN in the context of natural disasters.

BACKGROUND

This section summarizes previous research into online help-seeking behaviors, and the use of social media in disasters, with special attention to studies that have analyzed the use of the Twitter OSN platform during disasters.

Online Help Seeking

Generally, individuals asking for help expect social support to be provided in response to a situation or problem they are facing (Gourash 1978). Research into help-seeking behavior on OSN is a nascent topic. While there is a large body of work on the different types of social support individuals seek and provide (House 1983; Kahn and Antonucci 1980; Barrera 1986), there is still much to learn from the interplay between social support types and help-seeking behaviors.

Emergency managers rely on formal and informal communication channels to identify help-seeking individuals in post-disaster environments (Holguın-Veras et al. 2016). There has been an increasing interest in developing methodologies to identify needs based on OSN data during different stages of the disaster management cycle (Purohit, Hampton, et al. 2014; Zade et al. 2018; Yan and Pedraza-Martinez 2019; Saroj and Pal 2020).

The relevance of OSN as a tool to connect individuals seeking help with those that can provide the support needed was highlighted during the flooding event experienced in the aftermath of Hurricane Harvey in 2017. Many individuals were trapped in their homes in the rising waters of the greater Houston, Texas, area. With uninterrupted access to mobile communications, these individuals posted messages on OSN calling for help. Hundreds of rescue operations were effected by emergency managers and the citizen-led groups that responded to the OSN posts (Li et al. 2019; Mihunov et al. 2020).

Social Amplification of Messages after Disasters

In any OSN context, the social amplification of messages via retransmission is critical to increasing message exposure. Several frameworks have been proposed to understand the amplification process in real-time (Kempe et al. 2003; Java 2007). Other studies have examined the dissemination of public health messages related to natural disasters on Twitter. For example, Sutton and colleagues (Sutton, League, et al. 2015) found that terse messages with informational content were most widely disseminated. Similar results related to terse messages were revealed during the Boston Bombing event (Sutton, Gibson, et al. 2015).

Despite the importance of understanding the factors that determine the retransmission of messages in the disaster context, only a few studies have explored this topic. The work by Scott and Errett 2018 examined the dissemination of OSN posts made by officials during the 2016 Louisiana floods, and found that messages were more likely to be retransmitted when the original poster was a federal or state-level stakeholder versus a local actor. C. H. Lee and Yu 2020 evaluated how the linguistic characteristics of messages affected the retransmission of Twitter posts made during the 2013 Colorado floods; this study looked at both individual and official messages and found that retransmission increases with the use of concrete and interactive language. The authors also evaluated the impact of positive and negative sentiment on the messages, and found that these binary emotions did not impact the message's retransmission.

An analysis of risk warning messages posted on Twitter by emergency managers during Hurricane Irma in 2017 found that the presence of five warning elements: hazard, guidance, location, time, and source have a significant effect on the message's retransmission (Wang et al. 2020). More recent work by Sutton, Renshaw, et al. 2020 examined the performance of Twitter messages posted by accounts representing public health, emergency management, and elected officials during the early stages of the COVID-19 pandemic. The results showed that retransmission is determined by message content, message features, organizational type of the account, the number of followers for an account, and the time and day at which a message is posted. Research conducted during the COVID-19 pandemic analyzed help-seeking OSN posts made by individuals in mainland China and found that posts with emotionally salient features such as anger and self-disclosure facilitated the retransmission of the messages (Luo et al. 2020). These results are in contrast with previous work which indicated that emotional sentiment is not associated with the retransmission of informational messaging during a disaster (C. H. Lee and Yu 2020). However, the latter study only categorized the messages in positive or negative emotions and did not explore more nuanced emotional expressions. These previous findings indicate that, while the emotional displays contained in messages related to disaster communications play a role in the amplification of these messages, these emotions have different effects that depend on the message content and purpose. No previous research has examined the effect that expressed emotion has on the amplification of help-seeking posts during natural disasters.

There is a need to understand what determines the retransmission of OSN posts from help-seeking individuals during disasters. These messages are crucial in matching the impacted population with those that provide the support they need. To our knowledge, this research provides the first systematic study of the factors determining the social amplification of help-seeking messages by examining OSN posts' retransmission across four hazards in the United States during the 2021 calendar year.

RESEARCH QUESTIONS

This research aims to bridge the gap in understanding the factors that determine the social amplification of OSN posts made by individuals seeking help in the disaster context. The study focuses on the immediate aftermath of the disaster event, in the response phase. During this stage, emergency managers must quickly determine the needs, and the timeliness of the response efforts is critical. In this setting, the social amplification of help-seeking messages is crucial. The research seeks to understand the role that previously unexplored factors have in this process, including the type of support sought and the emotional charge of the message.

This research addresses the following research questions:

RQ1: What is the relationship between each support type and retransmission? Previous research has indicated that instructional or informational tweets from trusted authorities have higher retransmission rates during natural disasters. There needs to be more research on individuals' help-seeking messages during disasters and whether pleas for emotional or instrumental support are more likely to be retransmitted.

RQ2: What is the relationship between expressed emotion and retransmission? Previous research investigating the sentiment of OSN posts and its association with retransmission has mainly focused on binary sentiment (i.e., positive or negative); the findings concur that this binary sentiment has no impact on the social amplification of these messages. However, research from the field of psychology has found that negative emotional displays, particularly anger, engender social influence. Moreover, fear, anger, and sadness can have powerful effects on others. This research examines how displaying these emotions on OSN posts will relate to the retransmission of help-seeking messages.

These questions are investigated through an empirical analysis of a novel annotated Twitter dataset of help-seeking messages posted by individuals during four disaster events in the United States in 2021.

DATA COLLECTION

The data collected for this study was sourced from Twitter, a social networking site with over 330 million active monthly users (Twitter 2022). The Twitter interface allows users to create short text messages of up to 280 characters, including hyperlinks, pictures, and videos. Hashtags on Twitter enable users to find posts with similar themes; for example, searching the hashtag #COVID19 yields all tweets containing this search term. Moreover, besides posting their original messages, known as "tweets," users can also "favorite" and "retweet" other users' posts, disseminating the content to their followers.

The research in this paper focuses on messages posted during the following four extreme events, selected because they were the most significant disasters to impact the United States in the calendar year 2021:

Winter Storm Uri: Extreme winter weather affected North America in February 2021, impacting over 170 million individuals in the U.S. with ice and snow precipitation. The extreme weather caused major energy infrastructure failure in Texas. It is estimated that 11 million users lost power, 12 million individuals lost access to water due to freezing or breaking pipes, and 246 individuals lost their lives (Texas Comptroller of Public Accounts 2021).

Hurricane Ida: The second most powerful hurricane to make landfall in the U.S., Hurricane Ida reached the coast of Louisiana on August 29th, 2021. It continued impacting communities in the eastern U.S. until September 1st. Heavy winds and rain caused property damage and widespread flooding, and estimated total damages exceeded US$60 Billion and 91 fatalities (NOAA 2021b).

Kansas Wildfire Outbreak: A large wildfire spread over 365,000 acres in Kansas. Efforts to control the fire started on December 15th as the fire spread over four counties and destroyed properties and farmland. Two casualties were attributed to the fires (Gabbert 2021).

December Tornado Outbreak: The December 10th event produced 71 tornadoes that impacted a path of 250 miles over Arkansas, Illinois, Kentucky, Missouri, and Tennessee. With over $3.9 billion in damages and 89 confirmed fatalities, this outbreak is the deadliest late-season tornado event on record (NOAA 2021a).

The first step in the data collection process was assembling keywords and hashtags to identify posts related to each disaster event. The keywords were selected based on their ability to capture relevant posts while minimizing off-topic chatter. The complete list of keywords used can be found in the appendix. The data was gathered using the Twitter Developer API with Academic Access (Twitter 2022), which allowed the use of date ranges to select posts in addition to the keywords. This filter allowed for the identification of original help-seeking message characteristics. Moreover, the search queries allowed for retrieving original tweets only, disregarding any messages that are retweets of an actual help-seeking plea. When individuals retweet messages on Twitter, they are able to include more information, adding content to the original message. Focusing on original help-seeking posts allows modeling the message characteristics that impact their amplification, and understanding what features from the originator of the post play a role in the retransmission. The date ranges used for each disaster are reported in Table 1. After the data were collected, the first step was to eliminate tweets from official accounts, since they are out of the scope of the research.

Disaster Event	Deaths	Dates	Initial No. of Tweets	Help-Seeking
Winter Storm Uri	246	02/10/2021 - 02/17/2021	15,733	423
Hurricane Ida	91	08/29/2021 - 09/02/2021	6,339	224
December Tornado Outbreak	89	12/10/2021 - 12/12/2021	4,123	584
Kansas Wildfire Outbreak	2	12/15/2021 - 12/23/2021	1,019	12

Table 1. Disaster Events

Content Coding

The downloaded tweets were individually read and coded by two research assistants, and the authors resolved differences between the two initial coders. The reliability of initial coding was evaluated using Krippendorff's alpha, which yielded a coefficient of 0.897, indicating high consistency. A total of 27,214 tweets were classified into one of four categories. Individual help-seeking messages shared many of the exact keywords as other informational messages in the disaster context; this led to a high signal-to-noise ratio in the data collected for all disaster events, as shown in Table 1. The first category includes messages that were not help-seeking, while the following three categories comprise the type of help the poster sought; sample tweets for each category are reported in Table 2.

Different categories of aid or support were evaluated to understand the role of the type of help sought on retransmission. Social support can be categorized into four collectively specific types: Appraisal support, which includes expressions that affirm the appropriateness of acts or statements made by another (i.e., offering information for self-evaluation); emotional support is comprised of emotional demonstrations (e.g., providing care, empathy,

Label	Sample Tweet
NH	How to help and what to do if you need it during Texas' historic freeze
IH	36 hours without electricity and now my apartment frozen pipe burst ... need help now. LasColinas Irving Texas!!
EH	My anxiety is through the roof with everything going on here in Texas and I'm about to get on the road to go to treatment please send me wholesome content I'm in desperate need.
IEH	Send help I live in Texas and this week has me stressing about what next week will bring. I need groceries. Be a good sub and help relieve my stress

Table 2. Sample Tweets

or trust, among others), informational support involves the provision of information to one another (e.g., sharing actionable information), and instrumental support includes the provision of tangible goods (i.e., provision of aid or services) (Barrera 1986). In this study, we focus on two main categories of support: Instrumental and Emotional. Messages were categorized based on requests for these types of support or a combination of both.

Overall, the following four labels were coded:

Not Help-Seeking (N.H.): Comprised tweets that were not expressing an individual's need for help. These messages often contained information regarding the disaster event or were related to response efforts. The messages in this category were deemed out of the scope of this research and therefore discarded.

Seeking Instrumental Help (I.H.): Include messages where the poster sought help or assistance tangibly or physically, such as shelter, food, or other basic needs.

Seeking Emotional Help (E.H.): Emotional support messages sought care or compassion. Messages were labeled in this category when the tweets expressed emotional needs or distress.

Seeking both Instrumental and Emotional Help (IEH): A small percentage of tweets (6%) contained requests for both instrumental and emotional support; those were categorized as such.

Once the tweets were coded, the next step in the data processing stage was to identify the emotional charge of the messages. Studies that consider emotion in online communication have primarily been focused on identifying a binary spectrum of either positive or negative emotions (Wiebe et al. 2005). More recent research has developed automated classification techniques to identify genuine emotions. In this work, using the Latent Semantic Analysis method proposed by Gill et al. 2008, help-seeking posts were processed to determine the presence of eight primary emotions: Acceptance, Anger, Anticipation, Disgust, Fear, Joy, Sadness, and Surprise. These emotions are not mutually exclusive. Therefore, each message can be categorized as showcasing multiple emotions. Posts in the sample displayed two (2.3) emotions on average. Not surprisingly, given that the sample represents help-seeking messages in a disaster setting, none of the messages in the sample displayed acceptance. The most relevant emotions were displays of fear (56%), anger (42%), and sadness (47%). Overall, the final dataset contains 1,243 help-seeking messages; summary statistics of all variables are presented in Table 3.

The retransmission ranged from 0 to 394, with a mean of 3.24 and a median of 0. The variable is highly skewed to the left, reporting Skewness of 11.54 and Kurtosis of 157.02, which signifies a long right tail. Overall, only 27% of the messages were retransmitted. These results are similar to prior work on modeling retransmission on Twitter, which has found that most messages do not get retransmitted (Sutton, League, et al. 2015).

Most individuals posting help-seeking messages were not verified (verified accounts are those deemed of public interest), with only 6% of messages in the sample emanating from verified posters. Over half the posts included a link (58%), and only 20% mentioned another user in the message content. Most tweets (75%) seek instrumental support, while 18% request emotional support, and 6% ask for both.

METHODS

In the model development process, three functional forms are considered to assess the impact of the factors of interest on the dependent variable. All models include variables that control for users and post characteristics unrelated to the research questions. The control variables related to user characteristics are whether the user is verified, the number of followers, and the number of users the poster follows. Control variables that characterize

Variable	Description	Mean	Std. Dev.	Range
Retransmission	Number of retweets	3.54	22.01	0-394
Verified	User has been authenticated by Twitter	0.06	0.24	0-1
Followers	Number of users that follow the poster (log-transformed)	2.92	4.08	0-15.98
Following	Number of users the poster follows (log-transformed)	2.53	3.43	0-11.17
With Link	Post contains a hyperlink	0.58	0.49	0-1
With Mention	Post mentions another Twitter user	0.20	0.40	0-1
Tweet Length	Length of post in number of characters (log-transformed)	5.20	0.56	3.33-6.57
Winter Storm	Disaster: Winter Storm Uri	0.34	0.47	0-1
Hurricane	Disaster: Hurricane Ida	0.18	0.38	0-1
Tornado	Disaster: December Tornado Outbreak	0.47	0.49	0-1
Wildfire	Disaster: Kansas Wildfire Outbreak	0.01	0.12	0-1
Instrumental	Seeking Instrumental Support	0.75	0.43	0-1
Emotional	Seeking Emotional Support	0.19	0.39	0-1
Both	Seeking both Instrumental and Emotional Support	0.06	0.26	0-1
Anger	Post expresses anger	0.42	0.49	0-1
Anticipation	Post expresses anticipation	0.33	0.47	0-1
Disgust	Post expresses disgust	0.26	0.44	0-1
Fear	Post expresses fear	0.56	0.49	0-1
Joy	Post expresses joy	0.29	0.48	0-1
Sadness	Post expresses sadness	0.47	0.49	0-1
Surprise	Post expresses surprise	0.19	0.39	0-1

Table 3. Summary Statistics

each message account for message length, and whether the message includes a hyperlink or mentions another user. Moreover, variables that control for each disaster context are also included.

The first functional form (M1) models each help-seeking post i number of retweets (Rt_i^*) as depending on the controls for the user's characteristics (vector U_i), the characteristics of the text in each message (vector T_i), and the message's disaster context (vector D_i). The main effects estimate the impact that the support-seeking type (i.e., Instrumental vs. Emotional), represented by vector S_i, has on retransmission. The message-level random intercepts (ζ_i) incorporate individual message heterogeneity, including message-specific content, which our control or independent focal variables do not capture.

$$\mathrm{Rt}_i^* = (\beta_0 + \zeta_i) + \beta_u U_i + \beta_t T_i + \beta_d D_i + \beta_s S_i + \varepsilon_i \tag{1}$$

The second model (M2) builds on the first model's functional form and estimates the effect of expressed emotions (vector E_i), concurrently with the impact of support typology while controlling for the user, message, and disaster characteristics.

$$\mathrm{Rt}_i^* = (\beta_0 + \zeta_i) + \beta_u U_i + \beta_t T_i + \beta_d D_i + \beta_s S_i + \beta_e E_i + \varepsilon_i \tag{2}$$

Finally, the third model (M3) incorporates the interaction effects between the type of support sought and the expressed emotion of the posts.

$$\mathrm{Rt}_i^* = (\beta_0 + \zeta_i) + \beta_u U_i + \beta_t T_i + \beta_d D_i + \beta_s S_i + \beta_e E_i + \beta_{int}(S_i \times E_i) + \varepsilon_i \tag{3}$$

Poisson regression models were estimated to evaluate the research questions; this modeling approach was selected because the dependent variable is a highly skewed count measure of retweets per post. Several indicators were used to assess the model's goodness of fit. The Pseudo R^2 showed results in the range of 0.334-0.374, indicating that the models explain at least 33% of the variation in the observed values.

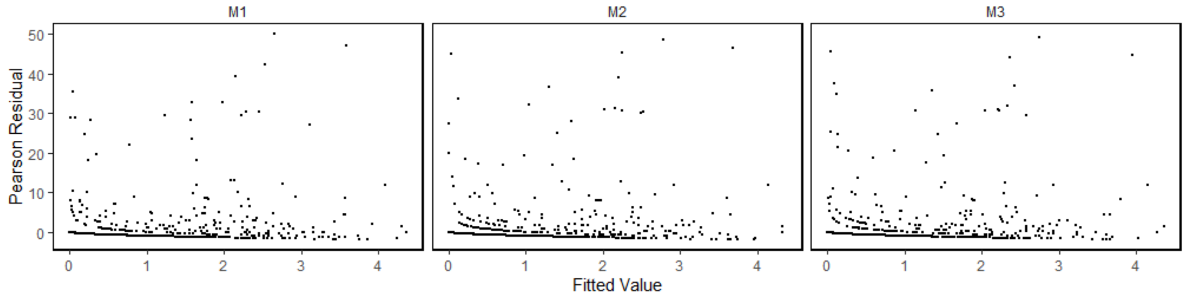

Figure 1. Plot of Pearson Residuals vs. Fitted Model Values: the Pearson Residuals correct for the unequal variance in the raw residuals, and are better suited to diagnose Poisson Regression Models.

Other techniques were considered to estimate parameters, including Ordinal Least squares (OLS), negative binomial regression, zero-inflated Poisson, and negative binomial estimation. The OLS method was outperformed by methods that accounted for the highly skewed nature of the dependent variable. Zero-inflated models did not produce statistically significant results, validating the assumption that there is only one zero-generating process in the sample (i.e., when tweets are not retransmitted). Finally, the Poisson regression produced the best fit for this sample.

Another tool used to diagnose the models was the estimation of the Pearson residuals, which are standardized distances between the observed and expected values of the dependent variable, estimated with the following equation:

$$\mathrm{Rp}_i = \frac{O_i - E_i}{\sqrt{E_i}} \tag{4}$$

Where O_i is the observed value for observation i, and E_i is the expected, or fitted value, for observation i . The results of the estimated residuals are plotted versus the fitted values for each model; see Figure 1 . The plot shows robust results for a Poisson fit.

RESULTS

Model estimation results show that most independent covariates are statistically significant at the 0.1% level, including the coefficient that captures the unobserved heterogeneity in the data. The model specification allows us to compare the magnitudes and direction of the β coefficients of interest; these comparisons are the basis for discussing the results. Results for model coefficient estimation for all functional forms are reported in Table 4, and coefficients for model M3 are illustrated in Figure 2.

The analysis will concurrently focus on control variables for the three models to organize the discussion. In contrast, the main effects will be discussed separately for the typology of support sought by the poster and the emotion expressed in the message.

Control Variables

When looking at the effect of controls, the first set of variables controls for the characteristics of the individual. When Twitter has verified a user, it increases the likelihood that the help-seeking message will be retransmitted. Moreover, the number of followers and users followed by the poster is also associated with increased retransmission. These results are consistent in all three models and follow previous results in the literature explicitly related to Twitter. These works have found that verified users are more likely to be retweeted (Liu et al. 2014), and that the poster follower count and engagement are positive factors influencing retweet counts (K. Lee et al. 2014).

Other controls included in the models account for intrinsic message characteristics. When testing for the effect of a link or a mention to another user in the post, all models consistently estimated negative coefficients, meaning the presence of these elements is negatively associated with retransmission. Results evaluating retweets in other disaster contexts have found the same adverse effects (Renshaw et al. 2021). However, in the context of health information dissemination, the presence of these components is associated with positive influence (Sutton, Renshaw, et al. 2020). This research supports previous findings that the topic of the message differentiates what factors determine its retransmission. More research is needed to understand the mechanisms that cause these differences in retweet preference. Another control variable included in the estimation captures the effect of the message length on its retransmission rate. All estimates reveal that longer messages are more likely to be retransmitted.

Variable	M1 Coeff.	M1 S.E.	M2 Coeff.	M2 S.E.	M3 Coeff.	M3 S.E.
Control Variables						
Verified	1.152***	(24.77)	1.097***	(22.87)	1.125***	(23.04)
Following	0.140***	(15.12)	0.153***	(16.55)	0.143***	(15.32)
Followers	0.142***	(17.12)	0.116***	(13.75)	0.115***	(13.35)
With Link	-0.468***	(-12.19)	-0.448***	(-11.53)	-0.374***	(-9.321)
With Mention	-0.555***	(-12.88)	-0.552***	(-12.61)	-0.510***	(-11.66)
Length	0.935***	(27.11)	0.849***	(22.71)	0.826***	(22.18)
Hurricane *vs Other*	0.632***	(18.24)	0.496***	(13.47)	0.541***	(14.72)
Winter *vs Other*	0.742***	(14.32)	0.542***	(10.46)	0.582***	(11.16)
Main Effects						
Instrumental	0.0172	(0.360)	0.213***	(4.339)	0.259*	(2.455)
Both	-0.954***	(-8.939)	-0.822***	(-7.653)	-1.259***	(-11.10)
Anger			0.103*	(2.466)	-0.472***	(-4.616)
Anticipation			0.0687*	(1.963)	-0.398***	(-4.257)
Fear			0.0545^{+}	(1.338)	0.125$^{\#}$	(1.074)
Sadness			0.751***	(17.20)	-0.324**	(-3.095)
Other Emotion			-0.457***	(-11.95)	1.726***	(13.58)
Interaction Effects						
Instrumental × Anger					0.659***	(5.915)
Instrumental × Anticipation					0.513***	(4.972)
Instrumental × Fear					-0.154$^{\#}$	(-1.246)
Instrumental × Sadness					1.247***	(11.05)
Instrumental × Emotion					-2.458***	(-18.46)
Constant	-5.302***	(-27.38)	-5.118***	(-25.29)	-5.054***	(-23.31)
N	1,243		1,243		1,243	
Pseudo R^2	0.334		0.355		0.374	
LL	-8,737.9		-8,456.9		-8,211.1	
Wald χ^2	8,757.0		9,319.0		9,810.6	

Table 4. Poisson Regression of Retransmission. The z statistics are reported in parentheses; coefficient significance indicated by: $^{\#}p<0.35, ^{+}p<0.20, ^{*}p<0.05, ^{**}p<0.01, ^{***}p<0.001$

Binary variables were created for each event to capture the heterogeneous effects of each disaster type. The estimated coefficients serve as a proxy for the different disaster characteristics. Since the percentage of Wildfire related messages was only 1% of the total, the effects of this type of disaster could not be captured with this data. Disaster effects were estimated using the December Tornado Outbreak as a reference. The results show that both coefficients are positive, indicating that retransmission was more likely in these events than in the case of the tornado outbreak. These results can be attributed to Winter Storm Uri and Hurricane Ida having more significant impacts than the December Tornado outbreak. These disasters impacted larger geographical areas and caused more economic damage. The findings are consistent with previous literature that has studied the effect of disaster impact on public attention (Ewart and McLean 2019).

Support Typology

The type of help individuals seek in their posts significantly affects their retransmission. The results show that the message is more likely to be retransmitted when strictly requesting instrumental help. When both types of support are requested, the effect is negatively associated with retransmission. These results highlight a negative association between emotional support-seeking messages and their retransmission. The effects are consistent in all three models estimated. The findings shed light on a topic that has not been previously explored in the disaster context. However, the results are consistent with the study of retransmission of help-seeking messages during the early stages of the COVID-19 pandemic (Luo et al. 2020), which found that messages seeking instrumental support were more likely to be retransmitted. When looking at the results in model M3, the magnitude of the support typology coefficient is shown to be a significant and large effect in determining the retransmission outcome. See Figure 2 for a detailed look at the coefficients in this model.

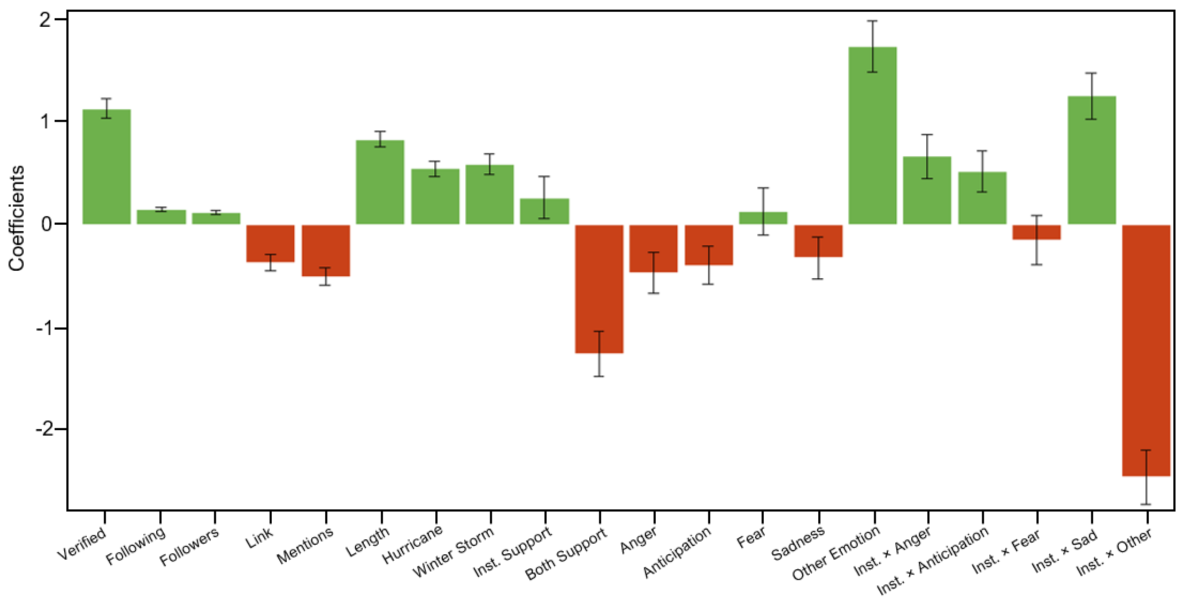

Figure 2. Effects of control factors and message features on message retransmission. Bars indicate effects of covariates (horizontal axis) on expected retweet count (M3); whiskers indicate 95% confidence intervals.

Expressed Emotions

The results reported in Table 4 show a significant interplay between the type of help sought in the message and the emotions expressed. The estimated models include coefficients for primary emotions expressed in the messages: Anger, Anticipation, Fear, and Sadness, and estimate effects for the presence of other emotions (i.e., Disgust, Joy, or Surprise). Since multiple emotions can be present in each message, coefficients could be estimated for all the binary variables indicating the expression of each emotion. The authors evaluated different functional forms and selected these main effects based on their statistical significance and functional validity. The main effects results are discussed for each emotion category. These effects are estimated in models M2 and M3, with M3 incorporating interaction effects.

When looking at expressions of anger, based on previous results in psychological research (Van Kleef et al. 2011), it is expected that messages containing expressions of anger will be influential and thus more likely to be retweeted. Both models confirm these results. However, Angry expressions in the message content do not have high statistical significance. Evaluating the effect of anger without including interactions is small, positive, and statistically significant at the 5% level. In M3, with the inclusion of interaction effects, the results show that expressed anger is not statistically significant. In contrast, messages that express anger while seeking instrumental support have a positive association with retransmission which is statistically significant at the 0.1% level. To note, when incorporating the interaction between instrumental support and anger, the coefficient of anger changes to a negative effect. This result measures the effect of anger in messages asking for emotional help. Overall, the evidence in this research does not show that anger is a significant predictor of retransmission in most settings, and that it has a significant and positive effect in the retransmission of messages seeking instrumental help.

Anticipation is the state of looking forward to future events and can include affective components such as pleasure or anxiety (American Psychological Association 2021). The modeling results show that expressions of anticipation increase their retransmission. When analyzing the interaction between anticipation and instrumental support, the effect is more significant, while the magnitude is negative. A similar mechanism to the one that drives the dynamic between anger and instrumental support is at play here: Emotional help-seeking messages that express anticipation are less likely to be retransmitted than those that express the same emotion while seeking instrumental support.

Expressions of fear in this setting are expected (Strümpfer 1970). While there are previous studies that have explored the role that fear plays on disaster donations (O'Loughlin Banks and Raciti 2018), no previous research has looked at the effect that fear in the impacted population has on response efforts. This paper's results show a positive association of expressed fear with the retransmission of help-seeking posts. However, the effect is smaller than those of other expressed emotions. In this case, the expression of fear is positively associated with retransmission in cases when emotional support is sought. If the message is seeking instrumental support, the presence of fear translates to a larger negative effect.

Sadness is an emotion associated with unhappiness that usually arises after losing something valued (American Psychological Association 2021). Since disaster events generate a significant loss, it is not surprising that 47% of help-seeking posts expressed sadness. The effect of this emotion on message retransmission was found to be significant. When considering sadness alone, the effect is positive and moderate, while the effect of expressions of sadness displayed on instrumental support-seeking messages is significantly larger in magnitude. For messages expressing emotional needs, sadness is negatively associated with retransmission.

The effect of other emotions, including Disgust, Joy, and Surprise, were significant retransmission factors. Overall, the effects captured by this variable show that emotional charge in messages negatively affects retransmission, both on its own and in the case of messages seeking instrumental support.

The evidence shows that support typology and expressed emotions have significant and varied effects on the retransmission of help-seeking messages during disasters. The interplay between these two drivers makes a difference in the direction and magnitude of the effect.

CONCLUSIONS

This study sought to explore factors associated with the retransmission of help-seeking messages in OSN, focusing on messages posted in the context of natural disasters. There are several notable findings. For one, messages that seek instrumental help, in the form of material support to overcome disaster impacts, are more likely to be retransmitted. Second, expressed emotions significantly affect the retransmission of messages: Anger is a positive driver of retransmission when the message is seeking instrumental help. Results show that expressions of fear positively correlate with the retransmission of emotional help-seeking, although the effect is negligible. Another significant emotion is sadness, which is positively associated with retransmission. Finally, results show that specific emotions impact the association between support type and retransmission. The expression of anger, anticipation, or sadness increases the likelihood of message retransmission for instrumental support. In contrast, fear is negatively associated with the retransmission of this type of help-seeking post.

These conclusions have significant implications. The research clarifies the role that expressions of emotion have on message retransmission, a previously unexplored topic in the context of disasters. With OSN playing an increasingly relevant role in assessing needs and disseminating information during natural disasters, it is crucial to understand the mechanisms that drive the amplification and diffusion of help-seeking messages. Thus, incremental steps toward understanding the role of emotions on social amplification of messages in OSN ought to be pursued, and this research is an essential first step.

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APPENDIX A: LIST OF KEYWORDS USED TO RETRIEVE SOCIAL MEDIA MESSAGES

- **Disaster Identifiers** `tornado tornados tornadoes wildfire wildfires hurricane ida hurricane ida Texas`
- **Support Identifiers** `help aid need`
- **Emotion Identifiers** `sad emotional anxious anxiety depressed depression stress stressed hysteric miserable hopeless disheartened sorrow heartbroken unhappy worried worry`