Dec 11th, 12:00 AM

Save Our Souls: Study of Twitter Use during India’s COVID-19 Pandemic

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Completed Research Paper

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Abstract

Twitter is a commonly used social platform for communication during disasters. Tweets by citizens during disasters to share information, seek, and offer help create a body of spontaneous, decentralized, emergent social media communication. Users' exploit Twitter's reach-enabling technological functionalities (hashtags (#), mentions (@), and 'reply-to') to draw attention to the messages. Set in context of the second wave of COVID-19 in India, that saw a surge in citizen-driven tweets seeking healthcare resources from fellow citizens and officials (i.e., SOS tweets), our paper empirically analyses the effects of Twitter's reach-enabling functionalities on online responses (i.e., retweets and replies) to these SOS tweets. We investigate the effects of inclusion of hashtags, mentions, and 'reply to' SOS tweets. We also examine the moderating effect of how the effects of the reach-enabling functionalities change as the social platform gets crowded with SOS tweets. The study offers various academic and practical implications.

Keywords: Social platforms, Twitter, COVID-19, disaster, hashtags, mentions, retweets, crisis communication, target messaging, broadcasting

Introduction

Recent years have seen increasing use of social platforms, especially Twitter, for citizen communication during crisis situations such as pandemic, natural disasters, wars, social uprisings, etc. In disasters such as 2014 Australian bushfire, 2015 Houston flood, and more recent crisis like COVID-19 pandemic, Twitter was used by the citizens to share disaster related information, coordinate volunteering efforts, and form communities and support networks transcending geographies (Abedin and Babar 2018; Liu and Xu, 2018; Leong et al. 2015). During the devastating second wave of COVID-19 in India, with the collapse of state-provided healthcare system, citizens took to Twitter, to directly seek help from authorities and fellow citizens. People posted tweets to access information about or crowdsource COVID-19 healthcare resources for their affected kin, acquaintances, and even strangers (Jena 2021; Kalra and Ghoshal 2021; Scarr et al. 2021). Such tweets were essentially a call for help which we term as SOS tweets. Figure 1 shows an example of an SOS tweet.

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Figure 1. An Example SOS Tweet (Fictional)

In the SOS tweets, users typically provided information (e.g., age, gender, health status) about the COVID-19 affected person(s) who were in dire need of healthcare essentials. Users also exploited reach-enabling technological functionalities of Twitter, such as hashtags, mentions and directly replying to someone else's tweet, hoping their tweets to gain more visibility. The competition for attention on the online platform becomes particularly crucial during crises where the social platform gets flooded with messages and the situation calls for timely response from the intended audience of the tweets. Reach-enabling functionalities of Twitter are meant for ease of searchability and rapid dissemination of information through the network of users. Thus, they aid communication at the time of crisis where the urgency is high, and the window of effective response is small. Users spontaneously posted SOS tweets with COVID-specific hashtags (e.g., #SOS, #Urgent, #ICUBedNeeded, etc.), mentioned Twitter handles of institutions and individuals (e.g., @PMOIndia[3], @SonuSood[4], etc.), and/or posted their messages in the reply thread of some other tweet. The tweets were created organically by common citizens without any institutional guidelines or centralized control, hence there was not any systematic strategy that users could have followed in designing the messages. Further, the actual outcome of such communication is uncertain to the users in such contexts. The urgency of the situation also rules out any possibility of premeditated strategy of communication. Thus, a large body of citizen-driven, organic and real-time SOS tweets emerged during the peak period of second wave of COVID-19. Spontaneous, decentralized, citizen-driven social media communication under high degree of urgency and uncertainty is not uncommon in disasters and extreme events. However, the effect of using Twitter's reach-enabling functionalities on the online responses received by citizen tweets, especially tweets with call for help during crises, is not conclusively studied. Although spontaneous and non-systematic, we posit that the use of various reach-enabling functionalities is likely to influence the responses that a tweet gets on Twitter. Retweets and replies are prominent types of response a tweet can get on the platform. Retweets and replies are indicators of the attention the tweet can draw. An SOS tweet gaining more attention on the platform would have an increased likelihood of receiving help in real world. This motivates our first set of inquiries where we investigate the effects of hashtags, mentions, and posting the tweet as reply to some other tweet, on the retweets and replies received by focal SOS tweet. In this regard, we pose our first research question:

RQ1. How do various reach-enabling functionalities of Twitter impact the online responses received by an SOS tweet during an emergency?

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[3] @PMOIndia is the official Twitter handle for the office of the Prime Minister of India. https://twitter.com/PMOIndia

[4] @SonuSood is the official Twitter handle of Mr. Sonu Sood, who is an Indian film actor and humanitarian. He received the 'Sustainable Development Goals Special Humanitarian Action Award' from the United Nations Development Programme (UNDP) for his humanitarian works during India's COVID-19 pandemic. https://twitter.com/SonuSood

In temporally spread disasters such as pandemic, social platforms get crowded with crisis-related communication as the disaster progresses and intensifies. As the second wave of the pandemic progressed, Twitter became more crowded with accumulated SOS tweets, inherently increasing the competition for attention on the platform. While extant literature talks about the effect of using reach-enabling functionalities (e.g., hashtags) in disaster communication (Takahashi et al. 2015; Venkatesan et al. 2021), it does not explore whether their effects change across the disaster lifespan with varying crowdedness of the platform. Hence, we pose our second research question:

RQ2. How do the impact of reach-enabling functionalities of an SOS tweet on its received online responses vary with the changing platform crowdedness as the emergency situation intensifies?

Using concepts of *visibility* and *addressivity* on social platforms, we attempt to hypothesize the effects of the reach-enabling functionalities on the online responses received by an SOS tweet. Twitter functionalities afford both broadcasting and targeting. Hashtags, mentions, and reply-to vary in the degree of broadcasting and targeting capabilities. Hashtags enable better searchability and visibility (Bakshy et al. 2011). Mentions enable varying level of addressivity, depending on the position of mention in the tweet (Honey and Herring 2009). Reply-to type tweets are highly targeted thus restricted in visibility. We posit that during crisis, in a crowded platform, SOS tweets with hashtags and mentions inside the tweet will receive more online responses owing to heightened visibility, whereas presence of mentions in start and reply-to will lead to lower online responses. As the crisis intensifies, in an overcrowded platform the effects of visibility and addressivity change. In an overcrowded platform, the probability of discovering a message declines and attention from crowd becomes less likely. On the contrary SOS tweets targeting an addressee may yield positive outcomes as it overcomes diffusion of responsibility (Latané and Darley 1970). We perform a set of rigorous empirical analyses to validate our conjectures.

We analyzed a sample of 7,266 SOS tweets that mentioned phone number and were posted for COVID-19 patients from Tier-1 and Tier-2 cities in India during 4th April 2021 to 6th June 2021 (approx. 2-month period). This period corresponds with the peak of second wave of the COVID-19 pandemic in India when reported daily cases of infection across the country was more than 100 thousand cases. We collected publicly available relevant tweets from Twitter and processed them employing complex steps of machine learning techniques and textual analysis to label the SOS tweets. For our empirical analyses, we control for various Twitter-specific user attributes, city fixed effects, and week fixed effects. Our empirical analyses suggest that inclusion of hashtags in SOS tweets led to a significant increase in online responses than SOS tweets devoid of hashtags. Specifically, use of hashtag in SOS tweets led to 15.7% significant increase in retweets and 8.1% significant increase in replies received by a tweet. Mentions, however, had differential effect depending on their position in the tweet. Embedding mentions anywhere except in front of the SOS tweet led to 33.7% significant increase in retweets and 14.3% significant increase in replies. Interestingly, for SOS tweets beginning with mentions, we found significant decline in both types of online responses. Another interesting finding is that SOS tweets that were posted in the reply thread of some other tweets received significantly lower online responses (number of retweets and replies) than SOS tweets that were posted as directly. We also performed robustness analyses to strengthen our findings. Using propensity score matching (PSM) on Twitter-specific user attributes of each SOS tweet, we identified matched samples of tweets with and without the presence of the reach-enabling functionalities. Repeating the empirical analyses on the matched samples of tweets we found the results to corroborate the findings of our main set of analyses.

Next, from our moderation effects study, we found several interesting results. We found that increment in the day of posting a SOS tweet led to 0.7% significant increase in replies when SOS tweets use mentions 'in front.' Similarly, we found a significant uptake of 1.1% for replies as the moderating impact between day of post and when SOS tweets were posted in the reply thread of some other tweets (i.e., 'reply to' type SOS tweets). In contrast, we found that the moderating impact of the day of posting on the effect of using hashtags was significant and negative for replies.

The implication of the study is threefold. First, our study adds to the broader theme of emerging literature on the use of social media (esp. Twitter) during disaster and extreme events (Abedin and Babar 2018; Oh et al. 2013). Past studies have shown the use of tweets to inform, update, and in some cases seek information and help from officials. This study adds to the literature by showcasing the unique case of emergence of a large body of citizen-driven SOS tweets during COVID-19 pandemic, seeking help from fellow citizens and authorities. It also demonstrates the effectiveness of using different reach-enabling functionalities of Twitter in tweets meant for call for help during crisis. Second, our study contributes to the literature on attention within online platforms. Given that human attention is a scarce resource and social media platforms are flooded with critical and non-critical tweets during any extreme event of prolonged disaster, it is important to examine which Twitter functionalities helps in gaining more attention online. The changing efficacy of reach-enabling functionalities with platform crowdedness informs communication strategies under a crisis. This is particularly insightful in the case of citizen-driven spontaneous and unregulated communication where the structure of such communication is emergent. Third, our study offers practical implications for social media platforms (especially Twitter) as well. They may use the insights to provide guidelines of communication to users during a crisis. They may show suggestions of or automatically append relevant reach-enabling functionalities to the user-written messages to gain more visibility on a crowded platform.

The remaining paper is as follows. Section 2 provides the context of the study and relevant literature. Section 3 describes the data and Section 4 describes our empirical methodology. Section 5 provides the results and robustness models. Finally, we draw our conclusions in Section 6 and discuss the relevant findings.

Study Context and Relevant Literature

Twitter Use During the Second Wave of COVID-19 Pandemic in India

The second wave of COVID-19 pandemic in India had severe consequences in the form of severe infection rate, reduced supplies of essential healthcare resources, and increased deaths. India's second wave of COVID-19 infections began in the first week of March 2021. The daily count of cases in India peaked on May 6th, with more than 414 thousand people getting new infection on that day[5]. India's death toll due to the second wave of COVID-19 had crossed 250 thousand. Highest death in a day were 6,148 on 10th June 2021[6]. The 2nd wave of COVID-19 in India continued till 30th June. With pressing need and inadequate supply of healthcare resources such as lifesaving drugs, oxygen, and plasma, etc., citizens resort to unconventional avenues to try to procure COVID-19 related healthcare resources. One such avenue was to use social media platforms, such as Twitter, Facebook, WhatsApp, etc. to appeal to fellow citizens for leads on COVID-19 related healthcare resources. Twitter became the most useful social media platform for common people to seek help from government and fellow citizens (Kalra and Ghoshal 2021) during the crisis. This is because Twitter is a social broadcasting site (Shi et al. 2014) enabling broadcasting (tweets), rebroadcasting (retweets), and networking (following other users, mentioning influential Twitter handles). Individuals posted on Twitter (which we define as 'SOS tweets' – See Figure 1 for an example) for their affected kin and even for strangers asking for help from authorities and other fellow members of society. However, the resulting surge in SOS tweets with urgent need (Hindustan Times 2021) ensued an increased competition for attention on Twitter (Iyer and Katona 2016). Each SOS tweet was posted with the intention to draw attention of the authorities and volunteers that would eventually translate into offline help.

Twitter Functionalities Used during Crisis Communication

Twitter provides technological functionalities such as hashtags and mentions, as components of tweets that enable reach to audiences.

A *hashtag* is a set of characters prefixed by the symbol #. Typically, it indicates a self-reported topic by a user that could be used by other users to express similar ideas (Tsur and Rappoport 2012). The purpose of hashtag is to categorize tweets topically that helps users to search tweets on a particular topic easily. Hashtags have been used in disaster communication for drawing user attention to the message, coordinating collective actions and articulating collective sentiments or ideas. For example, during Typhoon Haiyan in Philippines, hashtags such as #PrayforthePhilippines, #Haiyan, #ReliefPh, etc. were used for disseminating information, praying for victims, and coordinating relief efforts (Takahashi et al. 2015). During social movements and revolutions hashtags help in creating affective discourse that reflects societal sentiments developed during the movement (e.g., #BlackLivesMatter, #MeToo) (Blevins et al. 2019). Hashtags also capture the course of events during a movement or crisis, providing situational updates to

[5] https://www.worldometers.info/coronavirus/country/india/

[6] https://timesofindia.indiatimes.com/india/explained-why-india-reported-6148-covid-deaths-in-a-day-the-highest-ever/articleshow/83391653.cms

users (Oh et al. 2015; Venkatesan et al. 2021). Thus, use of specialized hashtags becomes crucial in Twitter communication during extreme events that call for faster and wider diffusion of messages (Venkatesan et al., 2021). However, previous studies offer inconsistent findings regarding the effects of hashtags on user engagement and responses to the tweets. While some studies show a positive association between hashtags and user engagement, a few studies reported negative effects of hashtags. For example, Suh et al. (2010) show inclusion of hashtags increases probability of retweeting behavior. Son et al. (2019) showed inclusion of disaster-related hashtags increased rapid dissemination of crisis information in terms of retweets. Another research demonstrated better reach of crisis information using hashtags (Lachlan et al. 2016). On the contrary, another study in the context of political social media messages found that inclusion of hashtags significantly decreased likes and retweets of tweets (Pancer and Poole 2016). Even in the case of extreme events, where inclusion of hashtags is a common practice for Twitter users, extant research shows mixed findings. For instance, during the Boston bombing incident in 2013 several hashtags such as, #boston, #bostonmarathon, and #bostonbombing were commonly embedded in the tweets about the incident. Lee et al. (2015) found negative effect of embedding hashtags on retweet numbers of these tweets.

Mention is essentially tagging other users on Twitter in a tweet. Mentioning using an @ sign followed by the Twitter username, notifies the tagged user that they have been included in the conversation (Shore et al. 2018). Thus, it draws the mentioned user's attention to the tweet, acting as targeted messaging, although the tweet is visible to others. Literature on the effect of mentioning users in tweets during crises is sparse. One of the recent studies shows the effect mention has on the centrality of the Twitter nodes (users) in the network and their eventual social influence in crisis communication (Venkatesan et al. 2021). Abedin & Babar, 2018 reported the use of mentioning institutional disaster relief organizations and digital volunteers in citizen-created tweets during 2014 Australian bushfire. In pandemic context, one study investigated the effect of crisis information flow through the network of information formed by the use of @mention in a tweet (Wang et al., 2021). However, extant studies do not inspect the effect of mentioning users or authorities on the online response (retweets and replies) received by the tweet that may indicate the actual possibility of receiving help during the crisis.

Another mechanism resorted by users to gain visibility for their SOS tweets was to post the focal tweet in the reply thread of another tweet. We term these as 'reply to' tweets. To the best of our knowledge, previous research in the context of crisis, has not focused on the effect posting a critical tweet as 'reply to' another tweet on the focal tweet's received response. In this paper, we attempt to uncover how effective this mechanism turned out to be in a scenario of urgency and uncertainty.

Visibility and Addressivity on Twitter

Message dissemination could be targeted (to a specific set of audience) or broadcasting (to a wide audience base) in nature. Twitter supports both types of message dissemination and its reach-enabling functionalities (hashtag, mention, etc.) affords the intended type of dissemination.

Hashtags are used for better searchability and visibility of messages. Tweets embedding the same hashtags appear together in search when someone clicks on the hashtag or search using the hashtag. This particular functionality helps in the spread of the message to not only the social network of the focal users, but also, a wider audience who may search for the particular hashtag (Bakshy et al. 2011). Thus, we can say that hashtags play an instrumental role in message broadcasting.

Use of mention (@<username>) in a tweet notifies the user who is mentioned to engage the target in conversation but in presence of others (Larsson and Moe 2012). Mentions can also be used as an *Addressivity* (Honeycutt and Herring 2009), i.e., referencing the mentioned user even if they are not participating in the conversation. Mention is intended to target a particular user, albeit making the message visible to a broader audience (followers of senders and receivers). There is a blend of targeting and broadcasting in use of mentions. Followers of both the sender and the receiver are exposed to the tweets with a mention anywhere in the tweet, except in the start. However, if the tweet starts with a mention, i.e., "@" is the first character in the tweet, it works as a reply or exclusive message to the receiver. This functionality is more restrictive than mention anywhere else inside the tweet, though it draws attention of the mentioned more. The mutual followers of both senders and receiver are only able to see the tweet. Thus, mention in the start of a tweet makes it narrower and more targeted in its reach.

'Reply to' is by default the most targeted and least broadcasting type of functionality. Replying to someone else's tweet has a greater chance of drawing attention of the tweeter. But the audience is restricted to only the receiver and the users who are participating in the thread of replies to the original tweet.

Visibility is imperative for social contagion in an information-rich environment (Hodas and Lerman 2014). Addressivity is when a user indicates in their message an intended addressee or receiver by explicitly mentioning the person's name (username in case of Twitter). To capture a targeted audience's attention in multi-participant public environments (such as social platforms) a high degree of addressivity is required in the message. Thus, different reach enabling functionalities yield different outcomes in terms of message dissemination. We posit that presence of hashtags and mentions inside an SOS tweet makes the tweet more visible, thus positively impacting the online responses (retweets and replies) received. However, mention in the start of a tweet and reply-to type tweets are more targeted and restrictive in reach, thus negatively impacting the online responses received.

With the progression of the crisis, as the platform becomes overcrowded, broadcasting fetches no benefit. It may in fact lead to diminished responses due to *diffusion of responsibility*, a phenomenon where responsibility for action is shared among many parties (onlookers) without exclusively placing it on any one of them (Latané and Darley 1970). However, target messaging may lead to positive outcomes due to addressivity that places the responsibility for intervention on the addressee. Addressivity may help in overcoming *diffusion of responsibility* in an overcrowded platform. Thus, we posit that presence of hashtags and mentions inside the SOS tweet may lead to negative impact on online responses as the pandemic intensifies. Mention in the start of a tweet and reply-to type tweets may garner more online responses as the pandemic intensifies.

Data

To arrive at the data set, in July 2021, we employ the Twint package of Python programming language to scrape tweets posted between 4th April 2021 and 6th June 2021 from Twitter using common search terms like 'Oxygen', 'SpO2', 'ICU' and 'Ventilation,' as these terms can capture commonly used words in SOS tweets. We scraped tweets which were written in English only and excluded regional language tweets. This helps us identify an initial pool of 2,330,975 tweets. To identify actual SOS tweets from this pool, we further applied machine learning (ML) techniques. Using the tweets' data as input to the Linguistic Inquiry and Word Count (LIWC) software (Tausczik and Pennebaker 2010), we create an elaborate textual feature space of 118 linguistic, psychological, and topical features. These features are used as predictors for our ML models. We manually label a random sample of 12,121 tweets as SOS or non-SOS tweets (which we split as training (10,061 tweets) and test data (2,060 tweets)). Using a 5-fold cross-validation to train several ML models, we find that the standard normal feature-scaled random forest classifier of Python's scikit-learn package (with hyper-parameter specifications as n_estimator=500 and max_leaf_nodes=16) showed a very high precision score (95.06%) and an acceptable recall score (40.96%). This led us to use this model for SOS tweet classification. Using this classifier on the entire dataset, we arrived at 54,048 SOS tweets. We further narrowed down the study sample by considering SOS tweets that mention phone number(s) of the attendant to the COVID-19 patient and location of the COVID-19 patient from Tier-1 or Tier-2 Indian cities only, which lead to 29,527 SOS tweets. Next, we arrive at a sample of 16,964 unique SOS tweets by preserving the earliest SOS tweet associated with each phone number in our study.

Next, in August 2021, using the Twint package we scrape user-level attribute information for the set of users who wrote SOS tweets. We merge the SOS tweets dataset with data on user-level attribute (i.e., our control variables) and arrive at the sample size of 7,266 observations to conduct the study. The distribution of SOS tweets across various Indian cities for our study time-period is reported in Figure 2.

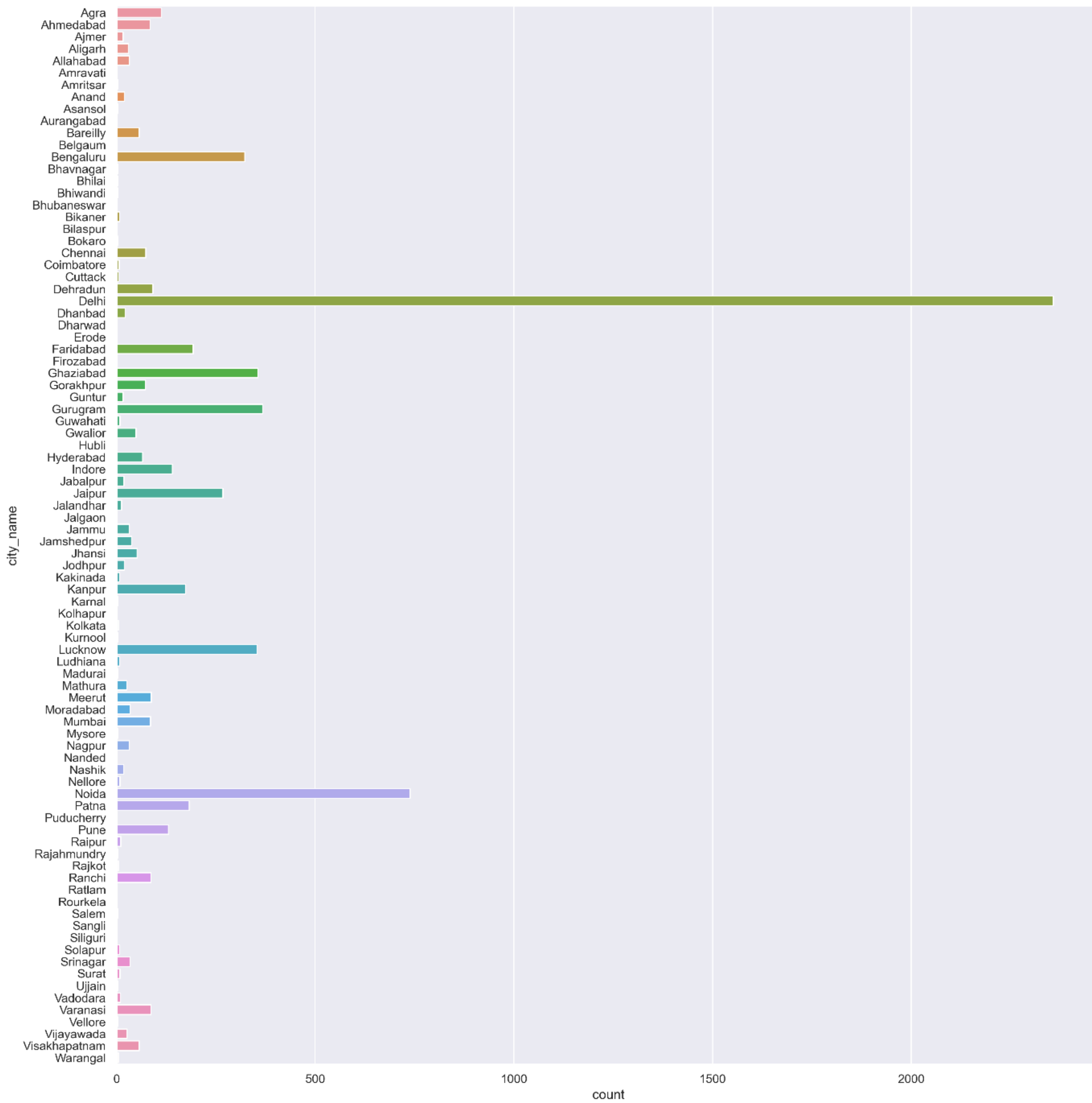

Figure 2. Count of SOS Tweets by Indian Tier-1 and Tier-2 Cities

For the analyses, we use log OLS econometric model. The independent variables are the presence of reach-enabling functionalities. Hashtags and mentions, despite being reach-enabling functionalities, are inherently different in terms of purpose and effects they ensue. Hashtags are embedded in tweets to improve their searchability on Twitter. Tweets with the same hashtags are organized together and are displayed upon clicking on the hashtag. We presume users included hashtags into their tweets with the intention of increased searchability of the tweet. In our context searchability of tweets become extremely important. Inclusion of mentions directs a tweet towards specific audience (Stieglitz and Dang-Xuan 2013). The effect of mentioning is likely to yield mixed outcomes. On one hand, it can immediately capture the tagged users' attention to the focal tweet and increase the likelihood of receiving a response from the tagged user. On the other hand, it may lead to decreased likelihood of overall response. A recent study set in the context of airlines industry has shown that mentioning a set of users in a complaint tweet reduces the likelihood of receiving response or help for that complaint (Gunarathne et al. 2018). Attributing such behavior to the bystander effect or diffusion of responsibility, the study explains that mentioning users, especially multiple, allows users to pass the responsibility to someone else tagged, eventually resulting in response from none. We would like to explore if such an effect is observed in the case of SOS tweets that mention one or more Twitter handles of individuals and authorities. Finally, posting a tweet as a reply to another tweet is another reach-enabling functionality that can be executed in Twitter. It allows the focal user to be a part of the conversation with the targeted user and gain visibility among the participants of the conversation thread.

We measure the online responses using retweets of the SOS tweet or using replies received by it. Retweeting a tweet or replying to a tweet are some of the ways to respond to a tweet. Retweet is essentially a message forwarding functionality (Yang et al. 2012). Retweeting a tweet ensures message dissemination to the re-tweeter's social network (Mallipeddi, Kumar, et al. 2021), ensuring higher visibility to the original tweet. Tweets which are made public and opened for comments could be replied to creating a thread of conversation following the focal tweet. Users may reply to a tweet to lend their support to the original tweet or present a difference in opinion. Past studies have used them as metrics of user engagement with tweets (Mallipeddi, Janakiraman, et al. 2021; Lambrecht et al. 2018; McShane et al. 2021).

Our model controls user level attributes, user location city fixed effects and week of the tweet fixed effects. Further, as robustness tests, we perform the log OLS econometric model on matched samples based on propensity score matching. For this, we calculate propensity scores from user level attributes. The summary statistics for the dataset is reported in Table 1.

Variables	N	Mean	Std. Dev	Min	Median	Max
DV: Online Responses						
Replies Count	7266	2.57	10.52	0	1	734
Retweets Count	7266	13.34	63.09	0	1	2330
Log (Replies Count)	7266	0.87	0.76	0	0.69	6.60
Log (Retweets Count)	7266	1.25	1.37	0	0.69	7.75
IV: Reach-Enabling Variables						
Is Hashtags	7266	0.41	0.49	0	0	1
Is Mentions (in front)	7266	0.20	0.40	0	0	1
Is Mentions (not in front)	7266	0.53	0.50	0	1	1
Is 'Reply to' SOS Tweet	7266	0.07	0.26	0	0	1
Controls: User-Level Attributes						
Log (User Tweets)	7266	7.35	2.33	0	7.47	13.23
Log (User Followers)	7266	5.39	2.51	0	5.15	16.44
Log (User Following)	7266	5.72	1.46	0	5.82	12.33
Log (User Likes)	7266	7.40	2.62	0	7.79	13.86
Log (User Media)	7266	4.49	2.34	0	4.51	12.64
Log (Biography Length)	7266	3.84	2.23	0	4.48	8.08
Years on Twitter	7266	7.60	3.81	0	8	14
Is background	7266	0.70	0.45	0	1	1

Is Url	7266	0.31	0.46	0	0	1
Is Multiple Users Same Tweet	7266	0.01	0.11	0	0	1
Is Same User Multiple Tweets	7266	0.39	0.49	0	0	1

Table 1. Summary Statistics

Methodology

For our main analysis, we run a log OLS econometric model. Mathematically, the econometric model used in our study has the following form:

$$\ln\left(Online\ Response_{z_{ij}}\right) = City_i + Week_{w(j)} + \alpha \cdot Controls_{z_{ij}} + \beta \cdot Reach\ Enabling\ Functionality_{z_{ij}} + \epsilon_{z_{ij}} \quad (1)$$

where i represents the city as mentioned in a SOS tweet, j refers to the day of SOS tweet, from 4th April 2021 to 6th June 2021, for each consecutive days, and z refers to each unique SOS tweet; $Online\ Response_{z_{ij}}$ is either number of retweets or number of replies to an SOS tweet; $\boldsymbol{City_i}$ represents a vector of 88 city fixed effects; $\boldsymbol{Week_{w(j)}}$ represents a vector of 9 week fixed effects, where $\boldsymbol{w(j)}$ refers to week w corresponding to day j; $\boldsymbol{Controls_{z_{ij}}}$ represents a vector of control variables, which includes – user-level attributes, whether multiple users posted the same SOS tweet, and whether same user posted multiple SOS tweets; $Reach\ Enabling\ Functionality_{z_{ij}}$ is the indicator variable capturing the independent variables – use of hashtag, use of mention in front of the SOS tweet, use of mention not in front of the SOS tweet, and whether a 'reply to' type SOS tweet; $\epsilon_{z_{ij}}$ is the error term.

In this set-up, the coefficient of interest is β, which captures the impact of using a reach enabling functionality on an online response. When $\beta > 0$, the reach enabling functionality positively impacts the online response, and when $\beta < 0$ the opposite is true. In the next section, we report the β values for all models along with the robust standard errors in parenthesis and significance levels.

Finally, we conduct moderation analyses to check for the moderating impact of 'day of post' on our independent variables. For these analyses, in the log OLS model (i.e. equation (1)), we additively introduce the following terms in the right hand side: (i) a 'day of post' variable; (ii) an interaction term between our independent variable *reach enabling functionality* and the 'day of post' variable. Here, the 'day of post' variable is a continuous variable for the sequence of days from 4th April 2021 to 6th June 2021.

Results

Main Results

Effect of Hashtags (#)

First, we report results for a reach-enabling functionality of Twitter – use of hashtags (#) – in Table 2. Based on the regression model, we find significant increase in online responses when SOS tweets have words starting with hashtags. Specifically, using a log OLS regression model, we find that retweets significantly increased by 15.7% (Table 2; column 1; p-value < 0.01). Against the baseline average of 13.34 retweets, we find that this percentage increase implies 2.09 additional retweets from the log OLS model when SOS tweets utilize hashtags. Increase in retweets is a desirable outcome as retweets expose the SOS tweets to a new pool of audience.

Besides the increase in retweets, we find that including hashtag-term(s) in SOS tweets leads to a significant increase in replies to those tweets. Results from the log OLS regression showcase 8.1% significant increase (Table 2; column 2; p-value < 0.01) for replies. In actual terms, we find 0.21 additional replies for the log OLS model where the baseline average is 2.57 replies. Getting additional replies is a highly desirable market improving outcome, since an online reply can provide information regarding the much-needed help directly as requested in SOS tweets.

Additionally, from our propensity score matching analyses, we find supporting evidence that inclusion of hashtags in SOS tweets leads to significant increase in both retweets and replies. Numerically, from our matched subsample, we find significant increase by 21.6% in retweets and by 9.6% in replies (Table 2; columns 3 and 4, respectively; p-value < 0.01) due to use of hashtags in SOS tweets.

Effect of Mentions (@)

Individuals posting SOS tweets also use mentions (@) as another reach-enabling functionality in the tweets. We separately model for tweets starting with mentions (i.e., mentions 'in front' of the tweet) and mentions elsewhere in the tweets (i.e., mentions 'not in front' of the tweet). Table 2 provides results showing impact of both these types of mentions on online responses.

When mentions are used 'in front' of the SOS tweets, across all online response outcome variables, we find significant decrease in engagement. Specifically, from the log OLS models, we find 52.1% significant decrease in retweets and 19.6% significant decrease in replies to SOS tweets (Table 2; columns 1 and 2 respectively; at p-value < 0.01). In actual numbers, this leads to 6.95 less retweets, and 0.5 less replies. Our results for the propensity score matched sample also show significant decrease in retweets and replies. In numbers, we find 55.9% significant decrease in retweets and 21.9% significant decrease in replies to SOS tweets (Table 2; columns 3 and 4 respectively; at p-value < 0.01). The results show that use of mentions 'in front' of the SOS tweets harms the online response, and this can lead to significant fall in the tweets capacity to garner actual help.

For both the online responses, the results are opposite when mentions are used elsewhere in the SOS tweets, instead of in the front. For the log OLS model, we find that retweets significantly increase by 33.7% (at p-value < 0.01), while replies show a significant increase of 14.3% (at p-value < 0.01) for SOS tweets. Comparing the results, we can infer that using mentions elsewhere rather than in front of the SOS tweets lead to 11.45 additional retweets, and 0.87 additional replies, which is a large improvement considering the position in SOS tweets where mentions are utilized. Redoing the analyses on the propensity score matched sub-sample also showcases significant increase in both retweets and replies for SOS tweets (Table 2; columns 3 and 4 respectively).

Effect of 'Reply to' SOS Tweets

The third type of reach-enabling functionality occurs when SOS tweets are posted in the reply thread of someone else's tweet. Online responses to this type of 'reply to' SOS tweets show significant dampening when compared with non-'reply to' type SOS tweets (i.e., SOS tweets that are directly posted on user's own Twitter account). From the log OLS models, we find that posting 'reply to' SOS tweets lead to 43.9% significant decrease in retweets (at p-value < 0.01), and 16.4% significant decrease in replies (at p-value < 0.01). In terms of effect size, 'reply to' SOS tweets account for 5.86 less retweets and 0.42 less replies. We find similar affirmation from the sub-sample analyses on the propensity score matched sample. On a matched sample size of 923 observations, we find that posting 'reply to' SOS tweets lead to 48.8% significant decrease in retweets (at p-value < 0.01), and 20.1% significant decrease in replies (at p-value < 0.01) (Table 2; columns 3 and 4 respectively).

	OLS		PSM	
	Log(Retweets)	Log(Replies)	Log(Retweets)	Log(Replies)
	(1)	(2)	(3)	(4)
Is Hashtags (#)	0.157***	0.081***	0.216***	0.096***
	(0.028)	(0.017)	(0.046)	(0.028)
N	7266	7266	3819	3819
Is Mentions (@) (in front)	-0.521***	-0.196***	-0.559***	-0.219***

	(0.029)	(0.019)	(0.048)	(0.032)
N	7266	7266	2185	2185
Is Mentions (@) (not in front)	0.337***	0.143***	0.388***	0.134***
	(0.027)	(0.017)	(0.046)	(0.030)
N	7266	7266	4549	4549
Is 'Reply to' SOS tweet	-0.439***	-0.164***	-0.488***	-0.201***
	(0.043)	(0.028)	(0.068)	(0.046)
N	7266	7266	923	923
Constant Term	✓	✓	✓	✓
Control Variables	✓	✓	✓	✓
User City FE	✓	✓	✓	✓
Week FE	✓	✓	✓	✓
Note: FE stands for fixed effects. Robust standard errors are reported in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01.				

Table 2: Effect of Reach-Enabling Functionalities on Online Responses

Results of Moderation Analyses

Moderation Effect of Day of Post on the Effect of Hashtags

Our results for the moderation analyses are reported in Table 3. We conduct analyses to check for the moderating impact of 'day of post.' At first, we report the moderation effect of the 'day of post' on the impact of use of hashtags (#) on online responses, i.e., retweets and replies. We find that there is a significant negative impact of the use of hashtags on replies when there is a unit increase in the day of posting an SOS tweet. In numbers, there is a 0.4% decrease in replies (at p-value <0.1) due to use of hashtags as day of post increases by a unit value. Note that, we measure the 'day of post' as a continuous variable that spans approximately two months during the second wave of the COVID-19 pandemic in India. Here, a unit increase in the day of posting an SOS tweet reflects the tweet being posted in a more crowded Twitter platform with more SOS tweets due to more prevalence of COVID-19 cases. Therefore, we can induce from the analyses that use of hashtags in SOS tweets is less beneficial towards garnering a reply if the SOS tweet with hashtag is posted in a more crowded platform as the COVID-19 pandemic progressed.

Figure 3 shows the margins plot for the interaction effect between hashtag and day of post on log(replies). Here, we find that, as the day of posting an SOS tweet increases (i.e., the Twitter platform becomes more crowded with SOS tweets), the advantage of using hashtags in SOS tweets decreases substantially when compared with not using hashtags in SOS tweets (since the blue line (= no use of hashtag) closes in on the maroon line (= use of hashtag), and finally overtakes it).

	Log (Retweets)	Log (Replies)
	(1)	(2)
Is Hashtags	0.223**	0.205***
	(0.113)	(0.072)
Day of Post	-0.001	0.005***
	(0.003)	(0.002)
Is Hashtags * Day of Post	-0.002	-0.004*
	(0.004)	(0.003)
Is Mentions (in front)	-0.641***	-0.370***
	(0.119)	(0.079)
Day of Post	-0.003	0.002
	(0.002)	(0.002)
Is Mentions (in front) * Day of Post	0.005	0.007**
	(0.004)	(0.003)
Is Mentions (not in front)	0.446***	0.203***
	(0.110)	(0.070)
Day of Post	0.001	0.005**
	(0.004)	(0.002)
Is Mentions (not in front) * Day of Post	-0.004	-0.002
	(0.004)	(0.002)
Is 'Reply to' SOS tweet	-0.459**	-0.474***
	(0.180)	(0.106)
Day of Post	-0.001	0.003*
	(0.002)	(0.001)
Is 'Reply to' SOS tweet * Day of Post	0.001	0.011***
	(0.007)	(0.004)
Constant Term	✓	✓
Control Variables	✓	✓

User City FE	✓	✓
N	7266	7266
Note: FE stands for fixed effects. Robust standard errors are reported in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01.		

Table 3. Moderation Effect of Day of Post for Reach-Enabling Functionalities

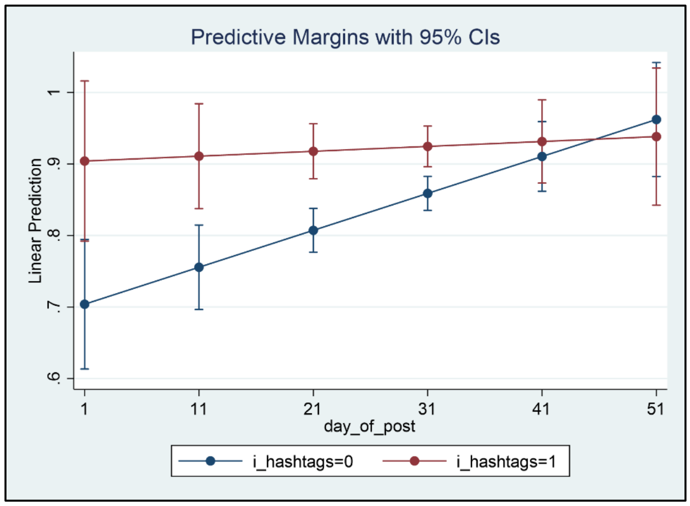

Figure 3. Interaction effect of hashtag and day of post on log(replies)

Moderation Effect of Day of Post on the Effect of Mentions

Next, we report the moderating effect of day of post on the effect of the two types of mentions in SOS tweets, respectively. We find positive and significant impact for the interaction term between mentions that are in front of the text of the SOS tweets and the day of the post. In numbers, we find a 0.7% significant increase in replies (Table 3; column 2; at p-value < 0.05) for using mentions in the front of the SOS tweets due to unit increment in day of posting. This suggests that mentions when used in front of the SOS tweets can garner more replies as the platform becomes more crowded with SOS tweets (which is a consequence of COVID-19 pandemic intensifying with time).

Figure 4 shows the margins plot for the interaction effect between mentions used in front of SOS tweets and day of post on log(replies). In the figure, we can see, as the day of posting SOS tweets progressed from 1st day to the 51st day, the disadvantage of using mentions in front of the SOS tweets (which is captured with the variable tweet_start_at_not_reply = 1) decreases substantially (due to increase in linear prediction of getting a reply for the maroon line (= use of mention in front of a SOS tweet)).

Finally, we do not find any interaction effects on online responses for the day of post and mention that is not used in the front of a SOS tweet.

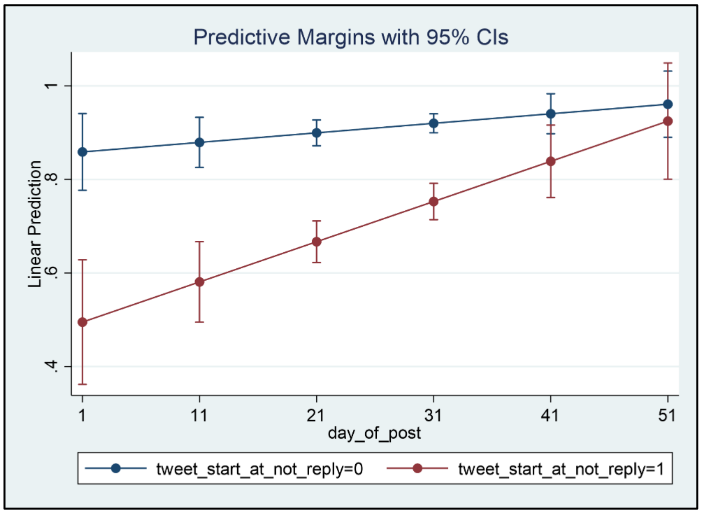

Figure 4. Interaction effect of mentions 'in front' and day of post on log(replies)

Moderation Effect of Day of Post on the Effect of 'Reply to' SOS Tweets

Finally, we look at the moderating effect of the day of post on the impact of 'reply to' type SOS tweets. In Table 3, we find that there is a significant and positive impact on replies for using the 'reply to' type SOS tweets due to unit increment in the day of posting. As the day of posting of SOS tweets progressed, the Twitter platform becomes more crowded with SOS tweets. In this scenario, 'reply to' type SOS tweets yield significantly better response, in the form of replies to such Tweets. In numbers, we see a 1.1% significant increase in replies due to the interaction between day of post and 'reply to' type SOS tweets (Table 3; column 2; at p-value < 0.01).

Figure 5 reports the margins plot for this interaction effect. We can see that, as the day of posting of SOS tweets progressed, the advantage of using 'reply to' type SOS tweets (i.e., the maroon line corresponding to is_reply = 1) towards getting reply responses increases substantially. Interestingly, the linear prediction of log(replies) for the maroon line (i.e., posting 'reply to' type SOS tweet) crosses that of the blue line (i.e., SOS tweets directly on tweet-sender's profile) around the 41st day during the second wave of India's pandemic (when the COVID-19 pandemic had progressed substantially).

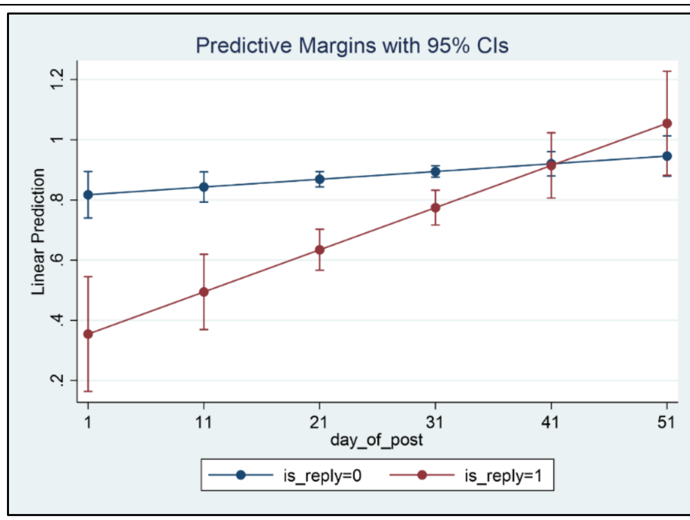

Figure 5. Interaction effect of 'reply to' SOS Tweets and day of post on log(replies)

Discussion And Implications

In this study we highlight the use of Twitter in yet another crisis situation, the second wave of COVID-19 pandemic in India. In this case Twitter was used to seek help and crowdsource medical resources by common public from fellow citizens and authorities. As a result, a huge body of citizen-driven decentralized spontaneous crisis communication ensued with hundreds of tweets competing for attention on the platform. Users used Twitter's reach-enabling functionalities such as hashtags and mentions spontaneously, without any pre-decided strategy for the communication. The effects of using such functionalities during crisis is not conclusively known in the literature. We found that inclusion of hashtags has a positive effect on online responses received by the tweets, whereas inclusion of mentions to different Twitter handles yields different effects depending on mentions positions. Mentions in the beginning of the tweet negatively affect the online response received by the tweets. Mentions inside the text of the SOS tweets or at the end (i.e., not at the beginning), positively impact the desired outcomes. Posting the SOS tweet as some other tweet's reply also negatively affects the outcomes.

Besides the main effects, we found several moderation effects of the day of posting SOS tweet on the effect of the reach-enabling functionalities. We found that using hashtags led to a negative effect on replies with increment in day of posting of SOS tweets. Thus, the reach facilitated by using hashtags diminished as the platform became more crowded with SOS tweets. Interestingly, we also found a positive and significant increase in replies as the moderating impact of day of posting an SOS tweet on the effect of use of mentions 'in front' of the SOS tweet. An explanation to this phenomenon could be that in a crowded Twitter platform, mentioning someone in front of the SOS tweet can be more eye-catching to the concerned person, and can lead to increase in replies. Finally, we found an uptake in reply responses due to the moderation effect between day of post and use of 'reply to' type SOS tweets. This finding points towards the immediacy of the 'reply to' type of SOS tweet. We know that a typical 'reply to' SOS tweet is a reply under another tweet (which in general are tweets promising to provide help for COVID-19 related medical emergencies). Therefore, in a crowded platform, a 'reply to' type of SOS tweet immediately brings the tweet to notice, which could lead to enhanced online response. Also, the high level of addressivity may outweigh the effect of diffusion of responsibility in a crowded platform. Further research is required to tease out the underlying mechanisms at play. This provides scope for future research in this area.

The study demonstrates the different impacts of Twitter's reach-enabling functionalities on the desired outcomes (retweets and replies) of the Twitter communication during crisis and how their effects change as the platform gets crowded and the competition for attention intensifies. The study adds to the literature of use of social platform in disasters and crisis, especially in the domain of citizen-driven crisis communication in form of cry-for-help or SOS tweets (Abedin and Babar 2018; Leong et al. 2015; Liu and Xu 2018; Takahashi et al. 2015). This is a novel contribution to the body of knowledge in this area. Particularly, it demonstrates the effectiveness of various reach-enabling functionalities of Twitter during a crisis. Further, the study shows the changing efficacy of reach-enabling functionalities with platform crowdedness. It helps in creating effective communication strategies under a crisis, especially during citizen-driven spontaneous and unregulated communication. Very few studies have looked into spontaneous emergence and evolution of citizen tweets during crises (e.g., Venkatesan et al. (2021) and our paper adds to the theme of this literature). As practical implication, our study provides usable guidelines for social platforms like Twitter to help citizens framing their communication during crisis. Platforms may suggest appropriate inclusion of reach-enabling functionalities or append them as needed for better reach of the messages. In a broader sense, our study highlights the case of unconventional use of social media platforms during crisis and emergencies (such as the COVID-19 pandemic) and shows how these social media platforms are used to garner online response that may lead to actual help.

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