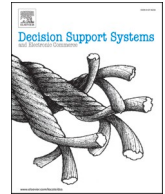




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Victim crisis communication strategy on digital media: A study of the COVID-19 pandemic

Suparna Dhar^a, Indranil Bose^{b,*}

^a NSHM Knowledge Campus, 124, 60, Basanta Lal Saha Rd, Tara Park, Behala, Kolkata 700053, West Bengal, India

^b NEOMA Business School, 59 Rue Pierre Taittinger, Reims, 51100 Reims, France

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ABSTRACT

The COVID-19 pandemic and the lockdown bore a devastating impact on organizations across the globe. In this crisis, organizations belonged to the victim cluster, with a low crisis responsibility. Nevertheless, organizations needed to strategize their crisis responses and communicate with stakeholders to reduce the threat to reputational capital and manage stakeholder reactions in the pandemic. In this paper, we studied organizational Twitter communication during the COVID-19 crisis through the lens of the situational crisis communication theory (SCCT). We analyzed 325,627 tweets collected from the Twitter pages of 464 organizations belonging to the Fortune 500 list. The Twitter data reflected organizational COVID-19 crisis response strategies and demonstrated organizational use of Twitter for crisis communication. We applied lexicon-based emotion mining to identify and measure emotions, and topic mining to measure crisis response topic scores from this large multi-organization dataset. We performed path analysis to test our research model derived from the SCCT. The analysis showed that instructing and adjusting information can minimize threats to organizational reputation in a victim crisis and manage stakeholder reactions. Positive emotions showed a stronger association with behavioral outcomes. Emotion neutral tweets generated more favorable stakeholder reactions. The paper contributes to the literature on situational crisis communication for a victim crisis. The multi-organization data addresses the sensitive inter-organization dependencies and improves the understanding of crisis communication. It provides practitioners an insight into the effect of the COVID-19 crisis response strategies on stakeholder emotions and behavior.

1. Introduction

The COVID-19 crisis hit the world towards the end of 2019 and devastated not only human life and health, but also business organizations. The pandemic and the ensuing lockdown posed a multitude of risks and challenges for organizations. The uncertainty is evident from Jeff Bezos', CEO of Amazon, message to the employees *"This isn't business as usual, and it's a time of great stress and uncertainty"*.¹ Organizations scrambled to protect business interests in the face of the crisis. Sundar Pichai, CEO of Google, commented, *"Once we realized this was going to be bigger than any of us imagined, two quick thoughts: First, how do we keep our employees safe? So as early as we possibly could, we had to move the company to a distributed, global, work from home model"*.² Experts termed the COVID-19 a sticky crisis, referring to the long-drawn and recurrent nature of the crisis [1]. Despite the uniqueness of the COVID-19 pandemic,

health and infectious disease experts warned that pandemics like the COVID-19 will continue to be a threat to the global economy and the global business environment [2]. It is imperative to analyze and learn from this crisis to be better prepared to manage such pandemics in the future.

In the COVID-19 crisis, organizations belonged to the victim cluster that reduced organizational responsibility for the crisis from an attribution theory perspective [3]. A victim crisis differs from other types of crises on three dimensions, (1) an organization's crisis responsibility is low, (2) the media does not press the organization for a crisis statement, and (3) typical crisis responses like no comment, denial, excuse, justification, and confession are not applicable [4]. Nevertheless, organizations across the world were affected by the COVID-19 crisis and needed to manage their reputational capital and stakeholder motivation during the pandemic.

* Corresponding author.

E-mail address: indranil_bose@yahoo.com (I. Bose).

¹ <https://www.aboutamazon.com/news/company-news/a-message-from-our-ceo-and-founder>

² <https://www.wired.com/story/sundar-pichai-google-not-entirely-remote/>

Strategic crisis communication helps an organization avoid reputational damage from a crisis and minimize negative stakeholder behavior [5]. Appropriate crisis communication strategies evoke favorable stakeholder emotions, which in turn determine positive behavioral response from stakeholders [6]. For example, communication to generate public awareness generated interest. The tweet “Correct technique to wash your hands for proper disinfection...” received >144,000 retweets. Another tweet “...launching a test that can detect COVID-19...”, offering useful information on COVID-19, received >112,000 likes. The situational crisis communication theory (SCCT) provides a framework for crisis communication [7]. The SCCT proposes response strategies to manage reputation, emotions, and stakeholder behavior.

Research Question 1. How can we analyze the crisis communication strategy of organizations during COVID-19 using the theoretical lens of the SCCT?

In the digital era, public social networking sites (SNS), such as Twitter, have become an important channel for organizational communication with stakeholders. Doug McMillan, CEO of Walmart, took to Instagram, LinkedIn, and Facebook to communicate to stakeholders to seek their support and remarked, “*As the U.S. continues to deal with COVID-19 (coronavirus), your service to our customers is important and necessary*”.³ Technological capabilities of SNS allow fast information propagation to all nodes in the network (e.g., followers, friends). Share and repost (e.g., retweets) features enable a quick spread of information to a wide audience [8]. The audience can react (e.g., like) or respond to the communication on the platform [9]. These technological features of the SNS enable them to play a critical role in organizational crisis communication [9]. Past research has illustrated the organizational use of SNS for communication and interaction with internal and external organizational stakeholders [10].

Data scientists have devised techniques to mine textual data to identify the topics, emotions, and moods embedded in digital communication [9,10]. Text mining techniques extract insights from SNS data. Researchers have applied text mining techniques to examine the business consequences of sentiments and emotions [11,12] and underlying topics [13,14] in the SNS data. Twitter has gained popularity in IS research as the platform allows stakeholders to freely express opinion and share product and brand-related information, and a large number of organizations have adopted Twitter for organizational communication [14].

Research Question 2. How do stakeholders respond to organizational crisis communication on Twitter?

Crisis communication has been an enigma for organizations and roused academic research interest [15]. Changes in social, political, technological, and business environments over the last few years have amplified the degree and the range of crises that threaten organizations. Despite the growing trend of crisis incidents with severe impacts on businesses, there is limited research on organizational crisis communication [3]. There is a need to study the causal dimensions of emotions from crisis response and stakeholder behavioral outcome in different crisis typologies [4]. Sticky crises, such as the COVID-19, are rare and more challenging for crisis managers [1]. A study of Twitter communication strategies and their outcomes during the COVID-19 crisis is expected to offer insights into the effectiveness of crisis communication strategies on SNS to benefit organizations not only for sticky crises but also for normal crises. In this paper, we use text mining techniques on Twitter data to identify emotions in crisis communication and determine their consequences on stakeholder behavior. We expect this paper to contribute to crisis communication theory and research and provide useful insights to crisis managers. A large number of studies on crisis communication have taken a single organizational approach assuming

that single organizations are microcosms that represent the crisis ecosystem [16]. A multi-organization system has sensitive-dependence on each other. To fully understand crisis communication in a multi-organizational environment, we investigate the behavior of a large sample of organizations that represents the global business ecosystem. Our analysis supported the key proposition of the SCCT that instructing and adjusting information can minimize reputational threats to the organization in a sticky victim crisis. Positive and negative emotions showed significant association with stakeholder behavioral outcome on Twitter. Strong emotions, both positive and negative, in organizational generated weaker behavioral response from stakeholders.

In this paper, we present the theory and the hypotheses in section 2, the research methodology and the text mining approach in section 3, the analysis and results of hypothesis testing in section 4, and discussions, research contributions, and the scope for future research in section 5. We provide our concluding remarks in section 6, and a brief review of the related literature in the Appendix.

2. Theoretical background and hypotheses development

A crisis is a sudden, unexpected, low-probability, and high impact event that threatens to disrupt an organization's business operations, exposes the organization to financial and reputational threats, and even risks the survival of the organization [5]. In the case of a natural disaster and pandemic, such as the COVID-19, the organization is as much a victim of the crisis as the stakeholders [3]. However, the ‘victimage’ status does not absolve the organizations from operational, reputational, and financial damages [5]. On the other hand, crises can be perceived as an opportunity to demonstrate leadership and engage with stakeholders [17]. With pragmatic crisis response strategies and crisis communication, organizations can convert the threat into an opportunity. Crisis managers can control chaos and confusion in a crisis, and harness information sharing opportunities to enhance organizational performance. Crisis managers play a critical role in organizing resources to contain stress, minimize the adverse impact of the crisis, and pave the way for faster business recovery [18]. Synchronization of efforts between business leaders, the crisis management team, and other stakeholders, tailor stakeholder actions towards a collective goal. Coombs [3] proposed the situational crisis communication theory (SCCT) to serve as a guideline for organizational crisis communication.

2.1. Situational crisis communication theory (SCCT)

The SCCT provides an evidence-based framework to minimize crisis-induced damage and protect organizational reputation assets. It provides a mechanism to gauge stakeholder emotions and reactions to crisis response strategies adopted by an organization. The SCCT proposes a model of causal relationships between crisis-related constructs. It draws from the attribution theory of social psychology [19,20]. The attribution theory posits that people search for the cause of an event (or crisis) to attribute responsibility for the event and experience an emotional reaction to the event. Emotional reactions command people's behavior. Based on crisis attribution, the SCCT classifies organizational crisis responsibility into victim cluster (weak attribution of crisis responsibility), accidental cluster (minimal attribution of crisis responsibility), and intentional cluster (strong attribution of crisis responsibility). The clusters have different emotional outcomes and levels of exposure to the reputational threat [3]. The victim cluster is exposed to a mild reputational threat.

An organization's reputation is considered to be a valuable resource with the ability to perpetuate organizational performance [9]. Unpredictable events, such as crises, disrupt an organization's operations and create a threat to organizational reputation. Organizations need to strategize their crisis response to limit the threat to the reputational assets and offset damages [5]. The SCCT links higher crisis responsibility to higher reputational threats. Past stakeholder relationships and

³ <https://www.facebook.com/dougmcmillan/posts/2849910228569735>

reputation alleviate organizational exposure to reputational threats [3]. An organization with a history of stakeholder discords is likely to be ascribed to higher crisis responsibility, leading to higher exposure to reputational threat. A favorable pre-crisis reputation buffers the organization from the adverse impact of a crisis on reputation [3].

Organizations perform in an ecosystem of stakeholders. The key stakeholders include employees, customers, suppliers, and investors [3]. The stakeholder theory extends the concept of stakeholders beyond owners, customers, suppliers, and employees. "A stakeholder in an organization is any group or individual who can affect or is affected by the achievement of the organization's objectives" [23], p. 46. Members of the general public engaging on an organization's social media pages are considered stakeholders as they can have social influence, that may affect the organization's performance [10]. Scholars engaged in social media research have referred to the stakeholder as all individuals that engage with the organization on SNS [22,23]. Stakeholders gain information about the organization, its strategies, and operations through SNS [3]. An organization's failure to meet stakeholder expectations affects organizational reputation, stakeholder emotions, and their behavioral response to the organization's actions.

In a victim crisis, communication plays a critical role in determining stakeholder perceptions of the crisis and the organization's crisis responsibility [3]. For an organization with a neutral or positive pre-crisis reputation, information sharing can dissipate the adverse impact of a crisis [3]. Victim crises, such as the COVID-19, have less potential to damage organizational reputation than accidental or intentional crises [24]. A victim crisis is more likely to evoke sympathy since stakeholders are more likely to empathize with the organization. Positive relational communication reinforces stakeholder commitment to the organization.

2.2. SNS in crisis communication

Organizations use SNS to engage with a wide spectrum of internal and external stakeholders. The crisis communication on SNS aims to motivate them and steer stakeholder emotions to favorable a behavioral reaction. SNS users are active information-seekers, willing to receive and act (spread, like, comment) on the information [25]. The SNS information and meta-information (information about information, e.g., likes, shares) contribute to information propagation [26]. Stakeholder reactions (likes and shares) on information act as a secondary form of communication, where the stakeholders act on behalf of the organization to mobilize the crisis communication [9].

SNS are changing the gamut of crisis communication [27]. SNS communication has a faster and wider reach as they are highly visible to a wide audience [2]. Crisis communication on SNS is more sensitive compared to traditional media. Emotional upheavals from organizational crisis communication on SNS can cause wildfire reactions from stakeholders [5]. A strong emotional association may make a post viral [28]. Adverse emotional consequences can cause negative stakeholder reaction and reputational damage to the organization.

Scholars have studied crisis communication on SNS using the lens of the SCCT [29,30]. The use of SNS for crisis communication has shown a positive influence on an organization's ability to control crises [30]. Higher crisis responsibility attribution generated stronger emotional reaction, while empathetic crisis response evoked favorable stakeholder reaction [29]. Several scholars have mined SNS data for crisis communication research. Text and content mining of SNS data have been used to extract sentiments, emotions, and topic classification [25]. From a technology perspective, some scholars have investigated the crisis communication on SNS as a whole [28,29], while others have focused on specific SNS platforms, such as blogs [31], Twitter [9], etc.

"Crisis communication scholarship reveals that Twitter is especially effective as an instant, two-way primary communication channel" [34], p. 2. The precise short length messages and alerts give Twitter the ability to provide real-time information to stakeholders, without overwhelming them [14,25,32]. Past research has shown that Twitter communication

was able to generate significantly more behavioral reaction from stakeholders [9]. Retweet, like, and follow are popular Twitter mechanisms for users to respond and react to tweets [23,25]. Users' retweet and like behaviors reflect stakeholders' evaluation of the message and their wish to spread it to their stakeholder network [26]. Followership demonstrates Twitter users' interest in the organization and the information communicated on the Twitter page of the organization [22]. The retweets, likes, and followership provide a measure of stakeholders' behavioral response to Twitter communication.

2.3. Research model

Organizational stakeholders include individuals or groups of people who can affect or can be affected by the performance of the organization. Organizations usually operate with primary stakeholder groups, such as suppliers, stockholders, customers, and employees [33]. However, organizational strategies and communications affect their secondary stakeholders as well. The stakeholder theory [21] stresses the necessity for an organization to manage the relationship with stakeholder groups in an action-oriented way. An organization operates in a multi-stakeholder environment, where internal and external stakeholders form power and influence networks with different stakes. In a crisis, the organization needs to communicate crisis response strategies to all internal and external stakeholders [33]. All stakeholder actions affect the organization. In the context of SNS, members of the general public engaging on the organization's social media pages are considered to be stakeholders as they can have social influence, that can affect the organization's performance [10].

Fortune reported that during the COVID-19 crisis, Fortune 500 companies have engaged in one or more of (1) donating personal protective equipment (PPE) or other critical supplies such as a mask, plane, or portable cell tower, (2) donating infrastructure, expertise, logistics, transportation, manufacturing equipment, or space, (3) converting production lines and/or manufacturing additional critical supplies, (4) conducting clinical research, (5) sharing data and technology, (6) taking measures to keep workers employed, paid, and insured, (7) helping customers get the products and financial assistance they needed, and (8) doing something beyond its ordinary workflow and what is necessary for company survival [34]. These activities have reflected organizational effort towards 'resource contribution' (resources and expertise) to combat the crisis (points (1) to (3) in the Fortune report), share data and information to 'raise general awareness' (points (4) and (5) in the Fortune report), ensure 'employee well-being' (points (6) in Fortune report), and take measures for 'business continuity' (points (7) and (8) in the Fortune report). Organizational communication is expected to cover these crisis response strategies [33].

The SCCT has posited that organizational communication on crisis response strategies leads to emotional reactions from stakeholders [3]. The coping behavior has involved cognitive adjustments to emotional reactions based on the positive value propositions provided by the crisis response strategies. Organizations' crisis response strategies – (a) business continuity, (b) employee well-being, (c) awareness generation, and (d) resource contribution, in crisis communication [35] expressed in Twitter communication are expected to stir positive emotions and diffuse negative emotions [5]. This leads us to hypotheses H1 and H2. Fig. 1 depicts the hypotheses in the proposed research model.

H1. In a crisis, the higher the organizational communication related to (a) business continuity, (b) employee well-being, (c) awareness generation, (d) resource contribution, the lower the negative emotions that are generated online.

H2. In a crisis, the higher the organizational communication related to (a) business continuity, (b) employee well-being, (c) awareness generation, (d) resource contribution, the higher the positive emotions that are generated online.

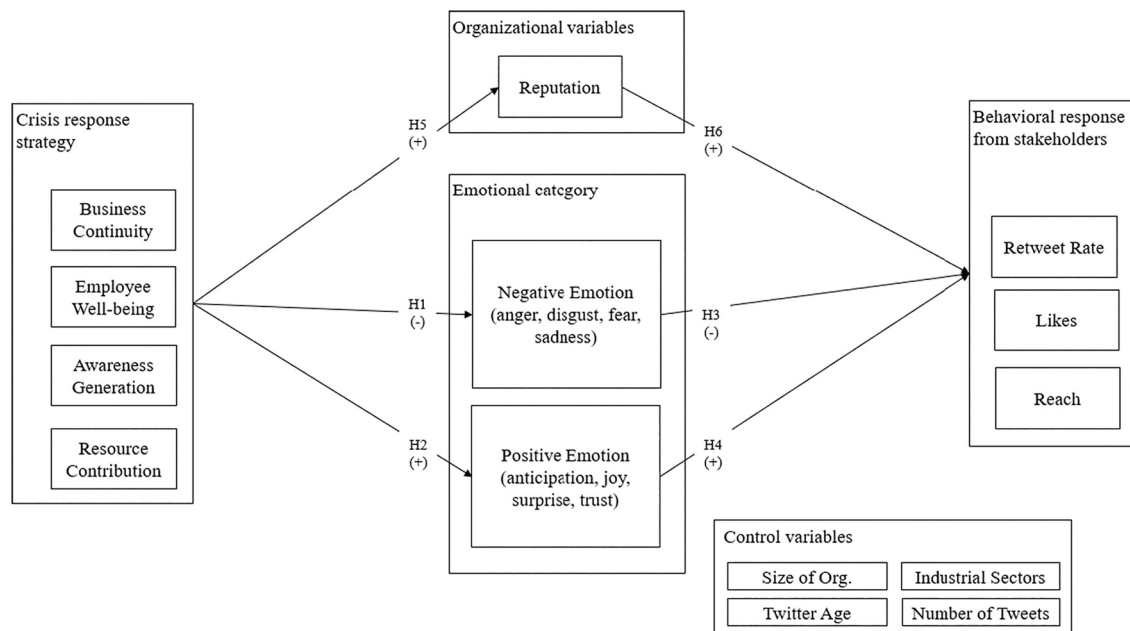


Fig. 1. Research model.

Human emotions affect behavior and decision-making [9,36]. Managerial decisions and stakeholder decisions affect organizational performance [36]. Emotional cues in organizational communication during a crisis influence stakeholder perception and behavior [6]. In a non-crisis scenario, emotionally charged tweets are likely to be retweeted faster and more often compared to neutral tweets [28]. The SCCT posits that emotions determine stakeholder behavioral reactions [3]. Crises are characterized by negative emotions such as fear, anxiety, worry which lead to negative reputational consequences. Typically, people react more to negative information (such as rumor) that fuels faster spread of such information in times of crisis [28]. In a crisis, the stakeholder behavior is governed by the prospect theory of behavioral economics [37]. Prospect theory posits that feelings of loss overshadow feelings of gain. Averseness to loss overrides the other emotional reactions [18]. The averseness to loss is expected to reduce human tendencies to react more to negative emotions in a crisis. The SCCT assumes that in a victim crisis, stakeholders' sympathy for the organization offsets the behavioral reactions to negative emotions [3]. We posit that people react less to negative emotions, adhering to the proposition of the SCCT. On Twitter, the most popular measures for stakeholder behavior include retweets, likes, and number of followers that denote reach [22,23]. This leads to hypothesis H3.

H3. In a crisis, the higher the negative emotions in organizational tweets, the lower the behavioral responses from stakeholders in the form of (a) retweet rates, (b) likes, and (c) reach.

In a crisis, positive emotions invoke positive behavioral outcomes [4]. Organizational strategy to steer crisis communication to generate positive emotions in stakeholders is expected to generate positive behavioral outcomes. To boost positive stakeholder emotions in crisis, managers present new, positive information and reiterate contributions by the organization in the past. The SCCT posits that in a victim crisis, stakeholders sympathize with the organization and react positively to their crisis response strategy [3]. This leads us to H4.

H4. In a crisis, the higher the positive emotions in organizational tweets, the higher the behavioral response from stakeholders in the form of (a) retweet rates, (b) likes, and (c) reach.

A crisis poses threat to organizational reputation. Crisis managers strategize organizational crisis communication to protect organizational

reputation [5]. Threat appraisal followed by situational approach and pragmatic formulation of crisis response strategies leads to protection of reputation [3]. Stakeholders value ethics and humanitarian concerns in crisis response strategies, such as relief logistics, fund-raising and donations, support for victims, and rebuilding and renewal [38]. Regular open crisis communication on crisis response strategies diminishes the adverse effects on organizational reputation. The nature, formation, and content of crisis communication hold cues to crisis response strategies [3]. The cues in the communication may absolve or reduce the stakeholder opinion on the organization's crisis responsibility. In a victim crisis, the lower crisis responsibility lowers the reputational threats to the organization [24]. This leads to hypothesis H5.

H5. In a crisis, higher levels of organizational communication related to (a) business continuity, (b) employee well-being, (c) awareness generation, (d) resource contribution, lead to higher organizational reputation.

Positive communication relationships with stakeholders lead to positive behavioral outcomes [33]. The SCCT posits that past reputation and no history of similar crises reduce the impact on the reputational threat. Organizational reputation has two components - inherited from the past and generated during the crisis. Either way, positive reputational outcomes are positively related to stakeholder behavioral intentions [39]. The SCCT posits that reputation affects stakeholder behavior intention. This leads to hypothesis H6.

H6. In a crisis, the higher the organizational reputation, the higher the behavioral response from stakeholders in the form of (a) retweet rates, (b) likes, and (c) reach.

Extant research has shown that organizational characteristics (e.g., size of the organization, organization age, industry) and organizations' SNS maturity (e.g., age, experience, expertise) are likely to influence the stakeholder engagement on SNS [37,40]. We have included the organizational characteristics (i.e., size of the organization, industrial sector) and the SNS maturity characteristics (i.e., Twitter age, number of tweets) as control variables. The financial and technology sectors together constituted 36% of the data. All other sectors had <10% representation. We controlled the model for the financial and technology sectors.

3. Data and methods

3.1. Data collection and pre-processing

For this study, we collected data from 1st January 2019 to 31st October 2020. To study a multi-organization sample, representative of the business ecosystem, we selected the top 500 companies from the list of Fortune 1000 companies [41]. From this list, we selected companies that were active Twitter users (companies that had a valid Twitter handle and shared at least one tweet since 1st January 2019). This resulted in a set of 464 organizations that formed our sample set of organizations. We manually collected the Twitter handles of these organizations from their websites and downloaded Twitter data for the organizations using the tweepy API. We validated and cleaned the data. This resulted in 325,627 tweets.

As per published reports, the World Health Organization (WHO) became aware of the COVID-19 occurrence in China on 31st December 2019 [42]. The US reported the first confirmed COVID-19 case on 21st January 2020 [43]. Consequently, we considered the period between 1st January 2020 and 31st October 2020 as the crisis period (during the crisis or DC) for the analysis. The data extracted from 1st January 2019 to 31st December 2019 was considered as before the crisis (BC). The crisis period consisted of 155,069 tweets and the BC period consisted of 170,559 tweets. We compared the measures before the crisis and during the crisis to check for significant differences between the two periods.

We collected the organizational reputation index from the list of most admired companies in 2020 published by Fortune [41]. We encoded the reputation into a dummy variable (O_REP), where all organizations on the reputation list were assigned a value of 1, and the remaining were assigned a value of 0. Text mining techniques were used to discover patterns in the content of text documents and gain knowledge from unstructured text [44]. We applied a lexicon-based approach to find emotion in tweets [11], and Latent Dirichlet Allocation (LDA) topic mining on tweet data to identify crisis response strategies [45].

3.2. Emotion analysis

Scholars have endeavored to mine emotions in organizational Twitter communication for business decisions and as a consequence of environmental stimulus [46]. Extant research on emotion analysis has largely focused on sentiment polarity (positive/negative) analysis. The psycho-evolutionary theory has identified anger, anticipation, disgust, fear, joy, sadness, surprise, and trust as eight basic emotions [47]. These basic emotions include four positive emotions (anticipation, joy, surprise, and trust) and four negative emotions (anger, fear, disgust, and sadness). We used the NRC emotion intensity lexicon [11], alternately known as the affect intensity lexicon, for emotion analysis. The emotion intensity lexicon is crowdsourced. It consists of emotion scores for 9921 English words grouped into eight basic emotion classes. The NRC emotion intensity score is a real-valued number between 0 and 1. The score represents the degree of emotion expressed by the word. We created a lexicon emotion score matrix $E = \{e_{i,j}\}$, where i represents the i^{th} word in the corpus and j represents the j^{th} emotion in set E , by cross tabulating the data. We applied word frequency analysis on tweets using the lexicon corpus to generate sparse vectors $[v_i]$, where $[v_i] = \text{number of occurrences of word } i \text{ in tweet } t$. We determined the scores for each of the eight emotions for each tweet by computing the dot product of the sparse vector and the emotion matrix. It resulted in a vector of scores $[s_{t,e}]$ for each $e \in E$ and each tweet t where $E = \{\text{set of basic emotions}\} = \{\text{anger, anticipation, disgust, fear, joy, sadness, surprise, trust}\}$.

Eqs. (2) and (3) were used to categorize the basic emotions into positive emotions (E_POS) and negative emotions (E_NEG) respectively.

$$[s_{t,e}] = V_t \cdot E^T, E^T = \text{Transpose of matrix } E \quad (1)$$

$$E_POS_t = \sum_{e \in \{\text{anticipation, joy, surprise, trust}\}} s_{t,e} \quad (2)$$

$$E_NEG_t = \sum_{e \in \{\text{anger, disgust, fear, sadness}\}} s_{t,e} \quad (3)$$

The results of the analysis were manually validated independently by the two authors. The interrater reliability was found to be high ($\kappa = 0.84$) [48]. Examples of tweets with high positive emotion scores were “No one knows how long this pandemic will last, but we do know that we are committed to help fight it until the end” and “Thank you to members of our commercial real estate team for continuing to provide excellent service without hesitation”. Examples of tweets with high negative scores were “Less burden, more focus on the bottom line” and “As we upgrade our transmission system, we also strive to respect & protect the environment”.

3.3. Topic mining

The topic modeling approach has gained popularity with researchers as a tool for extracting important topics from unstructured data gathered from SNS [14]. Scholars have used LDA for topic mining. Blei, Ng, and Jordan [45], the proponents of LDA, have described LDA as “a generative probabilistic model for collections of discrete data such as text corpora”. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities”. In this study, we used LDA for topic mining. Following the standard text mining procedure, we pre-processed the text to remove stop words and punctuations and tokenized and lemmatized the text corpus. We used Python libraries ‘nltk’, and ‘gensim’ to preprocess the data and build the model. We adopted the optimal coherence value approach to identify the optimal model [45]. We generated models for 2 to 20 topics and selected the model with 12 topics (coherence value 0.382) to generate the topic scores.

During the COVID-19 crisis, the companies shared their COVID response strategy on their websites. We analyzed the COVID response strategies for the organizations. Our analysis matched the four broad strategies discussed in section 2. The first major strategy was continuing business in the new normal through remote working, electronic commerce, online delivery, product launches, product customizations, and promotions; we named this strategy ‘business continuity’ (CRS_BC). The second broad strategy was ‘employee well-being’ (CRS_EW) through social distancing, cleaning, and decontamination of premises, medical support, telecommute, and virtual office. The third major strategy was raising public awareness through information sharing and providing COVID-related guidelines; we named this strategy ‘awareness generation’ (CRS_AG). The fourth major strategy was the direct contribution of resources, support, and funds to the community and we named this strategy ‘resource contribution’ (CRS_RC).

Crisis communication provides cues to organizational crisis response strategies [3]. We mapped the topics to COVID-19 crisis response strategies, using human judgment on the topic keywords, as per the practice adopted for topic mining [45]. The mappings were done independently by the authors. The interrater reliability was high ($\kappa = 0.75$) [48]. The differences were resolved through discussion. Table 1 lists the relevant topic mappings and sample tweets for the topics. We computed topic scores for the topics and generated crisis response data by summing them over the topic mapping, using Eq. (4). For example, topic 1, topic 4, and topic 8 in the analysis using LDA mapped to awareness generation. We added the topic scores for topic 1, topic 4, and topic 8 to generate the score for CRS_AG . We derived the scores for CRS_EW , CRS_BC , and CRS_RC in the same way.

$$CRS_AG_t = \sum_{i \in \{1,4,8\}} ts_{t,i} \text{ where } ts_{t,i} \text{ is the topic score for tweet } t \text{ for topic } i$$

Table 1
Topic mapping from LDA analysis.

Topic	Topic name	Keywords	Examples
1	Awareness generation	impact, key, read, available, research, story, takeaway, join, global, webinar, discus, ceo, chief	“Retweet to raise awareness about the importance and impact of early diagnosis ...” “Join us now! Webinar to learn about an integrated research solution”
2	Employee well-being	credit, risk, market, bank, monitoring, economic, economy, new, Europe, amid	“When thinking about restarting operations once #COVID19 lockdown measures are lifted, #riskmanagers will need to...” “Amid the coronavirus pandemic and its impact on everyone's life, we are doing everything we can ...”
3	Resource contribution	finance, curve, fight, middle, infection, good, future, rest, health, thank, shortage, worker, like	“We are grateful for all of the front line workers who are keeping us safe during this time...” “Front Line workers are critical to getting all of us through this pandemic. We are here to support ...”
4	Awareness generation	covid, pandemic, impact, coronavirus, testing, health, control, market, work, monitor, world, diagnostic, molecular, insight, research	“Have a question about the latest trends and future tech for diagnostics? Tweet us your questions...” “Antibody drug conjugates (ADCs) - our next wave of #immunology research. Learn how scientists are...”
5	Employee well-being	restriction, expert, world, trial, clinical, supply, join, discussion, chain, business, response, developed, today, resilience, ceo	“As COVID-19 restrictions begin to ease, safely reintroduce employees back into the workplace with this checklist...” “Join our experts as they discuss the innovations shaping the future of work...”
7	Resource contribution	line, front, tip, risk, child, new, demonstrates, epidemic, age, help, special, remote, asset, global	“Today is #WorldBloodDonorDay! Did you know that one #blooddonation can save up to three lives...” “...to make donation to food banks worldwide...”
8	Awareness generation	workplace, feeling, world, learn, employee, reopening, creates, digital, food	“Want to learn how #clinicaltrials are designed...” “In search of digital transformation, the state of Hawaii focused on a customer-first approach...”
10	Business continuity	corporate, coronavirus, community, business, spread, keep, need, work, customer, many, global, across	“We're now offering curbside pickup to our customers. Place your order online...” “As a new way of working emerges, both customers and retailers are trying to adjust.”

$$CRS_EW_t = \sum_{i \in \{2,5\}} ts_{t,i}, CRS_BC_t = \sum_{i \in \{10\}} ts_{t,i}, CRS_RC_t = \sum_{i \in \{3,7\}} ts_{t,i} \quad (4)$$

3.4. Operationalization of measures

We operationalized the dependent, independent, and control variables in our analysis by drawing from the best practices captured in extant literature. We treated the tweet as the unit of our analysis. Table 2 describes the measures used in our analysis.

3.5. Structural equation modeling

The Structural Equation Modeling (SEM) is a multiple regression technique to test patterns in a complex relationship between constructs. It is a popular technique to test and evaluate multivariate causal relationships in complex models with multiple endogenous and exogenous variables [52]. The SEM allows simultaneous testing of relationships, which is an advantage over linear regression. We applied the SEM path analysis in AMOS with the maximum likelihood approach to test the relationships among dependent and independent variables.

4. Results

Fig. 2 depicts the distribution of emotions in tweets and the topics over the period. A visual inspection of the plots shows changes in trend patterns since the onset of the COVID-19 crisis. The plots show a decline in positive emotions, and a rise in negative emotions, topic scores, and Twitter behavior through the crisis period. A comparison of the unstandardized data before the crisis (BC) and during the crisis (DC), presented in Table 3, shows significant differences. All measures, except the topic score for tweets on awareness generation and employee well-being, DC were significantly different from BC.

The correlation matrix, presented in Table 4, showed significant correlations, with a high intra-group correlation. In our model, the positive emotion (Cronbach's alpha = 0.616) and the negative emotion (Cronbach's alpha = 0.723) were latent variables. All remaining measures were observed variables. We developed the SEM-based path analysis with the constructs. The error terms for BR_RT and BR_AR were covaried to optimize the model. The absolute fit (SRMR = 0.003, RMSEA = 0.010) and incremental model fit (CFI = 0.999, TLI = 0.996) indices were in the acceptable range [53]. Hence, the model was accepted. Fig. 3 depicts the research model with path coefficients. The paths for H1b and H3c were found to be insignificant. The remaining path coefficients from the crisis response strategies to positive emotion, negative emotion, and reputation were significant and in the hypothesized directions. So, H1, H2, and H5 were largely supported.

The data analysis showed that the crisis response strategies (a) business continuity, (b) employee well-being, (c) awareness generation, and (d) resource contribution adopted during the COVID-19 crisis were effective in boosting positive emotions and reducing negative emotions. They were positively associated with reputation. The path coefficients from negative emotions to behavioral response from stakeholders were significant (except H3c) and in the hypothesized direction. H3 was largely supported. The path coefficients leading from positive emotions to behavioral response from stakeholders were all significant but opposite to the hypothesized direction. H4 was not supported. The path coefficients from reputation to behavioral response from stakeholders were significant and in the hypothesized direction. H6 was supported. The SEM tests the relationships and interactions between the set of independent and dependent variables simultaneously. To check the robustness of the results, the individual paths were tested in SPSS. The direction and significance of the paths remained the same. The hypotheses H1, H2, and H5 that involved crisis response strategies were not meaningful in absence of the crisis. The analysis was repeated with data for the time period BC to test hypotheses H3, H4, and H6. The results were similar to those obtained DC although the relationships were stronger DC.

4.1. Post-hoc analysis

Robustness check for neutral tweets: We retested the model by replacing positive emotions with their constituent emotions – anticipation, joy, surprise, and trust. None of the constituent positive emotions generated a significant positive behavioral response. Most of the associations between constituent positive emotions and behavioral response were significantly negative. The analysis for H3 and H4 showed lower

Table 2
Measures used in the analysis.

Measure	Variable	Code	Definition	Source	Range	Scaling for SEM
Behavioral response from stakeholders [3]	Retweet rate	<i>BR_RT</i>	Number of retweets [26]	Extracted Twitter data	[0, 351,019]	Standardized
	Affective response	<i>BR_AR</i>	Number of likes to a tweet [26]		[0, 1,080,437]	Standardized
Crisis response strategy [3]	Reach	<i>BR_RE</i>	Number of Twitter followers [22]	Topic mining on extracted Twitter data and formula (4)	[51, 22,350,753]	Standardized
	Business continuity	<i>CRS_BC</i>	Topic score of tweets on business continuity in new normal [49]		[0,1]	Standardized
	Employee well-being	<i>CRS_EW</i>	Topic score of tweets on employee well-being in new normal [50]		[0,2]	Standardized
	Awareness generation	<i>CRS_AG</i>	Topic score of tweets sharing information and raising public awareness on COVID [39]		[0,3]	Standardized
Emotional category [3,11]	Resource contribution	<i>CRS_RC</i>	Topic score of tweets declaring organizational resource contribution to fight COVID [38]	Emotion mining on extracted Twitter data and formulae (1), (2) and (3)	[0,2]	Standardized
	Positive emotions	<i>E_POS</i>	The intensity of anticipation, joy, surprise, and trust are measures of positive emotions [35]		[0.0,7.0]	Standardized
	Negative emotions	<i>E_NEG</i>	The intensity of anger, disgust, fear, and sadness are measures of negative emotions [5]		[0.0, 10.423]	Standardized
Reputation [3]	Reputation	<i>O_REP</i>	Organizational reputation	Fortune reputation index [41]	{0,1}	Dummy encoded {0,1}
Organizational parameters (control variables)	Size of the organization	<i>O_SOO</i>	Number of employees [40]	Fortune database	[1330,2,200,000]	Standardized
	Technology sector	<i>O_TIS</i>	Dummy variable to indicate technology sector		{0,1}	Dummy {0,1}
	Financial sector	<i>O_FIS</i>	Dummy variable to indicate the financial sector		{0,1}	Dummy {0,1}
	Twitter age	<i>O_TWA</i>	Number of days from the creation of Twitter page [51]	Extracted Twitter data	[163, 5085]	Standardized
	Number of tweets	<i>O_NTS</i>	Number of tweets during the crisis period		{0,1}	Standardized

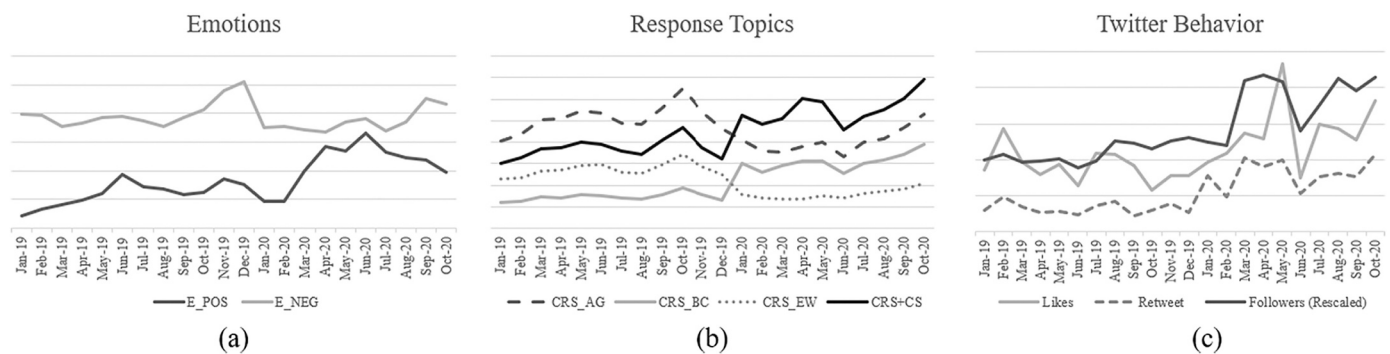


Fig. 2. Distribution of (a) emotions (b) response topics (c) Twitter behavior over the period.

Table 3
ANOVA for comparing the raw measures before and during the crisis.

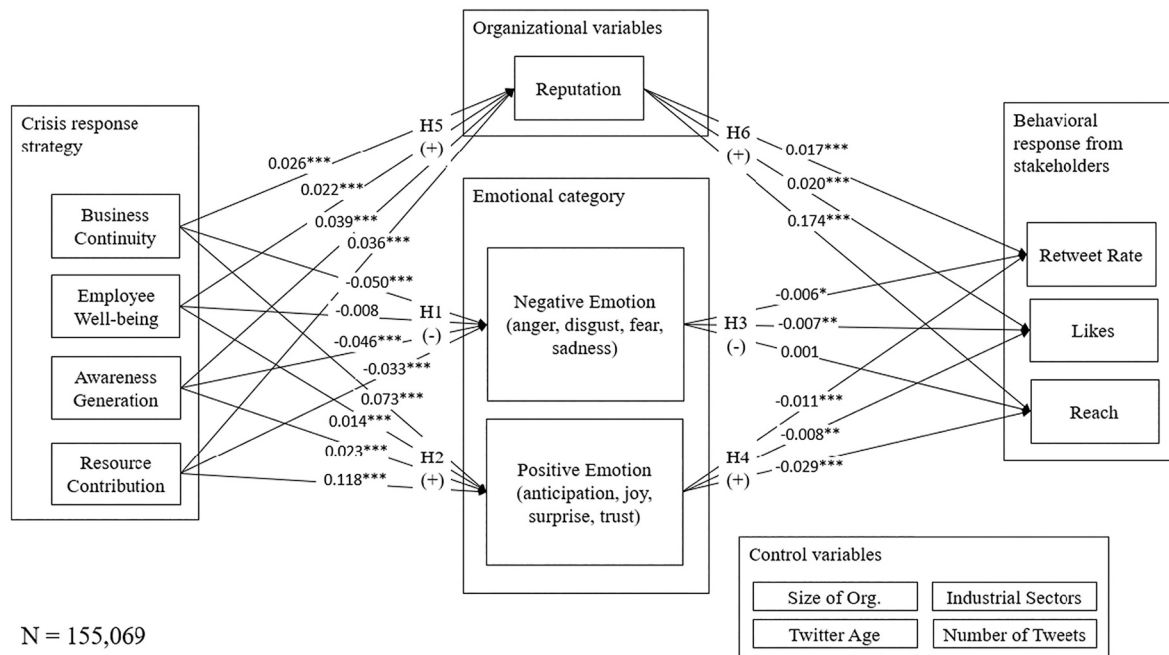
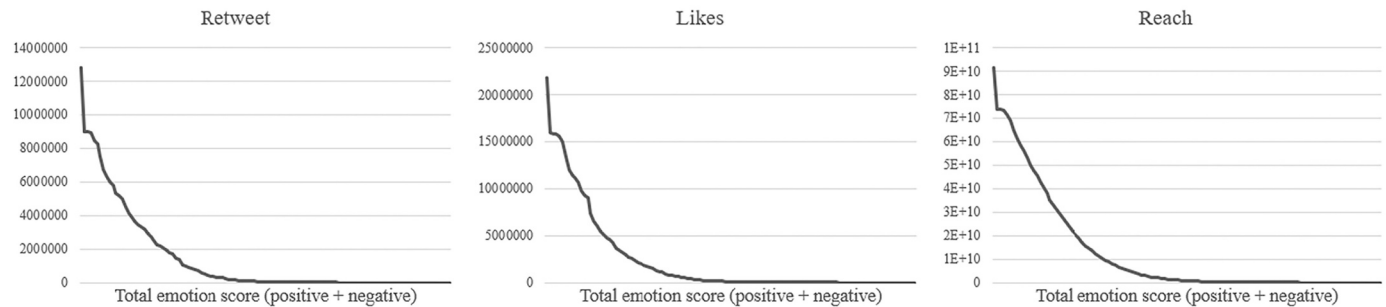
Measure	Mean _{BC}	Mean _{DC}	StdDev _{BC}	StdDev _{DC}	F	p-value
<i>CRS_AG</i>	0.260	0.261	0.220	0.228	0.690	ns
<i>CRS_EW</i>	0.102	0.102	0.138	0.143	0.016	ns
<i>CRS_BC</i>	0.192	0.199	0.215	0.223	73.878	<0.001
<i>CRS_RC</i>	0.359	0.357	0.251	0.259	4.735	<0.05
<i>E_NEG</i>	0.851	0.838	1.049	1.025	11.252	<0.01
<i>E_POS</i>	0.711	0.760	0.829	0.864	276.611	<0.001
<i>BR_RT</i>	31.62	82.89	723.322	2151.500	86.155	<0.001
<i>BR_AR</i>	88.958	140.908	1459.035	4198.669	23.050	<0.001
<i>BR_RE</i>	349,254.684	589,744.363	1,312,943.074	1,954,906.476	1725.235	<0.001

N = 325,627.

Table 4
Correlations.

	BR_RT	BR_AR	BR_RE	E_POS	E_NEG	CRS_AG	CRS_EW	CRS_BC	CRS_RC	O_TWA	O_SOO
BR_RT	1										
BR_AR	0.445**	1									
BR_RE	0.088**	0.104**	1								
E_POS	-0.012**	-0.010**	-0.039**	1							
E_NEG	-0.007**	-0.008**	-0.010**	0.112**	1						
CRS_AG	-0.001	-0.004	0.005*	-0.058**	-0.017**	1					
CRS_EW	0.003	0.008**	-0.008**	-0.030**	0.016**	-0.162**	1				
CRS_BC	-0.002	-0.003	-0.014**	0.011**	-0.020**	-0.316**	-0.162**	1			
CRS_RC	-0.003	0.001	0.003	0.073**	0.015**	-0.460**	-0.248**	-0.437**	1		
O_TWA	0.020**	0.017**	0.176**	-0.013**	-0.002	-0.012**	-0.003	0.001	0.003	1	
O_SOO	-0.005	0.003	0.096**	-0.013**	-0.001	0.008**	-0.038**	0.006*	0.016**	0.048**	1

N = 155,069.

**Fig. 3.** Results of the SEM with standardized path coefficients during the crisis.**Fig. 4.** More than ogive plots for (a) retweet, (b) likes, and (c) reach on total emotions.

behavioral response for higher emotions (negative and positive). We analyzed the effect of total emotion (computed as the sum of positive and negative emotions). Fig. 4 shows the ‘more than ogives’⁴ for total emotions of the behavioral reactions for retweets, likes, and reach

⁴ ‘More than ogive’, also known as ‘greater than ogive’ is a cumulative frequency graph where the y-axis denotes the cumulative frequency of all classes less than the value on the x-axis.

respectively. The plots indicate that stronger emotional intensity in tweets generated weaker behavioral response from stakeholders. Neutral tweets (low on total emotions) that provide information rather than express emotions [54], appear to generate more favorable stakeholder reaction.

Robustness check for alternate SNS: We repeated the analysis with posts collected from LinkedIn to validate the findings on an alternate SNS. Unlike Twitter, LinkedIn has a higher adoption rate among professional users [55] and does not have any limit on the number of

characters allowed for a post. We manually collected 8930 posts from the LinkedIn pages of Fortune 100 companies. The data included 2652 posts BC and 6278 posts DC. We extracted topics and emotions using similar techniques that were used for the Twitter data. There were significant differences in the measures BC and DC, similar to that observed in case of Twitter. We analyzed the data DC from LinkedIn to test the hypotheses. The hypotheses related to crisis response strategies and their emotions (H1,H2) and organizational reputation (H5) were supported. The hypotheses related to the impact of positive emotion in posts (H4) and organizational reputation (H6) on stakeholder response were supported as well. However, the hypothesized relationship between the negative emotion in posts (H3) and stakeholder response was not supported for LinkedIn.

Robustness check for engaged users: In the social networks the response come from stakeholders of varied “behavior activity” and “preference diversity” [56], p. 573. We conducted additional analysis to check if the findings hold good for stakeholders that had more engagement with the firms on Twitter. Following extant research, we identified connected stakeholders (i.e., Twitter followers) as the more engaged stakeholders of the firm [57]. We manually collected behavioral response from engaged stakeholders for a random sample of 1460 tweets. In our model, only hypotheses H3, H4, and H6 were related to stakeholder behavior. The analysis supported the hypotheses related to the effect of positive emotions (H4) and organizational reputation (H6) on stakeholder response. However, the relationship between the impact of negative emotions (H3) and stakeholder response was in the hypothesized direction but not significant.

The robustness checks showed that for general Twitter users, stronger behavioral response was evoked by emotion neutral tweets. However, for the more sincere stakeholders, such as the engaged stakeholders on Twitter and the professional users on LinkedIn, the behavioral response was significantly associated with the positive emotions but not with the negative emotions. The analysis supported the significant impact of emotions in crisis communication on the stakeholder psyche. Unlike the more sincere and engaged stakeholders, the diversified and less engaged stakeholders on Twitter were not persuaded by the positive emotion in crisis communication.

5. Discussion

The analysis supported the relationships between crisis response strategies, emotions, reputation, and stakeholder behavioral response proposed by the SCCT [3], except the behavioral response from positive emotions, in the COVID-19 crisis. The crisis response strategies (a) business continuity, (b) employee well-being, (c) awareness generation, (d) resource contribution, were useful during the victim crisis. The resource contribution strategy showed a stronger association with positive emotion compared to other strategies in the COVID-19 situation. The analysis supported the SCCT proposition that situational approach and pragmatic formulation of crisis response strategies lead to protection of reputational assets.

The analysis showcased the importance of reputation in crisis management and the efficacy of strategic crisis communication in preserving reputational assets. The stronger relationships DC compared to BC for hypotheses H3 and H4 indicated that emotions in crisis communication exerted a significant influence on the behavioral response from the stakeholders. Strong emotional intensity (both positive and negative) in tweets generated weaker behavioral response from stakeholders. Emotion neutral tweets generated more favorable stakeholder reaction from the broad, less engaged, and more diversified stakeholder base on Twitter DC as these tweets were viewed as more sincere [57].

5.1. Implications of the research

The paper enriches the scant literature on situational crisis communication in a victim crisis, especially for a pandemic with a large

impact. The multi-organization data used in this study ensures that sensitive inter-organization dependencies are addressed, which helps us to fully understand crisis communication in a multi-organizational environment. From the theoretical perspective, the paper contributes to the validation of the propositions of the SCCT in the case of the COVID-19 crisis. The paper identified the response strategies adopted by Fortune 500 organizations for its stakeholders. The analysis showed that communication on contributing funds and efforts, and empathy, solidarity, and moral support for the affected in organizational communication generated the strongest behavioral response in stakeholders. It confirmed the significant role of organizations' reputational assets in containing negative consequences from the crisis. Extant research has shown that negative information tends to spread faster in times of crisis [28]. Our data showed that in the COVID-19 crisis, stakeholders were averse to retweet, like, and follow Twitter accounts that communicated negative emotions. This finding supports the SCCT proposition that in a victim crisis, stakeholders sympathize with the organization and react less to negative emotions. Earlier research findings have shown that emotionally charged tweets invoked faster and more frequent retweets in a non-crisis scenario [28], and a typical crisis [25]. Our finding that emotionally charged tweets invoked lower behavioral response on Twitter during the COVID-19 crisis, adds a new dimension to crisis communication.

For the practitioners, the analysis showed that Twitter was an effective platform for crisis communication. It also showed that a victim crisis necessitated strategic crisis communication to manage stakeholder behavior despite the low responsibility attribution. The organization's reputational assets mitigated adverse crisis consequences and crisis communication involving stakeholders. The stronger relationship DC compared to BC for hypothesis H6 supported the vital role of reputation in crisis communication. The reputational capital provided the organization a positive reinforcement in managing the behavioral response of the stakeholders. Finally, in the pandemic, stakeholders responded most favorably to resource contribution strategy, and were averse to responding to tweets with strong emotions. Government agencies and business organizations may utilize the findings of this research in formulating crisis response strategies and crisis communication in a pandemic-like crisis. Organizations that have not adopted Twitter and other SNS for organizational crisis communication may revisit their communication strategy. Organizations involved in frontline operations, such as healthcare, can share authentic information devoid of emotion for positive stakeholder response. For organizations such as restaurants, regular operations were stalled during the pandemic. These organizations may engage on Twitter to spread awareness in their network, and in turn, strengthen ties with their customers. Twitter communication reaches customers, partners, media, and investor communities. Managers and brand ambassadors may share news on policies for internal stakeholders, such as employee well-being, and societal contributions, such as donations and effort contribution, on Twitter for positive branding. Brand ambassadors may focus on the news related to societal contributions for better brand leverage.

In addition to the crisis communication theory, the study contributes to the application of text mining techniques for understanding communication patterns. The study used text mining to analyze a large organizational crisis communication dataset extracted from Twitter. The techniques were used to extract eight basic emotions and crisis communication topics from Twitter data. The comparative analysis showed a significantly higher organizational adoption of Twitter during the crisis. Mining of organizational tweets showed the reflection of the COVID-19 crisis response strategies in tweets, and the use of Twitter to communicate crisis response strategies to stakeholders. Academic researchers and practitioners may apply the text mining approach to analyze crisis communication.

5.2. Limitations of the research

The research draws data from Twitter, which is the most popular SNS for organizational communication and is widely studied by academics. It can be extended to include the crisis communication on other SNS, such as Facebook, Instagram, etc. The paper analyzes the influence of crisis response strategies on stakeholder behavioral responses in a sticky victim crisis. It does not compare the results with other types of crises. The paper does not investigate industry or geography specific differences in crisis response strategies. Finally, the paper does not distinguish between the behavioral response from stakeholders with a wide range of “behavior activity” and “preference diversity” [56] and this could be pursued as a future research direction.

6. Conclusion

The paper opens up various avenues for further research. A visual inspection of the plots in Fig. 2 indicates changes in the trends of the measures over the long-drawn crisis period. The changes in the relationships between the measures during the different stages of the crisis need further investigation. This paper analyzed the data until October 2020, which forms a small part of the COVID-19 crisis. Researchers need

to compare the findings of our research with communication strategies and stakeholder responses for victim crises of lower levels of impact. Researchers need to extend this study to crisis of different crisis responsibilities and crisis history to make an empirical assessment of the complete SCCT [3]. Further research is needed to understand the industry sector-specific variances and cultural differences in crisis communication strategies and their corresponding outcomes. In this paper, we study the crisis communication of firms during the COVID-19 pandemic using the lens of the SCCT. We used a text mining approach followed by empirical analysis on a large multi-organizational Twitter dataset. The analysis supported our theoretically derived hypotheses. The paper offers interesting insights and makes several useful contributions to crisis communication. The paper elicits the COVID-19 crisis response strategies adopted by Fortune 500 companies from Twitter communication. The analysis shows that Twitter communication on crisis response strategies, and the emotional cues in the communication affect stakeholder reaction. We believe that this paper contributes significantly to the growing body of literature on response strategies of firms during COVID-19. We hope the discussions, techniques, and analysis offered in this paper will be of value to academic researchers and industry practitioners alike.

Appendix A. A review of the related literature

The available literature on COVID-19 focused largely on healthcare topics. We found a handful of related papers from the information systems discipline. Among these papers, a few covered organizational crisis communication [2,58,59]. Most of the papers conducted a theoretical analysis, and only two papers focused on empirical data analysis [58,59]. A summary is shown in Table A.1.

Table A.1

Topic mapping from LDA analysis.

Paper	The premise of the study	Method	Findings and contributions	Limitations/ future research directions
[2]	Strategic communication demands of COVID-19 for crisis managers	Analyzed crisis communication	Highlighted the demands of crisis communication for crisis managers in the public sector	There is a need to explore the use of social media for crisis communication
[49]	Impact of social distancing and employee well-being during the COVID-19 pandemic	Analyzed macroeconomic data and industry reports	Developed a framework to study the effect of social distancing practices on employee well-being	An empirical analysis of the proposed framework
[58]	The tone of official tweets during COVID-19, and the response of Twitter users to official communication	Conducted statistical analysis of topic data extracted from 26,264 official tweets for 80 Twitter handles	Provided insights to health officials and government agencies for information dispersion and reassuring the general public via SNS	Adding emotions and sentiment to tweet categorization, and increasing the period of the tweet data to provide more insights
[59]	COVID-19 crisis communication by the Prime Minister of New Zealand	Thematic analysis of 40 statements	Determined the linguistic and discursive aspects of leadership communication during a crisis	Extend to multiple political leaders of different countries
[60]	Use of digital technologies within small and medium enterprises to deal with COVID-19 and secure business continuity	Theoretical analysis	Identified managerial implications of using digital technologies to deal with COVID-19	Recommended the privacy and business operations for practitioners
[61]	Sustainable changes to business processes to fight the pandemic	Performed theoretical analysis	Determined that digital push during the pandemic created research opportunities in the field of IS	Analysis of the information orchestration for stakeholder engagement
[62]	COVID-19 related issues and impacts on IS	Performed theoretical analysis	Proposed a set of issues for future research	Study of IS to manage compliance and productivity

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Suparna Dhar is Professor of Computing & Analytics at the NSHM Knowledge Campus Kolkata. She has completed her Bachelor of Science in Mathematics and Masters of Statistics from Indian Statistical Institute, Kolkata. Her research interests are in machine learning and AI, social networking, blockchain, fintech, and Cybersecurity. Her research has been published in journals like *Journal of Organizational Computing and Electronic Commerce* as well as those of conferences like ICIS and *Workshop on e-Business* (pre-ICIS).



Indranil Bose is Distinguished Professor of Management Information Systems at the NEOMA Business School. He is the Head of the Area of Excellence in Artificial Intelligence, Data Science, and Business. He holds a BTech from the Indian Institute of Technology, MS from the University of Iowa, and MS and PhD from Purdue University. His research interests are in business analytics, digital transformation, information security, and management of emerging technologies. His publications have appeared in *MIS Quarterly*, *Journal of the MIS*, *Communications of the ACM*, *Communications of the AIS*, *Computers and Operations Research*, *Decision Support Systems*, *Electronic Markets*, *European Journal of Operational Research*, *Information & Management*, *International Journal of Production Economics*, *Journal of Organizational Computing and Electronic Commerce*, *Journal of the American Society for Information Science and Technology*, *Operations Research Letters*, *Technological Forecasting and Social Change*, etc. He serves as Senior Editor of *Decision Support Systems* and *Pacific Asia Journal of the AIS*, and as Associate Editor of *Communications of the AIS*, *Information & Management*, and *Journal of the AIS*.