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Evolution of corporate reputation during an evolving controversy

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Evolution of corporate reputation during an evolving controversy

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Abstract

Purpose – The purpose of this paper is to investigate the evolution of online sentiments toward a company (i.e. Chipotle) during a crisis, and the effects of corporate apology on those sentiments.

Design/methodology/approach – Using a very large data set of tweets (i.e. over 2.6m) about Company A's food poisoning case (2015–2016). This case was selected because it is widely known, drew attention from various stakeholders and had many dynamics (e.g. multiple outbreaks, and across different locations). This study employed a supervised machine learning approach. Its sentiment polarity classification and relevance classification consisted of five steps: sampling, labeling, tokenization, augmentation of semantic representation, and the training of supervised classifiers for relevance and sentiment prediction.

Findings – The findings show that: the overall sentiment of tweets specific to the crisis was neutral; promotions and marketing communication may not be effective in converting negative sentiments to positive sentiments; a corporate crisis drew public attention and sparked public discussion on social media; while corporate apologies had a positive effect on sentiments, the effect did not last long, as the apologies did not remove public concerns about food safety; and some Twitter users exerted a significant influence on online sentiments through their popular tweets, which were heavily retweeted among Twitter users.

Research limitations/implications – Even with multiple training sessions and the use of a voting procedure (i.e. when there was a discrepancy in the coding of a tweet), there were some tweets that could not be accurately coded for sentiment. Aspect-based sentiment analysis and deep learning algorithms can be used to address this limitation in future research. This analysis of the impact of Chipotle's apologies on sentiment did not test for a direct relationship. Future research could use manual coding to include only specific responses to the corporate apology. There was a delay between the time social media users received the news and the time they responded to it. Time delay poses a challenge to the sentiment analysis of Twitter data, as it is difficult to interpret which peak corresponds with which incident/s. This study focused solely on Twitter, which is just one of several social media sites that had content about the crisis.

Practical implications – First, companies should use social media as official corporate news channels and frequently update them with any developments about the crisis, and use them proactively. Second, companies in crisis should refrain from marketing efforts. Instead, they should focus on resolving the issue at hand and not attempt to regain a favorable relationship with stakeholders right away. Third, companies can leverage video, images and humor, as well as individuals with large online social networks to increase the reach and diffusion of their messages.

Originality/value – This study is among the first to empirically investigate the dynamics of corporate reputation as it evolves during a crisis as well as the effects of corporate apology on online sentiments. It is also one of the few studies that employs sentiment analysis using a supervised machine learning method in the area of corporate reputation and communication management. In addition, it offers valuable insights to both researchers and practitioners who wish to utilize big data to understand the online perceptions and behaviors of stakeholders during a corporate crisis.

Keywords Social media, Crisis communication, Strategic communication, Reputation management

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The crisis communication literature recommends apology as one of several effective organizational responses to reputational crises (e.g. Coombs and Holladay, 2001). However, none of the prior studies provides evidence on how apology affects online stakeholder sentiments and how quickly apologies can change online sentiments from negative to positive. Moreover, as these studies utilized focus groups and surveys, they were not able to provide a comprehensive picture of the development of sentiments during a crisis and the effects of corporate apologies on sentiments.

To investigate the evolution of sentiments toward a company during a crisis and the effects of corporate apology on these sentiments, this study employed a large Twitter database on Company A's food poisoning case (2015~2016). Company A was one of the leading fast-food restaurant chains in the USA. In October 2015, 52 people across nine states fell ill after eating Company A's food that was tainted with *E. coli* (Zuraw, 2015). In total, 20 were sick enough to be hospitalized. The high-profile crisis had such a severe effect on the company's reputation that it was still struggling one year after the crisis ended (Little, 2016). This case was selected because it is widely known, drew attention from various stakeholders and had many dynamics (e.g. multiple outbreaks and across different locations). The authors obtained over 2.6m tweets about this case and analyzed the data using the supervised machine learning approach and Linguistic Inquiry and Word Count (LIWC[1]) 2015.

This study aims to add to the literature on reputation management as a dynamic and interactive discipline. Recent studies point out that reputation management should be seen as a more dynamic and interactive process. Accordingly, more attention should be paid to the ongoing dialogue between organizations and their stakeholders (Elsbach, 2012; Heugens *et al.*, 2004). This is especially true in today's highly volatile environment: in order to develop and maintain a positive reputation among their stakeholders, organizations need to pay ongoing attention to their changing environment (Jones and Chase, 1979) "to predict the effect of internal and external environmental changes on the performance of the overall corporate system" (Chase, 1979, p. 34).

This is one of the very first studies to use big data analysis to empirically investigate the dynamics of corporate reputation as it evolves in a crisis. In addition, it is one of the first to utilize a very large social media data set (i.e. over 2.6m tweets), which provides a comprehensive picture of the communication dynamics during the entire crisis, which stretched over six months. Many studies that used tweets used only a very small number of tweets in a very short period, and used only specific keywords in the search. For example, the study by Getchell and Sellnow (2016) investigated 41 Twitter accounts associated with the West Virginia Water crisis in 2014. Kim *et al.* (2015) analyzed 20,773 tweets about the Domino Pizza Crisis in 2009. Other studies used tweets in experimental designs and measured the emotional responses and attitudes toward companies or brands during corporate crises (e.g. Jang and Hong, 2017; Schultz *et al.*, 2011; Utz *et al.*, 2013). However, these studies investigated a small number of tweets or were conducted in an artificial setting, which is not suitable for studying a real-life corporate crisis that usually generates a large volume of social dialogue on Twitter.

Last, this study employed the supervised machine learning approach: sentiment analysis using a supervised machine learning approach can help researchers and practitioners understand what sentiments were salient and how sentiments evolved during the crisis (Van Der Meer, 2016).

This study has potentially significant implications for researchers and practitioners. By understanding how audiences respond in real time to a company's online reputation management strategies, reputation management practice may move towards greater flexibility and sensitivity to contextual factors (Whittington and Yakis-Douglas, 2012).

The following sections will review the literature on corporate reputation, social media, crisis management and apologies. This will be followed by a description of the methodology, the results, and the discussion. Finally, the limitations and implications for future research are discussed.

Literature review

Corporate reputation, social media and crises

Corporate reputation has received considerable attention from management practice, as it is widely recognized as one of the most valuable intangible assets an organization possesses (e.g. Fombrun and Shanley, 1990; Fombrun, 1996; Dowling, 2004; Waller and Younger, 2017). Corporate reputation has been defined as the "stock of perceptual and social assets – the quality of the relationship it has established with stakeholders and the regard in which the company and brand are held" (Fombrun and van Riel, 2004, p. 32). A company's reputation is valuable because it sends strong signals to stakeholders about its status (Fombrun, 1996). Reputational assets can attract customers, generate investment interest, improve financial performance, attract top-employee talent, increase the return on assets, create a competitive advantage and garner positive comments from financial analysts (Carmeli and Tishler, 2005; Fombrun and van Riel, 2004).

However, corporate reputation may diminish in favorability and strength if it is not properly managed in critical situations (Elsbach, 2006). A crisis can undermine the reputation of a company, as it "threatens important exigencies of stakeholders and can seriously impact an organization's performance and generate negative outcomes" (Coombs, 2007, p. 2). During a crisis, the difficulty of navigating the contextual factors that influence the effectiveness of reputation management (e.g. the valence of each event, historical context) is amplified (Elsbach, 2012; VanSlyke Turk *et al.*, 2012; Rhee and Valdez, 2009).

Corporate reputation management during a crisis is complicated by the ubiquity and characteristics of social networking sites such as Facebook and Twitter. In the internet age, news about crises can spread rapidly through online social networks and reach large audiences virtually instantaneously (Stephens and Malone, 2009). During a crisis, social media use increases, as stakeholders use them to access information, share updates and emotional support, band together virtually and demand resolution (Liu *et al.*, 2011; Veil *et al.*, 2011; Choi and Lin, 2009; Stephens and Malone, 2009). Through social networking sites, an individual or a small group of people can draw the public's attention to an issue and "public attention to the issue can expand exponentially through online interactions" (Chung, 2011, p. 1885). Communication on Twitter, for example, has been found to have agenda-setting effects (e.g. Lee and Xu, 2018). Moreover, the constant and rapid flow of real-time communication in social media can result in the temporal dominance of a single topic, which in turn leads to a large volume of communication that generates widespread attention (Pfeffer *et al.*, 2014). Indeed, the half-life (i.e. the time after which 50 percent of the overall traffic is reached (Burton and Kebler, 1960) of Twitter memes and hashtags can be just in the order of minutes (Fang and Huberman, 2007). To complicate matters, crises tend to be associated with high-arousal emotions, and content that evokes high-arousal emotions such as anger and anxiety has been shown to spread faster and more broadly online than others (Berger and Milkman, 2011; MIT Technology Review, 2013). Social media such as Twitter also tend to have a hierarchical structure where only a handful of highly popular users attract disproportionately large numbers of followers (Lee and Xu, 2018). Moreover, information dissemination on social networking sites may rely to a disproportionate extent on just a few content creators in the network (Jang and Pasek, 2015). Thus, social networking sites make organizational crisis management more unpredictable and complex (Jin *et al.*, 2014).

Nonetheless, social media and the internet also offer companies the platform and tools to manage organizational crises. By facilitating online media monitoring, stakeholder mapping, and the active engagement of stakeholders before and during times of crises, the internet and social media have the potential to empower communication practitioners within organizations (Strauß and Jonkman, 2017).

In times of crises, many organizations have used corporate advertising to restore their reputation. For instance, BP spent $93m on apologetic advertising between April and July 2010 after the Gulf of Mexico oil spill. Kim and Choi (2014) found that crisis type – accident or transgression – affects consumers' response to post-crisis corporate advertisements. More specifically, consumers are likely to perceive a corporate ad message to be more credible in an accident crisis than in a transgression crisis. As consumers are likely to view the latter type of advertising as persuasion rather than sincere communication (and thus have a less favorable assessment of the organization), corporate advertising during a transgression crisis could be counterproductive (Kim and Choi, 2014).

Apologies

Firms that commit transgressions often issue apologies in the hope that they can repair stakeholder relationships and protect corporate reputations (Lazare, 2005). While apologies can often be beneficial (Basford *et al.*, 2014; Darby and Schlenker, 1982; Eaton *et al.*, 2006; Exline and Baumeister, 2000), they can also have harmful results, especially if they are not done well (DeCremer *et al.*, 2010; Zechmeister *et al.*, 2004).

Apologies have been grouped into three overarching categories: an acknowledgment of violated rules and norms, an expression of remorse, and an offer of compensation (Hill, 2013). Acknowledgment of violated rules and norms involves transgressors publicly acknowledging that they have violated rules and norms and assuming responsibility for their "deviant" actions. Their assumption of responsibility validates victims' sense of mistreatment, signals the organization's intent to prevent a repeat of the offensive behavior, and provides the assurance that future transgressions are unlikely (Hill and Boyd, 2015). Remorse has been defined as an expression of guilt for having done something wrong (Boyd, 2011). Expressions of remorse that combine a cognitive and affective approach have been shown to elicit forgiveness (Schmitt *et al.*, 2004). Compensation involves the transgressor doing something to redress the wrong and restore equilibrium. It can be monetary in nature or comprise efforts to restore respect and reputation for the victim (Hill and Boyd, 2015). The effectiveness of compensation in an apology has been confirmed by some studies (e.g. Conlon and Murray, 1996; Scher and Darley, 1997).

Based on the above discussion, the authors explored the following research questions:

RQ1. What type of sentiment was reflected in individuals' tweets related to the Company A crisis, and what was the proportion of negative to positive sentiments during the crisis?

RQ2. How did the sentiments change over the period studied in this particular crisis?

RQ3. What effects did corporate apologies have on the sentiments?

RQ4. What were the characteristics of popular tweets about the crisis? We define the popularity of tweets by the number of retweets that a tweet gets.

Method and data

Sentiment analysis

Since the 2000s, sentiment analysis has drawn attention from researchers in various fields. This interest is driven in large part by the exponentially increased data sets from social media such as Facebook and Twitter. In sentiment analysis, data pre-processing is critical. The authors performed two-step data processing to reduce irrelevant tweets from the tweet data set. First, tweets that originated from Company A's official Twitter account and the top 25 news agencies that reported on Company A were removed: this study focused primarily on public sentiments about the crisis (i.e. not on corporate communication), and legitimate news agencies are generally deemed to be neutral sources of information (i.e. lacking in sentiment). Second, the study was limited to English tweets. Third, the training sample was limited to the top 80 percent of tweets by tweet length. The 80 percent mark was chosen, as tweets at the 80 percent mark have about 47 characters (or roughly five words, including spaces). The authors felt that tweets with fewer than five words would be too short for the research assistants (RAs) to label accurately. Nonetheless, all tweets were included in the final analysis; only non-English tweets were excluded.

The crisis

Company A's food-borne illness outbreak was selected. Company A Mexican Grill had the worst crisis in its history between October 2015 and February 2016. The outbreaks hit Company A restaurants in 12 states and sickened 58 customers.

Twitter data

The Twitter data for the Company A crisis were acquired from Gnip. To examine the global spreading pattern on Twitter, it is important to use all the tweet posts during the given period. The keywords used to extract the tweets were @companyATweets, #CompanyA, #CompanyAllTeam and Company A. These keywords yielded 2.6m tweets from November 1, 2015 to March 31, 2016.

Supervised machine learning approach

This study's sentiment polarity classification and relevance classification consisted of five steps: sampling, labeling, tokenization, augmentation of semantic representation, and the training of supervised classifiers for relevance and sentiment prediction.

Sampling

Tweets related to news articles or from news agencies were classified as neutral and, thus, excluded from the analysis. Tweets from Company A's corporate Twitter account and tweets that were too short were also excluded. A set of 3,000 tweets (i.e. 0.112 percent of the complete data set) were randomly sampled for labeling[2] (Set 1). Next, 300 tweets from Set 1 were randomly drawn for inter-rater reliability testing using Cohen's κ (Cohen, 1960).

Labeling

Three RAs were recruited and trained (using examples) to manually label the tweets using two aspects: whether the tweet was relevant to the crisis, and what the perceived sentiment of each tweet was. The RAs were instructed to adopt the perspective of a lay person when labeling the tweets.

The relevancy criterion was used for two reasons. First, the data set had many tweets that were irrelevant to the crisis in question. Using specific keywords to select tweets would cause the study to lose a substantial number of tweets that referred to the crisis but which did not contain the specific keywords. Conversely, using only "Company A" as the keyword created the problem of including too many irrelevant tweets. Therefore, the RAs manually labeled the relevancy of the tweets along with the sentiments, so that the classifiers could distinguish relevant tweets from irrelevant tweets.

In addition, the RAs classified the tweets into three sentiments: i.e. positive, neutral and negative. The inter-rater reliability test scores for relevancy and sentiment were both at the satisfactory level, as recommended by Munoz and Bangdiwala (1997). A voting system (Nakov *et al.*, 2015) was used to further improve reliability. Table I shows the inter-rater reliability test results for relevancy and sentiments for the sample of 300 tweets.

Even with the aforementioned steps, the results still showed a high level of neutral tweets and insufficient sentimental tweets for training the model. In order to expedite the process, subjectivity lexicons (Wilson *et al.*, 2005) were used to filter highly subjective tweets. This resulted in a second set of tweets (Set 2), of which 81.22 percent contained sentiment. To train the model, a balanced number of tweets for each category of relevancy (i.e. relevant and irrelevant) and for each class of sentiment (i.e. positive, neutral and negative) was required. Hence, Set 1 and Set 2 were combined to create a set of "all labeled tweets," which comprised 6,515 tweets.

Feature extraction

Features were generated through two steps – tokenization and word n-grams. There are various tokenization methods, such as Whitespace tokenization, treebank-style tokenization and sentiment-aware tokenization. This study used Treebank style tokenization, as the authors' test results showed that it performed better than the other methods on $F1$ score and accuracy.

There are various methods to create word features after a tweet has been tokenized, including bigram, trigram and skipgram (Guthrie *et al.*, 2006). The authors tested various methods and found Unigram to have the highest accuracy for the data set.

Even though LIWC is commonly used to assess the sentiment of text (Pennebaker *et al.*, 2014), it cannot accurately detect subtleties in language, such as sarcasm and humor. Hence, the authors developed a sentiment model using a statistical method that calculated the probability of each sentiment using a variety of inputs (e.g. subjectivity scores and LIWC scores). This model yielded accuracy and $F1$ scores that were 14.7 and 14.2 percent higher (respectively) than the corresponding LIWC scores. Figure 1 shows the process of the supervised machine learning approach. An explanation of technical terms used in the figure can be found in the Appendix.

Results

As this study focused on public responses to Company A's food-borne crisis, only the relevant tweets (i.e. 610,319 tweets) were analyzed. In total, 326,219 distinctive users posted at least one tweet about the crisis. In total, 16,427 or 2.70 percent of the tweets were mentions or replies to other tweets. Among all tweets, 275,579 or 45.15 percent were retweets:

RQ1. What type of sentiment was reflected in individuals' tweets related to the Company A crisis, and what was the proportion of negative to positive sentiments during the crisis?

The initial data set contained 73 percent neutral tweets, 14 percent positive tweets and 13 percent negative tweets. Thus, the sentiments appear to be evenly divided between

Table I. Inter-rater reliability test results for relevancy and sentiment for the 300 tweets

Labeling	Pairwise CK Raters 1 and 3	Pairwise CK Raters 1 and 2	Pairwise CK Raters 2 and 3	Average Pairwise CK
Relevancy	0.826	0.789	0.922	0.846
Sentiments	0.767	0.745	0.931	0.814

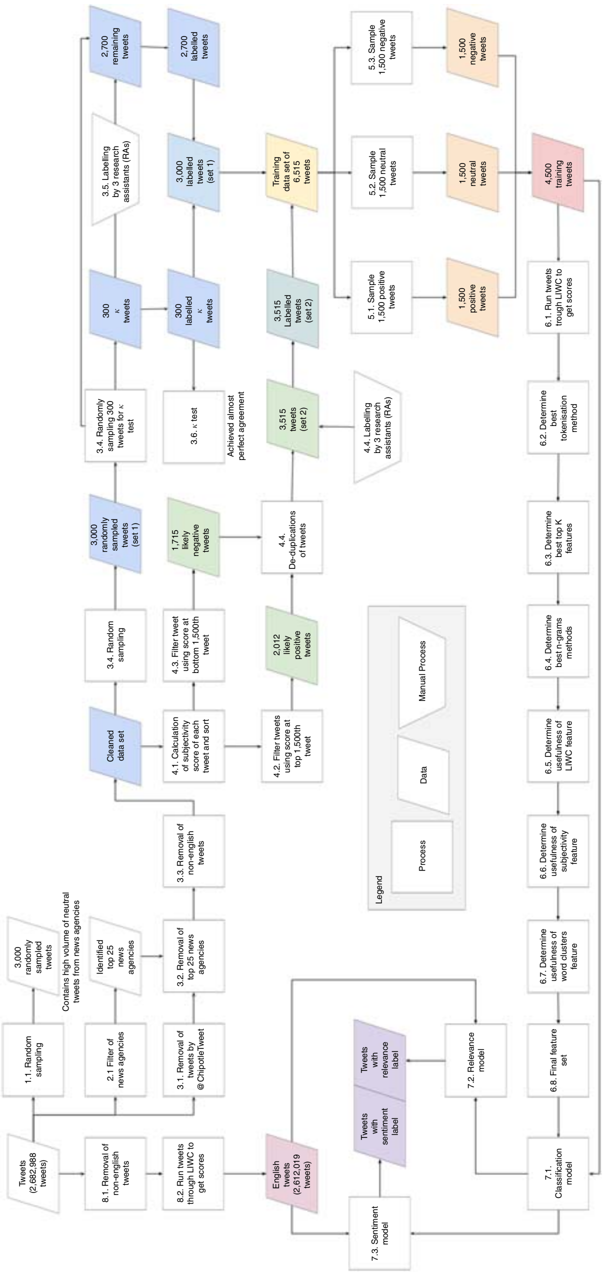


Figure 1.
Process of supervised machine learning approach

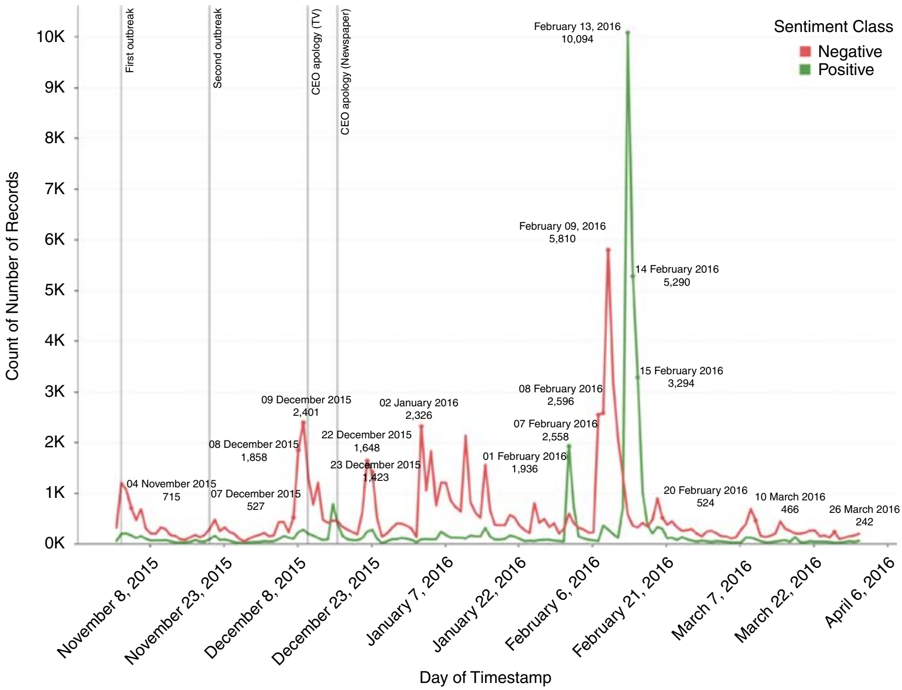
positive and negative, excluding neutral sentiments. However, this changed when the sentiments of the relevant tweets (i.e. tweets that specifically mentioned Company A's food poisoning incidents) were analyzed. Among the relevant tweets, neutral tweets were 80 percent (e.g. "So can I eat Company A now?"), followed by negative tweets (14 percent; e.g. "Been eating Company A every day praying I get *E-coli*. That lawsuit would be clutch to pay off my student loans"), and positive tweets (6 percent; e.g. "if Company A thought they could buy back my trust after the *E. coli* breakout with a free burrito then they were right"). Thus, negative sentiments outnumbered positive sentiments about the crisis. Table II summarizes the sentiments in the tweets:

RQ2. How did the sentiments change over the period studied in this particular crisis?

To answer this question, the number of tweets created during the study period and the sentiments of those tweets were analyzed. Figure 2 shows the daily volume of tweets regarding the crisis. The number of tweets about the crisis rose significantly when

	Relevancy		
Sentiments	Irrelevant	Relevant	Total
Positive	324,656 (16%)	39,462 (6%)	364,118 (14%)
Neutral	1,422,553 (71%)	485,538 (80%)	1,908,091 (73%)
Negative	254,490 (13%)	85,319 (14%)	339,809 (13%)
	2,001,699	610,319	2,612,018

Table II. The sentiments of relevant, irrelevant and total tweets



Note: Peaks near the outbreaks indicate possible social media discussion

Figure 2. Trends of the volume of tweets over the study period

Company A announced the closure of their restaurants in Oregon and Washington due to *E. coli* contamination on November 1, 2015, and again when the second outbreak occurred on November 23, 2015 in six states. This shows that a corporate crisis draws attention and sparks public discussion on social media. Other peaks, such as those on February 9 and February 13, were not responses to the crisis.

Next, the sentiments of the tweets were analyzed. The graph in Figure 2 shows the degree of positive affect (green) and the degree of negative affect (red) of the tweets, while the graph in Figure 3 shows the difference between positive and negative sentiments (the values below the *X*-axis represent negative sentiment while the values above represent positive sentiment). The overall sentiment on Twitter about the crisis was negative during the study period. There were immediate surges of negatively charged tweets when the two outbreaks were announced on November 1 and on November 22 in 2015:

RQ3. What effects did corporate apologies have on the sentiments?

Company A made two corporate apologies. The first apology was made on December 10, 2015 by Steve Ells, CEO of Company A, when he apologized on the Today Show, a television show. That day, the sentiment on Twitter about Company A was predominantly negative, with 1,319 negative tweets. After the CEO's apology on TV (the 1st apology), the number of negative tweets gradually decreased and was reduced to 469 on December 15, 2015. This represents a reduction of 850 negative tweets. The second apology also decreased the number of negative tweets. When the company launched the full-page apology advertisement on December 16, 2015 in 61 newspapers (including the *New York Times*, *Wall Street Journal* and *USA Today*), the number of negative tweets decreased from 456 on December 16 to 195 on December 20, 2015 – a reduction of 261 negative tweets. Comparing day to day, this is a 45 percent decrease (see Figure 4).

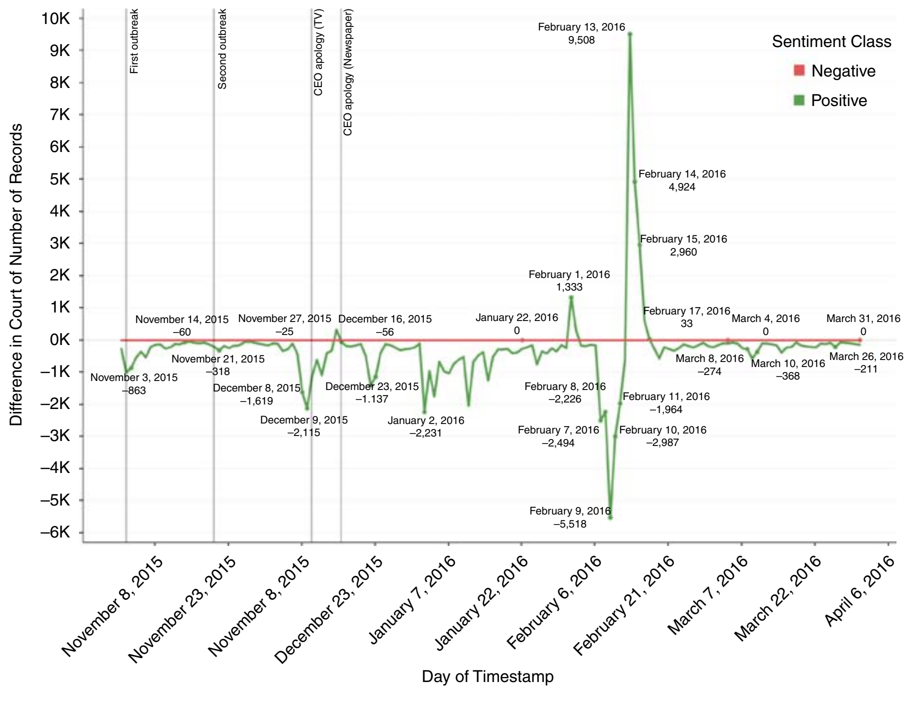


Figure 3.
Sentiments (positive minus negative) during the study period

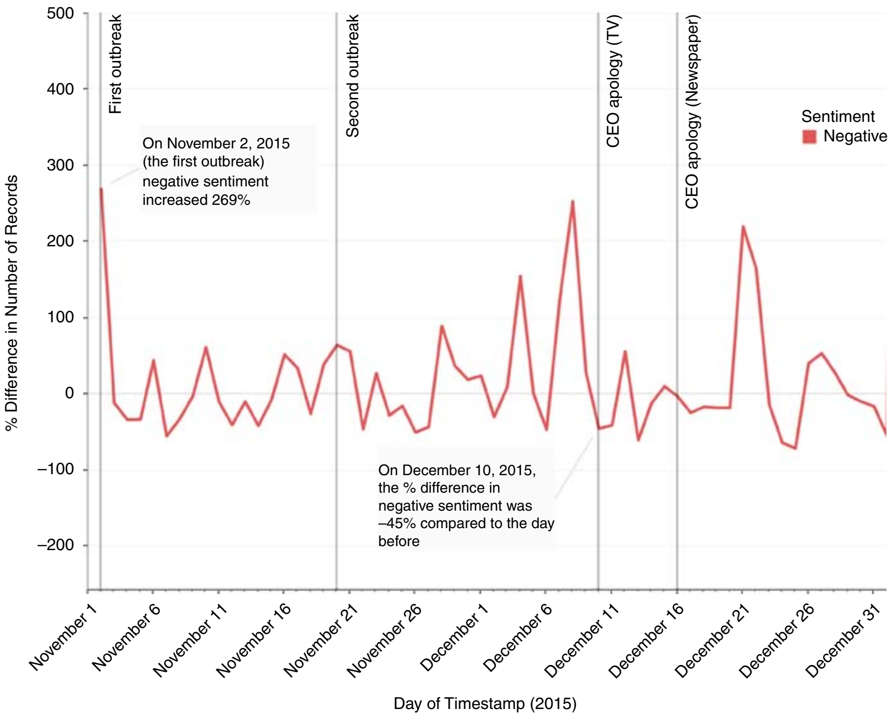


Figure 4.
Corporate apologies and sentiments on Twitter

However, the effects of both apologies did not last long, as negative tweets spiked in accordance with more crisis events taking place. By examining the tweets sent to Company A's corporate Twitter account it was found that tweets mentioning @companyATweet were predominantly negative throughout the study period (see Figure 5).

On February 8, in the midst of the crisis, Company A offered customers who texted the word "raincheck" an SMS coupon for a free burrito within the next few days. The response

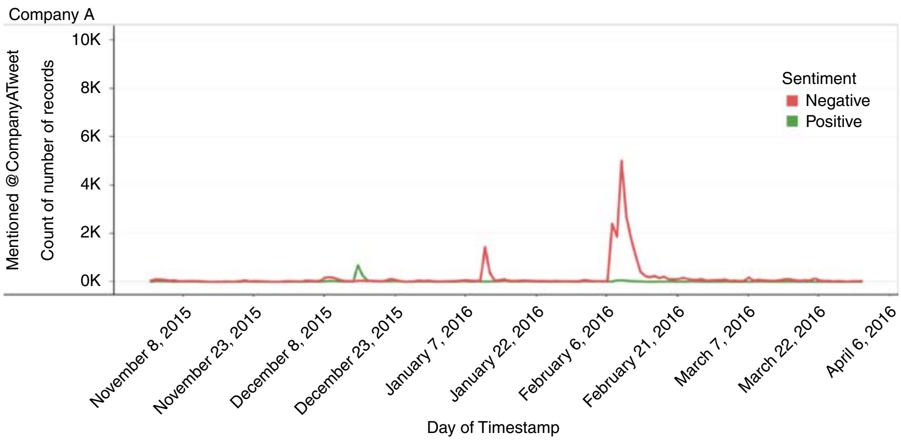


Figure 5.
Sentiments of the tweets that mentioned @CompanyATweet

to the promotion was very minimal at first. However, positive sentiments gradually increased for a couple of days and reached their peak on February 14. A closer examination revealed that the peak was created by one tweet ("If Company A thought they could buy back my trust after the *E. coli* breakout with a free burrito then they were right") that was retweeted 7,733 times (76.6 percent) on that day. At first glance, it would seem that the promotional campaign had some positive effect on the sentiment. However, the positive sentiment created by this tweet did not last even for a day. Hence, Company A's promotional effort during the crisis was only temporarily effective:

RQ4. What are the characteristics of popular tweets?

To answer this question, the top 10 tweets (from the data set) that were heavily retweeted were examined (see Table III). The first one was @jaylan_glover, who had 900 followers. This negative tweet, which contained rhyme and an image, was heavily retweeted – 21,357 times in total (as of 23rd April 2017 on Twitter.com) – and reached external networks 23 times bigger than @jaylan_glover's network size. The second most retweeted tweet was a news article written by @SatiraTribune about Company A's marketing campaign to regain customer trust. This account belonged to a news agency and had 861 followers. The tweet reached seven times its network size. The third most retweeted tweet was written by @KhadiDon about her eating Company A and dancing about it. This tweet contained a video. @KhadiDon had 343,000 followers. Her negative tweet about Company A was retweeted 6,712 times.

Table III.
Top 10 retweeted content

	Author	Content	Media type	Retweets	Sentiment	Posted
1	@jaylan_glover	Cook my chicken all the way through next time and this won't happen @ChipotleTweets https://t.co/71fxQ22Hjj	Image	21,222	Negative	February 7, 2016
2	@SatiraTribune	Chipotle Selling $1 Burritos All Week To Regain Public Trust #Chipotle https://t.co/DPGhHaPq8t https://t.co/ZzByb6N0n7	Image	6,769	Neutral	January 10, 2016
3	@KhadiDon	When you eat chipotle and don't get *E. coli* https://t.co/OhuuYCvHOS	Video	6,686	Negative	January 2, 2016
4	@TweetLikeAGirI	If chipotle thought they could buy back my trust after the *E. coli* breakout with a free burrito then they were right	None	4,795	Positive	February 14, 2016
5	@adamkrauskopf	If chipotle thought they could buy back my trust after the *E. coli* breakout with a free burrito then they were right	None	4,283	Positive	December 2, 2016
6	@lordflaconegro	I'm happy asf I never stopped at a fuckin chipotle https://t.co/AyAulRkye2	Image	3,948	Negative	July 11, 2015
7	@RT_America	*E. coli* outbreak: Chipotle shuts down 43 restaurants in two states, beef products affected https://t.co/YFyRxNRdGe https://t.co/TlQZwuabZI	Link	3,586	Neutral	March 11, 2015
8	@CNN	Chipotle is closing all of its restaurants on Feb. 8 for a food safety meeting https://t.co/S1aqC6gVHx https://t.co/fXfpk6dipg	Link	3,191	Neutral	January 15, 2016
9	@DMVFollowers	Chipotle has closed 43 Restaurants after *E. coli* outbreak hospitalized about 19 customers. https://t.co/FlViJuRk2x	Image	2,449	Neutral	February 11, 2015
10	@ConanOBrien	My plan to defeat ISIS? Get them to eat at Chipotle	None	2,154	Negative	May 1, 2016

Discussion

The key goal of this study was to investigate the public response to a corporate crisis using the supervised machine learning approach. For this study, Twitter data about Company A's food-borne illness crisis between November 1, 2015 and March 31, 2016 was used. In particular, this study investigated the overall sentiments on Twitter toward the crisis, the evolution of sentiments during the crisis, the effect of corporate apologies on the sentiments, and the characteristics of Twitter users who influenced the sentiments. To achieve these aims, a computer model using the supervised machine learning approach was developed through a rigorous process of filtering, labeling and analysis of the sentiments of over 2.6m tweets about the crisis.

Overall, the findings show that: the overall sentiment of tweets specific to the crisis was neutral; promotions and marketing communication may not be effective in converting negative sentiments to positive sentiments; a corporate crisis drew public attention and sparked public discussion on social media; while corporate apologies had a positive effect on sentiments, the effect did not last long, as the apologies did not remove public concerns about food safety; and some Twitter users exerted a significant influence on online sentiments through their popular tweets, which were heavily retweeted among Twitter users.

First, the overall sentiment about the crisis during the study period was predominantly neutral. This is because the majority of tweets were either tweets from news agencies (e.g. CNN or *New York Times*) or tweets sharing news about the crisis that were devoid of personal comments. Our results show that the top 25 news media in our data sent 2,139 tweets about the crisis, which were retweeted 65,383 times by Twitter users. This study confirms that Twitter is a popular social media platform for sending and receiving news.

This finding has an important implication for companies that are in a crisis. First, companies should use social media such as Twitter and Facebook as official corporate news channels and frequently update them with any developments or plans about the crisis, and use them proactively. During the crisis period, Company A did use Twitter, but in a "reactive" or "defensive" manner. While the company's Twitter account answered questions from consumers and provided information or websites, it did not proactively discuss the crisis or announce its current actions and plans. During a crisis, consumers are concerned and anxious to learn more about the development, which leads them to voraciously consume news and actively share the news with others. News articles that report on the crisis are a good source of information, but they may not have the complete information or the perspective of the company. Moreover, some of the so-called news media on Twitter are not authentic news companies. For example, @SatiraTribune, an online news source, tweeted "Company A Selling $1 Burritos All Week To Regain Public Trust." Although the information was not true, the tweet was retweeted 6,769 times by users. Our data show that Company A did not take any action to correct the misinformation in this tweet.

Second, the results show that promotions and marketing communication may not be effective in converting negative sentiments to positive sentiments. This is similar to what happened to Target when they offered a 10 percent discount to US customers along with their apology for a data breach in 2014. The promotion instantly backfired and received severe criticism, creating the impression that the company was irresponsible and only interested in making profits (McGrath, 2014). According to reactance theory (Clee and Wicklund, 1980), consumers expect to enjoy the freedom to choose many alternatives in life, and when this freedom is lost or threatened, they tend to react negatively to the source of threats. Marketing efforts such as advertising and promotions are viewed as a "freedom-threatening influence attempt" (Clee and Wicklund, 1980, p. 389), as they aim to influence consumers' decision making. During or after a crisis, consumers' "resistance" to marketing efforts increases because: consumers are exposed to negative news about the company involved in the crisis and thus possibly develop negative attitudes toward the company (Kim and Atkinson, 2014);

and consumers expect the company to show more responsibility and commitment to solving the problems. Thus, promotional campaigns during a crisis may be perceived as attempts by the company to find a quick and easy way out of the sticky situation. This study suggests that a company in crisis should refrain from marketing efforts such as giving freebies, offering discounts or inviting consumers to promotional events. Even communication to consumers should be done with caution, so as not to create an impression that the company is more interested in seeking financial gains or "managing its image" than in solving the problems at hand. This suggests that a company that is going through a crisis should first and foremost focus on resolving the issue at hand.

Third, the results show that a corporate crisis drew public attention and sparked public discussion on social media. All crisis-related news and events such as the outbreaks, restaurant closures and violations of the health safety code by Company A drew much attention and generated negative sentiments. The results of this study confirm that social media, which are characterized by high speed and interactivity, provide concerned stakeholders with an avenue to share news and express concerns and feelings about a corporate crisis.

Fourth, the results indicate that while the two corporate apologies from Company A reduced the number of negatively charged tweets, the positive effects did not last long, as the apologies did not remove public concerns about food safety. The finding that corporate apologies have greater impact on mitigating negative sentiments than on boosting positive sentiments toward a company is consistent with past studies (Kim *et al.*, 2015; Park *et al.*, 2011). Company A used television and newspapers for delivering apologies to the public. Interestingly, these apologies did not generate much discussion on Twitter. This seems to suggest that TV and newspapers may not be effective media platforms for delivering apologies. Indeed, one Twitter user, @GregTrotteTrib, said in his tweet that the newspaper apology was the wrong choice for a generation that does not read newspapers. However, it cannot be ruled out that the TV and newspaper ads had an effect (positive or negative) on the audience of the TV or newspaper ad – the same audience need not have been active on Twitter. To reach the mass audience, traditional media platforms such as television and newspapers are still important. However, relaying that message on social media such as Twitter and Facebook is critical in creating more social discussion and amplifying the positive effects.

Finally, this study shows that the type of content, and who you are, matter. A close examination of the top 10 retweets in the data set revealed that the type of content and the size of the user's social network are critical in reaching Twitter users beyond one's own network. First, the content matters. Six of the top 10 popular tweets were written in a humorous or sarcastic manner (e.g. "My plan to defeat ISIS? Get them to eat at Company A") Malhotra *et al.* (2012) have suggested that humanized and personalized corporate tweets are more likely to be retweeted while Molyneux (2015) claimed that journalists tended to retweet humorous tweets more than non-humorous tweets. Similarly, Gurman and Clark (2016) reported in their quantitative content analysis of tweets about emergency contraception that humorous tweets were the second most popular tweets following tweets that shared the news. The use of sarcasm is also common on social media and tends to generate popularity. Sarcastic language is a type of verbal irony (Nunberg, 2001) that is deeply situated in the context of communication participants. Sarcastic tweets are often considered funny and thus frequently retweeted. In addition, tweets with an image, a video or rhymes were popular. As the 140-character limit on Twitter places constraints on users, Twitter users often add videos, pictures, stickers, memes, GIF animations, rhymes and other features to their tweets to overcome this challenge.

In addition, this study shows that the size of one's personal network matters. A Twitter user who had 1.71m followers was able to spread tweets in his or her own Twitter network fast and wide. Some previous studies (e.g. Harrigan *et al.*, 2012; Romero *et al.*, 2011) showed a weak correlation between a person's popularity and his/her ability to influence others on social networks. However, the results of this study show the opposite. The size of one's online social networks clearly has a significant impact on the reach and the velocity of diffusion of messages. Despite the claim by Jenkins *et al.* (2013) that "the influencer is one of the major myths of the Web 2.0 world" (p. 80), this study shows that an individual with large online social networks can be quite influential indeed. Hence, organizations should consider leveraging video, images and humor (where appropriate) as well as individuals with large online social networks to increase the reach and diffusion of their messages.

Limitations and future research directions

This study is one of the few studies that employed sentiment analysis using a supervised machine learning method in the area of corporate reputation and communication management. Using a data set of 2.6m tweets about a real corporate crisis, this study discovered important findings about evolving public sentiments toward organizations during a crisis. However, this study also has several limitations that warrant attention for those who wish to use sentiment analysis of big data.

First, as reported in other sentiment analysis studies using big data, coding and screening the data are a major challenge. Even with multiple training sessions (both individually and in a group) and an additional voting procedure (i.e. when there was a discrepancy in the coding of a tweet, three coders exchanged opinions and voted for the sentiment in each tweet), there were still some tweets that were not accurately coded for sentiment. For example, disappointment about not being able to eat Company A is a favorable emotion for the brand, as it indicates brand loyalty. However, in sentiment analysis, words such as "sad," "unhappy," "disappointment," or emoticons (i.e. a sad face) are coded as negative. An approach that can further distinguish this kind of negativity can help managers gauge sentiments about a brand more accurately. Moreover, future research can perform more in-depth analysis of tweets using aspect-based sentiment analysis, which allows one to predict the sentiment polarity of various aspects in a tweet (e.g. positivity toward price, and negativity toward food hygiene). Deep learning algorithms such as LSTM (Long Short Term Memory) networks can also be used to improve the accuracy of sentiment analysis.

Second, this study did not test for a direct relationship between Company A's apologies and online sentiment. To establish a direct relationship, the authors could have examined tweets that contained words such as "Company A apology, –ies, or –ized" after the company issued its apologies. However, this would oversimply the data by excluding tweets that mentioned the apologies but that did not contain the specific keywords in the tweets. So, the authors used the entire data set to gauge public responses to the corporate apologies, which included tweets that were not responses to the apologies. Future research that investigates the impact of corporate apologies on sentiment should use manual coding to include only specific responses to the corporate apology.

Third, there was a delay between the time social media users received the news and the time they responded to it. This may be due to time zone differences or to the time that they checked their Twitter feed. Time delay poses a significant challenge to the sentiment analysis of Twitter data, as it is difficult to interpret which peak (positive or negative) corresponds with which incident/s. For example, when there was a development of the crisis (e.g. the closure of Company A restaurants in multiple cities), there were tweets that were both immediate (i.e. within a few days) and much delayed (i.e. after several days). Therefore, when interpreting social media responses to a particular event, researchers and practitioners should expand the period under investigation.

Finally, this study focused solely on Twitter. As Twitter is simply one of many social media on which communication about the Company A crisis unfolded, the findings of this study may not be generalizable to other platforms (e.g. Facebook and Instagram).

Nonetheless, the authors believe that the findings from this study can be applied to other areas in business, such as consumer engagement and customer services to understand how strongly people feel about brands and products for specific issues (e.g. product recalls, new product releases or new brand endorsements). Governments can also use sentiment analysis of social media to gauge public emotions after big social and political events such as accidents, natural disasters or elections.

Conclusion

Understanding how stakeholders respond on social media to corporate crises as they evolve is critical to effective reputation management. In this study, the supervised machine learning approach to sentiment analysis was used to understand stakeholder responses to a corporate crisis. Using 2.6m tweets over a six-month period, this study offers valuable insights to both researchers and practitioners who wish to utilize big data to understand the online perceptions and behaviors of stakeholders during a corporate crisis.

Managing corporate reputation during a crisis is arguably more challenging than ever in a highly networked world. However, rather than being intimidated or stymied by the complexities of communicating on social networking sites, organizations can take comfort from the fact that many of the principles of reputation and crisis management are still relevant in the online world: do not leave an information vacuum; follow up on apologies with solutions; tread carefully with promotional communication; and so on. But they can also benefit from strategic engagement with influencers who have large networks and from storytelling that taps into emotions and images.

Notes

1. LIWC is a dictionary word-based, text-analysis program.
2. The sample was created strictly for labeling purposes. The final analysis included all tweets.

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Further reading

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Appendix

Subjective lexicon

Wilson *et al.* (2005) compiled a lexicon of over 8,000 subjectivity clues. Subjectivity clues are words that are used in a subjective expression. The authors used this lexicon to calculate a subjectivity score that is used to sort the tweets.

Subjectivity score

To calculate the subjectivity score, the authors defined scores for the polarity and subjectivity labels. There are four different types of polarity: positive, negative, positive and negative, and neutral. Each word also belongs to one of two types of subjectivity: strong subjectivity or weak subjectivity. The authors gave each polarity and type a score and computed the subjectivity score as follows:

$$\text{scorepolarity} = \{\text{positive} = 1,\ \text{negative} = -1,\ \text{both} = 0,\ \text{neutral} = 0\}$$

$$\text{scoretype} = \{\text{strongsubj} = 2,\ \text{weaksubj} = 1\}.$$

Given a tweet *t*, and each tweet *t* contains a set of words, $t = \{w1, w2, w3, \ldots, wn\}$, subjectivity score is defined as:

$$\text{scoresubjectivity} = \sum \text{scorepolarity}\ (wi) \times \text{scoretype}\ (wi) - (1).$$

Training data set

The complete data set was spilt into two sets: the training data set and the testing data set. The training data set was used to train the classifier while the testing data set (also called the holdout set) was used to test how good the classifier performed on various measures, such as accuracy, recall and $F1$ scores.

Tokenization

Tokenization is a process of breaking up a sentence into individual words or group of words that could be measured. For example, a whitespace tokenization method will tokenize the sentence "Tomorrow is Independence Day" into "Tomorrow", "is," "Independence" and "Day."

Top *K* features

A gap was observed between the training and test error scores, which indicated that the model was unable to generalize the pattern it was observing. Therefore, the mutual information algorithm (Peng *et al.*, 2005) was used to select the top 100 features from among all the features.

n-grams

There are various methods to create word features after a tweet has been tokenised. For example unigrams will produce "Tomorrow," "is," "Independence," "Day," while bigrams will produce "Tomorrow is," "is Independence," "Independence Day."

Word clusters

Owoputi *et al.* (2012) have compiled a 1,000-group hierarchical cluster with over 217,000 words. Each cluster groups similar words together under a label. The authors used labels as a feature for training the classifier.

F1 score

$$F1 = 2 \times (\text{precision–recall}) \div (\text{precision} + \text{recall}).$$

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