SOCIAL MEDIA ANALYTICS AND CORPORATE CRISSES - A CASE STUDY OF BOEING’S 737 MAX CRASHES

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SOCIAL MEDIA ANALYTICS AND CORPORATE CRISES - A CASE STUDY OF BOEING’S 737 MAX CRASHES

Research in Progress

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Abstract

Contemporary corporate crises demand conscientious communication efforts to save stakeholders and firms from preventable loss. Social media, in this regard, have proven to create a climate of high emotional volatility. Consequentially, firms travail to leverage social media in a way that reliably moderates negative emotions towards the firm and its actions. Underpinned by the assumptions of Situational Crisis Communication Theory (SCCT), this study presents a social media analytics approach that is applied to a case study of the US-based airplane manufacturer Boeing, which suffers from a corporate crisis due to repeated fatal crashes of their 737 MAX 8 model. Based on a dataset of 417,583 Twitter postings, preliminary results suggest that prevalent negative emotions amend in distinct crisis phases that differ in responsibility attribution. This study informs theory and practice by exposing emotional climates on social media that might serve as a decision aid for corporate crisis response.

Keywords: Social Media Analytics, Corporate Crisis Communication, SCCT, Boeing.

1 Introduction

Time and again, large enterprises have come under pressure, some of them facing severe corporate crises. In part, those resulted from second-order effects of natural disasters such as the COVID-19 pandemic but also risks peculiar to certain sectors and self-inflicted crises (Cheng and Lee, 2019; Stieglitz et al. 2019). Regardless of the cause, such instances require meticulous crisis communication addressing a variety of stakeholders by traditional PR channels and, with growing importance, social media (Cornelissen, 2013; Mirbabaie & Marx, 2019). In this context, scholarship deploying social media analytics (SMA) has focused on depicting a variety of data-driven case studies to observe how firms leverage their crisis communication efforts with social media. For instance, BP’s oil spill scandal yielded insights on how diminish and bolstering strategies fail on social media in absence of transparency (Mirbabaie et al. 2017). Domino’s Pizza, on the other hand, was able to quickly recover after a preventable crisis with emotional rebuild measures on social media (Veil, Sellnow, & Petrun, 2012). The diffusion of crisis-related content is thereby largely affected by the emotions associated towards a firm and its actions (Stieglitz & Dang-Xuan, 2013). Corporate crisis communication on social media, therefore, may have implications in both ways; it may enkindle even more incensement towards the company but, in other cases, it is able to promptly prevent a firm from further damage (Schultz et al., 2011). Recent studies, as a result of this uncertainty, have observed firms to be quite hesitant to actively follow a timely crisis response strategy on social media. In fact, the only pattern in their efforts can be
found in their inaction. Jong (2020) coined this strategy ‘acknowledge and await’, whereas Stieglitz et al. (2019) refer to it as ‘silence’. Especially in preventable crises with high attributions of responsibility and ongoing investigation, corporations seem to be reluctant to take action publicly on social media. A seminal model that aggregates relevant influence factors and response strategies of corporate crisis communication is Coomb’s (2007) situational crisis communication theory (SCCT). Although scholarship that builds on the assumptions made by SCCT has extensively covered different types of crises such as natural disasters, technical-error accidents, or organizational misdeed (Zheng et al. 2018; Barkemeyer et al. 2020), the ambiguity among scholars and practitioners about appropriate measures, their timing, and the role of the external emotional climate remains high. In this regard, this research aims to understand the role of emotions and how certain emotional climates develop during corporate crises by exhausting the possibilities of achieving (i) analytical depth and (ii) temporal breadth with regards to social media data scrutiny. With continuously refined analysis techniques, information systems research, and the field of SMA in particular, hold the potential to uncover hitherto-unknown and emerging mechanisms that determine the outcome of social media crisis communication. Our research questions read as follows:

RQ1: What emotions are prevalent in corporate social media crisis communication?

RQ2: How does the emotional climate concerning a corporate crisis develop over time?

To answer these questions, this paper presents an in-progress case study of the US-based aviation manufacturer Boeing, suffering from an ongoing corporate crisis. Within less than five months (2018-2019), two of Boeing’s 737 MAX aircrafts crashed due to a software error. We collected keyword-related Twitter communication following the crashes, resulting in a dataset of 417,583 postings. The application of a dictionary-based approach covering regular sentiment analysis and seven distinct emotions is set out to contribute to a deeper understanding of the mechanisms behind and temporal effects of emotionally charged crisis communication. Ultimately, our findings may extend the theoretical understanding of emotions and crisis response timing, which will add value to existing conceptions such as SCCT and inform practitioners about the management of appropriate actions to meaningfully leverage social media in times of crisis.

2 Theoretical Background

2.1 Dynamics of Corporate Crisis Communication on Social Media

The primary objective of crisis communication is to protect stakeholders from physical and psychological damage (Marx et al. 2018; Mirbabaie et al. 2020). Both can be sustained if stakeholders remain ignorant and do not obtain information. Thus, providing continuous information in a timely manner is crucial for a firm to manage a corporate crisis (Coombs, 2007). This may incorporate leveraging the social capital of individual profiles, e.g., through retweeting (Jöntgen, 2020). Once harm is averted, secondary objectives such as reputational damage limitation and rebuilding obtain priority (Schultz et al., 2011). This particularly applies to large-scale, globally acting firms, with a focus on business-to-consumer relations. Depending on the nature of the crisis and its advancement, different concepts become salient in the layout options of crisis communication. For instance, ad hoc incidents that require quick action and clarification are subject to accountability management, that is, the firm’s perceived accountability based on the interpretations within the social system in which the firm is embedded, and its attribution by the firm itself or others (Lerner & Tetlock, 1999). Crisis communication addressing the firm’s health in the medium term is mostly subject to reputation management, that is, measures to influence “a stakeholder's overall evaluation of a company over time.” (Gotsi & Wilson, 2001, p. 29). When considering the effects of corporate crisis communication in the long term, it becomes a matter of legitimacy management, that is, ensuring lasting resilience and the (re-)alignment with norms, values, beliefs, and definitions of the social systems in which the firm operates (Suchman, 1995).
Scholarship on corporate crisis communication seldom takes the temporal dimension into theoretical consideration. As a matter of fact, social media as a subject of research entices scholars to make conclusions about effects of crisis communication of a given firm on a basis of situational data that bank on an entirely different account. In other words, scholarship needs to consider that different types of social media data have valid explanatory power for distinct concepts such as accountability, reputation, or legitimacy. Whereas social media analytics methodologies have been applied to investigate emotional climates in different contexts (e.g., Wrycza and Maślankowski, 2020), this approach is rather underrepresented in the literature (Choi et al., 2020). Both social media algorithmic mechanisms and management decisions often foster rash reactions (Jong, 2020), which may cause the firm severe damage in case of misinformation or self-conflicting communication (Shpiro et al., 2011). Consequently, we equip this work with the theoretical lens of SCCT, which considers medium-term effects of social media crisis communication and was built around the concept of corporate reputation.

### 2.2 Emotions in Situational Crisis Communication

The *Situational Crisis Communication Theory* constitutes an often-applied model to theoretically inform scholarship on corporate crisis communication. It has been adapted in various contexts and improvements were made (Hegner, Beldad, & Kraesgenberg, 2016; Jin & Liu, 2010), particularly to cover the complexities of online communication, i.e. social media. Yet we refer to the original model as it reveals how, in the original and its extensions, emotionality is linked to crisis communication. In the original model, emotions are merely a product (rather than an outcome) of applied crisis response strategies. Figure 1 shows the relations within SCCT.

![SCCT Diagram](image)

*Figure 1. SCCT and the role of emotions (adapted from Coombs, 2007).*

As Vignal et al. (2018) point out, emotions may play an important role to inform the crisis response strategies that initially aroused them. Those strategies, divided by Coombs (2007) into denial, diminish, and rebuild strategies, we argue, may experience a significant enhancement in effectiveness when aligned to address the prevalent emotional climate in stakeholder communication. We refer to the term ‘emotional climate’ when speaking of a pervasive and inter-subjective form of emotionality, whereas emotions refer to individual and temporary moods (de Riviera, 1992). Coombs’ work originally builds on attribution theory to identify sympathy and anger as the most crucial emotions. This perspective, however, inevitably leads to the gridlocked dichotomy of positive/negative polarity that methodically translates to sentiment analysis, which is rather fragile on its own. To attain a significant contribution to theory and conceptual depth in analysing firm and stakeholder communication over time, we approach this matter with an improved approach to sentiment analysis and apply it to the recent and pertinent case of Boeing’s 2019 corporate crisis.
3 Research Design

This research examines prevalent emotions and their development over time in social media crisis communication. To this end, we follow a single case study methodology as outlined by Yin (2003) to explore contemporary corporate crisis. Our aim is to investigate the case of Boeing as a “bounded system [...]” over time, through detailed, indepth data collection involving multiple sources of information” (Creswell, 2013, p. 97). As for the gathering and analysis process of the data, we follow a Social Media Analytics approach that proposes a tracking, a preparation, and an analysis stage (Stieglitz et al. 2018).

3.1 Case description and data collection

Boeing is one of the biggest airplane manufacturers in the world, headquartered in Chicago (USA). In 2016, an adaption to their bestselling plane, the ‘Boeing 737 MAX 8’ had its maiden flight. A newly implemented software, the Maneuvering Characteristics Augmentation System (MCAS), caused two crashes of Boeing’s 737 MAX. The first incident occurred on 29th October 2018 near Jakarta, Indonesia, and claimed the lives of all 189 passengers (Tjahjono, 2019). The second crash took place on the 10th March 2019: an Ethiopian Airline’s plane crashed shortly after the start near Ejere in Ethiopia, with all 157 passengers dead (Abada, 2020). After the second crash, all Boeing 737 MAX were grounded by the Federal Aviation Administration (FAA), the governmental flight control of the USA. It was determined that both planes crashed because of erroneous data within MCAS (Johnston & Harris, 2019).

To obtain relevant data around Boeing’s resulting corporate crisis, we collected Twitter postings with an API-based tracking approach. Due to its timeliness, large user base in the US, and relevance for crisis communication as outlined in extant research (Stieglitz et al. 2019; Barkemeyer et al. 2020), Twitter was chosen as a valid data source. Data was gathered during the time period of April 18th and October 25th (2019) by applying a self-developed Java crawler using the Twitter4J library and a MySQL database. For Twitter, relevant tweets were filtered by using the keywords “Boeing”, “Boeing737” and “Boeing737MAX”. The keywords were chosen to retrieve all relevant data that may represent the emotional climate towards Boeing. Irrelevant postings, e.g., concerning planespotting, were deleted prior to the analysis phase. Moreover, all contents outbound (tweets, retweets) and inbound (@mentions) of the profiles “Boeing Airplanes” and “The Boeing Company” were included. The final dataset comprises 417,583 tweets.

3.2 Sentiment Analysis and Emotions

To assess the stakeholder emotions throughout Boeing’s corporate crisis, we fall back on automated text-mining techniques, as those are most appropriate to analyse the given social media data (Brünker et al. 2019; Brünker et al. 2020; Mirbabaie & Youn, 2018). Sentiment analysis, which is the basic technique, contents can be assessed on three levels: document, sentence, and entity and aspect level. With the document level, information can be provided about the entire document and whether it has positive, negative, or neutral connotations. At the sentence level, sentences are considered individually, so that the statement about the polarity per sentence can be depicted. The most finely granulated level is the entity and aspect level, in which individual words are given positive, negative, or neutral values (Kaur & Kumar, 2015).

We follow a knowledge-based approach, that is, the sentiments are perceived "as the average aggregate of the semantic orientations of its words and phrases" (Turney, 2006). Here, the sentiments are assigned on a scale from -5 to +5. To do this, our method rests on a lexicon-based approach. For example, the word "love" will have a high positive connotation of +5. To determine the sentiments, we use the open-source software SentiStrength and its lexicon (Thelwall, 2017). After the sentiment analysis is conducted, a positive and a negative sentiment-value is provided. Out of these values, we create two measures. First, polarity is the sum of the positive and negative sentiment-values. It enables us to identify the content as positive, negative, or neutral. Second, emotionality is the absolute value of the sum of the positive and the negative sentiment-values. It enables the author to identify expressed positive
and negative emotions. For example, contents can be identified as neutral (due to polarity), whereas a lot of emotions are used in this comment (due to emotionality). To determine the expressed emotions, we use a lexicon extension by Risius and Akolk (2015). In fact, this extension consists of seven dictionaries, each of them representing one emotion: fear, anger, depression (all positive); and contempt, affection, happiness, and satisfaction (all negative). Those emotions were chosen based on existing scholars, which suggests them as relevant for crisis communication (Choi and Lin, 2009; Jin et al., 2014; Weiner, 2006). Table 1 provides an overview and description of all seven emotions.

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Description</th>
<th>Emotion word</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valence  State</td>
<td>Description</td>
<td>Emotion word</td>
</tr>
<tr>
<td>positive</td>
<td>Affection</td>
<td>Genuine fondness and liking that is attributed to a particular person or object.</td>
</tr>
<tr>
<td></td>
<td>Happiness</td>
<td>Amplified enthusiasm and excitement about attaining something desired or desirable.</td>
</tr>
<tr>
<td></td>
<td>Satisfaction</td>
<td>Proud acknowledgment of and contentment with reaching a predetermined goal.</td>
</tr>
<tr>
<td>negative</td>
<td>Fear</td>
<td>Anticipatory horror or anxiety in unpredictable or potentially harmful situations.</td>
</tr>
<tr>
<td></td>
<td>Anger</td>
<td>Animated animosity towards male that can motivate rectification.</td>
</tr>
<tr>
<td></td>
<td>Depression</td>
<td>Impeding sadness evoked by an aversive event that may hinder activity.</td>
</tr>
<tr>
<td></td>
<td>Contempt</td>
<td>Revulsion to something considered socially offensive or unpleasant.</td>
</tr>
</tbody>
</table>

Table 1. Explanation of used emotion dictionaries (taken from Risius & Akolk, 2015).

As a first step to provide insights on the research questions of this research-in-progress paper, we determine peak phases of the corporate crisis. This approach is adapted from Stieglitz et al. (2019), who classify a day as a peak in communication if the postings per day are greater than standard deviation plus mean (peak > MAD + Mean). Due to the increased time span and multiplicity of events, we added the factor 1.74 to MAD + mean to a meaningful and manageable number of peak phases. Subsequently, we calculated polarity and emotionality for each emotion in our Twitter data and tested if they changed over time with a statistical analysis of variance. Subsequently, we present those changes over time in accordance with the previously defined crisis peak phases.

## 4 Preliminary Results

The distribution of tweets per day about and from Boeing ranges from 414 to 15,311 tweets per day. This includes retweets and @mentions. On the basis of our threshold, seven peak phases could be determined. Six of them occurred during the first half of the observed period (from 18th April to 24th July), one later peak occurs on 18th October. Two of the peak phases last more than one day (from 4th to 6th May and from 29th to 30th June). Thus, there are ten days identified as peak days. Figure 2 provides an overview of the peak phases.
Figure 2. Tweets per day including Boeing-related keywords over the data tracking period

To compute a variance analysis, the Kruskal-Wallis-test was found as suitable because the values for polarity are identified as ordinal- and emotionality as interval-scaled. Furthermore, the test contains more than two groups of data (one group for each emotion). Moreover, a significant Levene-Test showed that the data is not normalized. Table 2 shows the results of the Kruskal-Wallis-test.

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Df</th>
<th>Chi-square</th>
<th>η²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Affection</td>
<td>14</td>
<td>1080.1***</td>
<td>0.003°</td>
</tr>
<tr>
<td>Happiness</td>
<td>14</td>
<td>955.75***</td>
<td>0.002°</td>
</tr>
<tr>
<td>Satisfaction</td>
<td>14</td>
<td>2889.2***</td>
<td>0.008°</td>
</tr>
<tr>
<td>Anger</td>
<td>14</td>
<td>9019.1***</td>
<td>0.024°°</td>
</tr>
<tr>
<td>Contempt</td>
<td>14</td>
<td>5356.2***</td>
<td>0.014°°</td>
</tr>
<tr>
<td>Depression</td>
<td>14</td>
<td>27439***</td>
<td>0.072°°°</td>
</tr>
<tr>
<td>Fear</td>
<td>14</td>
<td>9311.2***</td>
<td>0.024°°</td>
</tr>
</tbody>
</table>

sign.: ‘*’ p>0.05; ‘**’ p<0.05; ‘***’ p<0.01; eff. size: ‘°’ no, ‘°°’ small, ‘°°°’ moderate, ‘°°°°’ large

Table 2. Results of Kruskal-Wallis-test of negative emotions and the effect size

The conducted Kruskal-Wallis-test points to significant changes of all emotions, both in polarity- and emotionality-values (see table 2). However, since the particular effect size eta-square (η²), based on the H-statistic (Tomczak & Tomczak, 2014), is neglectable (η² < 0.01) for the positive emotions, the significant chi-square must be handled with care. Moreover, all negative emotions have small effect sizes (0.01 < η² < 0.06), except “depression”, which has a moderate effect size (0.06 < η² < 0.14). When observing the development of the emotions over time, that is, which emotions were prevalent in distinct peak and non-peak phases, it is noticeable that the three positive emotions (“affection”, “happiness”,

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P1. Boeing shareholder’s meeting; P2. Boeing 737 emergency landing; investigations about MCAS become public; P3. Announcement of further FAA investigations about cracking wings; P4. New software issue occurred; P5. News about MCAS being programmed outside the US to save wages; P6. Report about economic losses; P7. Internal leak: Boeing has known fatal problem and tricked FAA wilfully.
“satisfaction”) remain rather similar over time, whereas the negative emotions (“anger”, “contempt”, “depression”, “fear”) have perceivable variations. Figure 3 shows a comparison of all seven emotions over time.

![Figure 3](image.png)

*Figure 3. Development of emotions (polarity) throughout the tracking period.*

The computed emotionality of the determined periods is similar to the polarity, but not displayed to avoid redundancy. Since the positive emotions have neglectable effect sizes (see table 2) and have just small changes of polarity (see figure 3) and emotionality values, one can conclude that negative emotions are prevalent over the course of the six-month period.

## 5 Discussion

The analysis of seven emotions uncovered that positive emotions such as “affection”, “happiness”, and “satisfaction” have significant differences but neglectable effect sizes in their development over time. In contrast, the negative emotions “anger”, “contempt”, “depression” and “fear” reveal significant differences and show small to moderate effect sizes. The development of the emotions over time clearly shows that negative emotions toward Boeing prevail. For instance, the negative emotion “anger” decreases over time. It is most distinct on June 27th, when media reports about a new software issue occurred (peak 4). Conclusively, “anger” is connected to the occurring software problem but is expressed to a very low degree when the focus shifts to another issue about the MCAS software. The emotion “contempt” exhibits a peak on June 3rd in polarity- and emotionally-values. This is connected to a statement of the FAA about ongoing investigations that point to the fact that the wings of Boeing’s 737 are likely to crack (peak 3). The peak in “depression” on July 24th can be explained with news about jobs that might be in danger and a report by Boeing about their losses, which resulted in high emotionality among Twitter users. Lastly, “fear” was most expressed between June 29th and 30th, when it became public that the erroneous software was programmed outside the US to save costs. Mapping the negative emotions to the specific peak phases of Boeing’s crisis, it becomes apparent that certain emotions emerge in distinct situations. For instance, “fear” has to be taken care of when information about external problems (low attribution) are revealed, whereas the same emotion is neglectable when internal problems (high attribution) occur.

In general, the most dominant emotions within the seven peaks are “anger” (four out of seven), “fear” (two out of seven) and “depression” (one out of seven). These findings are partly in line with existent literature, since Weiner (2006) already mentioned “anger” as an important emotion next to “sympathy”. Moreover, we were able to characterize this type of firestorm by disclosing the arrangement of emotions in such a case, which adds to Jöntgen’s (2020) work. With reference to SCCT, Choi and Lin (2009), too, stated that “fear” and “anger” are important emotions in times of crisis. Our preliminary findings...
provide useful evidence for subsequent work on theorizing the role of emotions in corporate crisis communication. The preliminary results of this paper indicate that the identification of prevalent emotions allows us to explore the relationship of emotions and response strategies. With the data on hand, we are able to identify the changes in polarity and emotionality resulting from measures taken by Boeing. On a conceptual level, this will inform SCCT and its extensions as it adds a backchannel to the relationship between emotions and response strategies (Coombs, 2007). This is based on the proposition that emotions exert an effect on the choice of crisis response strategies. In its current state, SCCT represents this relation only one-directional (see Figure 1). In connecting the emotions with appropriate (and disadvantageous) response strategies, the model will win additional depth by attributing a bi-directional role to prevalent emotions. Furthermore, knowledge about the emotional development of stakeholder communication over time provides fertile ground for new theory that incorporates additional outcomes additional to corporate reputation (Choi et al. 2020). In doing so, distinct response strategies may be developed that address accountability in the short term or, in case of prevalent emotions pointing to an accountability problem (Lerner and Tetlock, 1999); and strategies for long-term issues of corporate legitimacy (Suchmann, 1995). Such advancements in theory will translate to practical contributions once this research in progress paper is developed to a full study.

6 Conclusion and Next Steps

The paper on hand presents a case study about Boeing’s corporate crisis in 2019. To gather relevant data, we collected postings from Twitter, including communication about Boeing and the firm’s original responses and publications. So far, the communication on social media about Boeing has been analysed regarding prevalent emotions and their development over time. We found that negative emotions such as “fear”, “anger”, “contempt”, and “depression” towards Boeing are predominant. Moreover, we were able attribute single emotions to specific events throughout the crisis. Here, the emotions significantly differ in certain peak phases of crisis-related communication. The preliminary findings of this study point at a hitherto theoretically not considered function of emotions. In fact, we propose that emotions do not only result from response strategies, as suggested by SCCT, but may iteratively inform those strategies in specific crisis phases. This poses a useful contribution to existing theory and expands IS literature by giving account to the critical use of information systems such as social media during corporate crises. This research comes with limitations as a single case study is not suited for rigorous theorisation and generalisation. Nevertheless, its explorative and contemporary character may still expand our knowledge and pave the way for a multiple case study or grounded theory approach. Therefore, future research should realise a design that incorporates multiple angles as a basis to build full-fledged theory. Moreover, interviewing crisis communication experts in these particular cases will further enhance the breadth of data.

To complete this research, we perform four additional analytical steps. First, we manually code a subsample of the tweets to confirm the automated classification. Second, we determine the performed response strategies of Boeing by qualitatively assessing the contents authored by the corporate social media profiles. Third, we temporally match Boeing’s responses with the development of emotions about Boeing as presented in this paper. This will allow us to determine to what extend the responses were able to affect the emotions attributed towards the firm. Fourth, we will add YouTube as an additional data source. So far, we have collected 44,102 YouTube comments across 18 videos relevant to the 737 MAX crashes. This will allow us to compare the responses authored on Twitter (text-based) and published YouTube (text-based and audio-visual) to identify how different kinds of social media content trigger certain emotions in the context of corporate crisis communication. We will apply the same analytical measures to the comment sections of the YouTube videos and will compare the emotional climates with the ones we found in the Twitter data. Meta data of the comments and videos will also allow an analysis over time. For the video content itself we will apply a qualitative content approach to be able to identify response strategies (some of the videos are authored by Boeing), which will provide more insight about the emotion-response relationship proposed by SCCT. In performing these steps, we are confident to be able to report a case study that serves as a sentinel for crisis communication intelligence in increasingly turbulent times.
References


