Exploring the Social Broadcasting Crisis Communication: Insights from the Mars Recall Scandal

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Abstract

Social media has become a popular platform of interpersonal communication in which users can search for news and convey real-time information. This study aims to investigate and analyse how Twitter has been used by its citizens during a massive international product recall to share and convey information. Based on the SMCC model and the Crisis Response framework, this study proposes a new crisis communication research model, namely Social-broadcasting Crisis Communication (SBCC), and uses it to analyse the 2016 Mars product recall dataset which formed of 10,930 Twitter messages. The study finds that the overall attitude of Twitter citizens towards the scandal was negative; the Twitter platform has mainly been used to spread the repetition of information from news media and ask questions; and the information diffusion (retweeting) has positive associations with the number of followers and the use of Hashtags. The findings suggest effective methods for organisations to supervise crisis communication and protect reputational assets during a crisis event (e.g., to pay more attention to Twitter citizens who have a large number of followers and how to disseminate information to control rumour-related information).

Keywords: Social media, Social broadcasting crisis management, Crisis communication, Twitter mining

1. Introduction

With the advent of social media, the means of creating and sharing information have changed dramatically (Mangold and Faulds 2009). Social media, or consumer-generated media, has previously used as an online marketing tool (Neti 2011) mainly to improve brand awareness and reach customer needs (Malthouse et al. 2013; Li et al. 2017). In recent years, Social media (e.g., Twitter) is also an effective way to understand users' behaviours, emotions and attitudes (Dennis et al. 2009; Ma et al. 2019), particularly during crises (Roshan, Warren, and Carr 2016).

In food industry, there are a growing number of social media studies which have paid attention to crisis events (e.g., Casey, Hill, and Gahan 2011; Chunara, Andrews, and Brownstein 2012; Tse et al. 2018). Rutsaert et al. (2013) argued that social media is an appropriate platform to discuss the risk of food crisis events. Therefore, organisations involved in food crisis events can make appropriate response to inquiries and develop crisis communication strategies. This study selects one of the recent food quality crisis events - the Mars Plastic Scandal/Mars Recall Scandal to investigate the crisis communication. The scandal was a major food recall in 2016. It affected customers from 55 countries and made Mars lose tens of millions of dollars (The Guardian 2016). On Friday, 8 January 2016, a consumer in Germany found a piece of red plastic inside the Snickers he had purchased. After lodging a complaint about this, the plastic was retraced back to its production plant in the southern Dutch town of Veghel, where it was decided that the plastic derived from a protective guard utilised in the productive process. Mars then made an announcement on 23 February 2016 to recall its products around the world due to the concern about its customers choking on the plastic again. There were various products affected, such as Milky Way, Snickers, Bars of Mars, Mini Mix and Celebrations (The Guardian 2016).

Twitter, as a popular social media platform, has a total number of 1.3 billion registered users, with approximately 326 million of them are monthly activated (until 12/2018) and the number is still growing fast. The platform offers to search for news, convey real-time information and plays an important role in crisis communication (Heverin and Zach 2010). Organisations have now learned to use information obtained from this platform to reconsider their crisis management strategies and policies, but also facing challenges such as providing in time response and controlling rumour-related information spread (Wendling, Radisch, and Jacobzone 2013). This study aims to investigate how Twitter has been used by its citizens during a massive international product recall to share and convey information. Following are the research questions:

- RQ1 What information was shared by Twitter citizens during the 2016 Mars Plastic Scandal/Mars Recall Scandal?
- RQ2 What were the most common concern regarding the recall? Were there any prevalent topics or contents?
- RQ3 What was the sentiment towards the recall? Were there any patterns of communication and information diffusion?

The study follows preliminary research on the project (Ma et al. 2018) and has the following important theoretical and practical contributions. First, it intends to bridge the current research gap to give useful insights into the crisis communication and respond to the recent research call in the field to study the Twitter communication channel in international crises (Roshan, Warren, and Carr 2016). Second, this study provides new insights to the Situational Crisis Communication Theory and proposes a revised Crisis Communication Model based on the Social-mediated Crisis Communication model and the Crisis Response Framework. Third, the study demonstrates an effective method to capture and understand public expectations during crisis events.

The study is organised as follows: Section 2 reviews the literature on social media big data and crisis management research within the social media context. Section 3 explains the data capture and analysis process. Section 4 presents the study results and implications. Finally, the conclusions and recommendations for future research are presented in Section 5.

2. Theoretical Background

2.1 Twitter data in Social Media research

Social media is defined as web-based platforms which allow individuals to 'construct a public or semi-public profile within a bounded system; articulate a list of other users with whom they share a connection; and view and traverse their list of connections and those made by others within the system' (Boyd and Ellison 2007, p219). Although social media is a relatively emerging research area, because of its rapid growth, it is at the top of the agenda for many business executives (Kaplan and Haenlein 2010) and academia (Fuchs 2017). Social media employs mobile and web-based technologies to create highly interactive platforms makes the world borderless, which to a large extent facilitates the communication of users (Kietzmann et al. 2011). This phenomenon connects people from over the world and derives social big data (Rainie and Wellman 2012).

Ishikawa (2015) defines social big data as 'the large amounts of data that are produced every moment in various fields, such as science, internet, and physical systems'. They can be collected, stored and analysed (Xu and Duan 2019), hence they are readily used (Boyd and Crawford 2012; Singh 2019) for research in various disciplines (Buccafurri et al. 2015), such as politics (Kruikemeier 2014), sociology (O'Keeffe and Clarke-Pearson 2011), pedagogy (Dabbagh and Kitsantas 2012), business management (Kim and Ko 2012) and supply chain management (Tse et al. 2016). Social big data are produced directly by individuals (Agrawal et al. 2011) and can be captured from social media site distributors and collected manually (Tufekci 2014). This is almost an effortless method which is in contrast with the conventional data collection methods (e.g., interview and survey), but can generate big impacts (Chen, Chiang, and Storey 2012).

Twitter is a social media networking site (Kwak et al. 2010) with a retweet mechanism to produce enormous amounts of data per day (Claster, Cooper, and Sallis 2010). It creates an interactive online platform for users to engage in information collection and distribution (Maleszka 2018). Common features of Twitter include: ‘Twittering’ – to share short posts (or tweets) within the 280-character limit (used to be 140); ‘Following’ – to follow other Twitter users (or followees); ‘Retweet’ – to share the tweets posted by the followees; and ‘Update’ – to share new posts (or new tweets) based on the current one (Jansen et al. 2009).

Twitter, as a proxy for interpersonal relationships (Li and Li 2014), allows users to follow others and are followed freely (Java et al. 2007) and uses a hash sign (# hence Hashtag) to tag a keyword to disseminate information (Lee, Agrawal, and Rao 2015). Hashtags can be used to label keywords or hot topics which describe a tweet, aide in search and organise discussion around specific topics or events (Small 2011). The use of Hashtags can help to search for messages more quickly, therefore, it increases the number of retweets and help to spread the messages. Many have used Twitter to disseminate information (Roshan, Warren, and Carr 2016; Stewart and Wilson 2016), especially during sudden crises (Helsloot and Groenendaal 2013; Tse et al. 2016).

2.2 Crisis Communication within the Social Media Context

Crises can be seen as events which cannot be predicted, but significantly threaten stakeholders' expectations. They have strong impacts on organisations' performance and could have long-term negative effects on organisations' reputational assets (Jin, Liu, and Austin 2014). Technical advance has revolutionised the way of viewing, broadcasting and interacting with communities affected by crisis events, especially for relevant stakeholders (Veil, Buehner, and Palenchar 2011). As emphasised by Hui et al. (2012), crisis events and disasters related information could be transmitted, spread, and cascaded from one to another rapidly in online social networks.

According to Coombs and Holiday (2011), crisis communication is the method to collect, process and disseminate information to address a crisis situation. Previous studies have developed communication strategies and guidelines that can be utilised during crises to develop response (Coombs 1995, 2007), protect reputation and repair reputational damage (Birkland 1997; Benoit 1995; Fishman 1999). They were later revised and become the Situational Crisis Communication Theory (SCCT) which became an evidence-based framework to model different crises and maximise protection of reputational affected by post-crisis communication (Coombs and Holladay 2002; Coombs 2007). This theory has been tested empirically in recent case studies (Claeys, Cauberghe, and Vyncke 2010; Sisco, Collins, and Zoch 2010).

As the recent increased use of social media for risk and crisis communication (Freberg, Palenchar, and Veil 2013; Austin, Fisher Liu, and Jin 2012), more and more people prefer to voice and obtain crisis information online and they perceive the source from social media is more up-to-date and credible (Procopio and Procopio 2007). The 'large amount of fragmented and user generated contents' (He, Zha, and Li 2013, p464), have however, made the channel for crisis communication far more complex (Coombs 2014). This has made many organisations to face new challenges in managing responses to stakeholders during crisis events (Schultz, Utz, and Göritz 2011; Freberg, Palenchar, and Veil 2013). As Freberg et al. (2013) indicated, in social media, the focal companies are no longer the only influencer, but, there are peripheral stakeholders that can also gain legitimacy and become new influencers by creating and propagating crisis information. Thus, organisations are expected to act in time to demonstrate their participation to reduce stakeholders' anger and aversion emotions (2014), but this means the requirements of new methods and enhanced leadership skills to collect and handle crisis information (Gruber et al. 2015).

Therefore, the traditional SCCT needs to be updated (Roshan, Warren, and Carr 2016) to guide the new development of crisis responses in the realm of social media (Freberg 2012). Based on SCCT, new models, such as the Blog-mediated Crisis Communication model (BMCC) (Liu et al. 2012; Jin and Liu 2010) and its variant the Social-mediated Crisis Communication model (SMCC) (Austin, Fisher Liu, and Jin 2012), are developed to handle the more complex crisis information on social media platforms. The SMCC model divides the social media citizens into three groups, they are (a) influential social media creators who create crisis information directly for (b) social media followers and indirectly for (c) social media inactives. More recently, Roshan (2016) proposed a Crisis Response Framework which have detailed the different types of information and response strategies organisations should provide and adopt for the stakeholders during the crisis event. This study incorporates the social media citizens from the SMCC model and the types of crisis information from the Crisis Responses Framework to propose a new research model. As illustrate in Figure 1, the research model has three Social Media Citizens (a, b and c), namely the Organisation, the Traditional Mass media and the Social Media; in which the Organisation will (1) provide status update about the crisis to the Social Media Citizens and the Medias, and (2) reply messages to the Social Media Citizens (a, b and c).

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Insert Figure 1 here.

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3. Analysis

This study follows a four-step Tweets Analytic Framework to analyse the collected Twitter messages. A similar framework has been developed and used in recent works to study crisis communication (Tse et al. 2016; Tse et al. 2018; Ma et al. 2018). As illustrated in Figure 2, the framework in this study has four steps, they are Tweet Data Preparation (to collect and refine data), Descriptive Analysis (to identify key information and diffusion), Content Analysis (to create key topics) and Sentiment Analysis (to comprehend the motive behind the tweets). The QDA Miner software package is selected and employed based on it is extensive features on exploring textual data (Mostafa 2013; Roberta Pereira, Christopher, and Lago Da Silva 2014).

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Insert Figure 2 here.

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3.1 Tweet Data Preparation

This step is a prerequisite for later analyses and involves techniques to retrieve overview information from each 140-character tweet. The dataset is first captured and refined. The dataset used in this research represents the entire set of the Twitter posts related to the recall incident for a span of the 10-day period (23/02/2016-03/03/2016) following the product recall announcement made by Mars Inc on 23 February 2016. All tweets must contain at least either “Mars recall” or “Snickers recall” and written in English. This sampling strategy may capture tweets that are originated from any countries (Takahashi, Tandoc Jr, and Carmichael 2015) but avoid complications related to multilingual tweets analysis (Thelwall, Buckley, and Paltoglou 2011). The tweets are then filtered with Hashtag (#) and Mentioned (@) for later analyses. The final dataset contains 10,930 tweets which are sent from 55 countries. Prior to the analyses, these tweets are then tokenised to break up sentences into discrete words (e.g., identify meaningful keywords and remove punctuation) and normalised to stem (e.g., convert 'chocolates' into 'chocolate') and remove stop words (articles: e.g., 'a', 'an', 'the'; prepositions: e.g., 'this', 'that', 'these', 'those'; and personal pronouns: e.g., 'I', 'me', 'you', 'it') (Liau and Tan 2014). Other high frequency but meaningless words (e.g., HTTP, HTTPS, RT, etc.) are also removed (Tse et al. 2016) and common misspellings are carefully corrected (e.g., 'chocolete' instead of 'chocolate'). The statistics of the dataset used in this study is illustrated in Table 1, there are 17,423 sentences or 155,507 words from the 10,930 tweets, which are on average 9 words per sentence. In addition, the number of the tweets that include Hashtag is 3,367, URL is 9,207, Mentions is 4,648 and Retweet is 3,725.

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Insert Table 1 here.

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3.2 Descriptive Analysis

The descriptive analysis aims to identify the information shared by the Twitter citizens, their patterns of communication and diffusion. It has three analyses: word categorisation, word counts analysis, and regression analysis.

3.2.1 Word categorisation

A text categorisation is performed to explore the use of the word patters in the dataset (Mostafa 2013). QDA Miner's WordStat Dictionary (Provalis Research 2018), which combines negative and positive words from the Harvard IV dictionary, the Regressive

Imagery Dictionary (Martindale 1975) and the Linguistic and Word Count dictionary (Pennebaker, Francis, and Booth 2001), is employed to identify the word pattern. Table 2 shows the result of word pattern categorisation, in which over 95% of the tweets include words in negative pattern and they are accounted for almost 40% of the included words. In contrast, only 27.06% of the tweets contain words in positive pattern which are about 9.29% of the included words. The rest of the 51.24% included words are no pattern and categorised as 'to be ignored'.

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3.2.2 Word counts analysis

The frequency of word appearance is performed to identify the importance of the words in the dataset. Analysing the frequency of appearance of words may capture important information (Tse et al. 2016; O'Leary 2011). This study uses frequency of appearance to measure some popular contents, they are listed in Table 3: top 3 Hashtags, Mentions and Retweets.

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TF-IDF is employed to measure how important a word is to a tweet in the dataset. TF-IDF is the product of term frequency (or TF – the frequency of a word appears in a tweet) and inverse document frequency (or IDF – the frequency of tweets in which the word appears) which computes the frequency of word appearance (Sohrabi and Akbari 2016). The method weights a word important if it appears many times in a tweet. As illustrate below, for a word w in a tweet t, the weight Ww,t is given by:

$$Ww,t = TFw,t \log(N/DFw)$$

Where TFw,t is the number of appearance of word w in tweet t;

DFw is the number of tweets containing the word w; and

N is the total number of tweets in the tweet dataset.

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Analysing the frequency of appearance from the Table 4, the trending words such as “BARS”, “CHOCLOLATE”, “PLASTIC” and “GERMAN” are among the highest frequency of word appear in the incident. They may provide interesting information to highlight the “MARSRECALL”. Other trending words include the affected product lines “MILKY”, and the most mentioned “COUNTRIES” affected by the recall, such as “GERMANY”, “UK” and “NETHERLANDS”.

3.2.3 Regression analysis

In order to determine the retweeting behaviour in the Mars recall scandal, two hypotheses are formulated and illustrated in the hypothesized model in Figure 3, namely (H1) the number of followers and (H2) the use of Hashtag could contribute the information diffusion. Three control variables are also considered, they are the URL usage, Sentiment Score and Mention

Usage.

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Insert Figure 3 here.

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The following example shows how this information is extracted:

@SNICKERS does this affect us in the States? Asking for uh "friend" German recall of Mars and Snickers bars" https://t.co/pJx4CswP30 #news

(1) Number of followers: the measure can be found on Twitter
(2) Number of retweets: the measure can be found in each tweet
(3) Use of Hashtag: coded as 1, the tweet has one hashtag (i.e. #news)
(4) URL usage: coded as 1, the tweet has a link
(5) Mentions: coded as 1, the tweet has mentioned Snickers (@SNICKERS)
(6) Sentiment Value (SentiScore): SentiStrength for this tweet is -1

Prior to the regression analysis, the following Table 5 provides an overview of the potential interrelationship among the above variables:

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To understand the determinants of user's retweeting behaviour, a logistic regression is applied. The results of the logistic regression can be found in Table 6, the *Cox-Snell R*2 (i.e. 0.585) indicates a good model fit and the model supports both hypotheses. Thus, the usage of the Hashtag (H1, $p<0.001$) and the number of followers (H2, $p=0.042$) are significant determinates of retweet, which suggests that the use of the Hashtag and the number of followers can significantly and positively impact on the retweeting behaviour. This study also finds that the sentiment value was negatively associated with the diffusion of tweets ($p<0.05$).

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3.3 Content analysis

The content analysis aims to associate the trending words to create topics from the tweet dataset. It has two steps: keyword association and Multi-Dimensional Scaling.

3.3.1 Keyword association

Based on the results of above frequency analysis, some of the trending words are further analysed to look for their interrelationships. Figure 4 illustrates the top keywords frequency of appearance associate to recall. They are used to support the analysis of Multi-Dimensional Scaling.

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3.3.2 Multi-Dimensional Scaling

The co-occurrence of the trending keywords is grouped to create meaningful topics by using Multi-Dimensional Scaling (MDS) (Taboada et al. 2011; Péladeau, Dagenais, and Ridde 2017) which is a classic dimensional reduction technique to discern structure among data points (Clarke, Fokoue, and Zhang 2009). Jaccard's Coefficient of Similarity (Dunn and Everitt 2012) is applied as the index of co-occurrence to identify underlying dimensions that can explain the majority of the variability (Luchman, Bergstrom, and Krulikowski 2014). As illustrate below, for a word w, the Jaccard's Coefficient of Similarity $J(w)$ is given by:

$$J(w) = [a/(a + b + c) \times 100]$$

Where a is word w's number of occurrence in both tweets;

b is word w's number of occurrence in the first tweet; and

c is word w's number of occurrence in the second tweet.

A matrix of distances between the trending keywords are illustrated in Figure 5, in which the circles indicate the clustered major keywords of the dataset and the distances between the circles indicate the strength of the association. Hence, the closer the circles, the higher the tendency of co-occurrence and vice versa. From the 2D MDS map, some meaningful topics are illustrated by the clustered keywords and illustrated in Table 7.

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3.4 Sentiment analysis

The sentiment analysis is applied to comprehend the motive behind the tweets. It first uses the lexicon-based classifier to systematically understand and interpret the semantic orientation towards the recall incident, a timeline is then added to investigate the tweet distribution over the 10-day period.

The study adopts the SentiStrength (Thelwall et al. 2010) and employs Hu & Liu's (2004) sentiment lexicon to classify the sentiment expressed in the tweets. SentiStrength is a popular freeware with high human-level accuracy performance for sentiment detection (Saif et al. 2016; Hopp and Vargo 2017). As illustrated in Table 8, it involves the use of a sentiment lexicon to capture polarity (positive or negative sentiment) and explain strength on a scale of 1 (no sentiment) to 5 (very strong sentiment). It has been successful applied in recent studies to extract sentiment from social media texts (Ibrahim, Wang, and Bourne 2017; Gao, Berendt, and Vanschoren 2015). Hu & Liu's (2004) sentiment lexicon contacts 6,800 words (2,006 positive and 4,783 negative semantic orientation). It is publicly available and has been previously tested (Gilbert 2014; Tse et al. 2016).

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Insert Table 8 here.

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The following examples showcase the binary score and scale sentiment score of the tweet:

- *'Hey Chocolate lovers!'* [sentence: 5, -1], [scale result: 4]
- *'Devastating Recall Shock for Chocolate Giant Mars'* [sentence: 1, -5], [scale result: -4]
- *'This is very worrying!'* [1, -5], [scale result: -4]

In the first example, the rationale is: Hey [2], chocolate [proper noun], lovers [4], ![+1 punctuation emphasis], hence [sentence max: 5, -1] [scale result: 4 (sum of pos and neg scores)]. In the second example, the rationale is: Devastating [-5] Recall [proper noun] Shock

[-2] for Chocolate [proper noun] Giant [proper noun] Mars [proper noun], hence [sentence max: 1, -5] [scale result: -4]. In the third example, the rationale is: This is very [-1 booster word] worrying [-4]! [-1 punctuation emphasis], hence [sentence max: 1, -5] [scale result: -4].

From the results of the SentiStrength classifier, the overall average sentiment score of the Mars Scandal tweets is -0.26169 which indicates a negative attitude towards the recall incident.

3.4.1 Time series analysis

This section is to further investigate the tweet distribution of the recall scandal over time, a 10-day timeline is added to the above sentiment classifier, and a time series analysis is employed to compare and contrast the numbers of the tweets and their sentiment scores captured in different time. The 10-day period (23 February to 3 March 2016) is broken down into a half-day manner (am/pm) to study the variations in the popular topics and sentiment. Hence, the original dataset is separated into 20 sub-datasets for the time series analysis in Figure 6.

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4. Results and Implications

4.1 Descriptive Analysis

From the results of word pattern categorisation in Table 2, the tweet dataset contains over 95% words are categorised in negative pattern. The more frequent negative words may suggest a strong negative emotion is driven by the recall scandal. It also provides evidence to justify the negative sentiment scores in the later analysis.

The dataset contains 3,367 Hashtags and the top most popular Hashtags, as illustrated in Table 3, are highly relevant to the topic of product of recall, they are #Marsrecall (n=582), #Recall (n=407) and #Snickers (n=272). Other high frequency Hashtags are linked to the names of countries such as #Singapore (n=59), #Netherlands (n=49), #UK (n=36) and #Germany (n=23). According to the news media, they are the most affected locations - the scandal is triggered by a report from a German customer, the products being recalled are made in the Netherlands (Bhushan 2016) and sold in Europe like the UK (FSA 2016), as well as the duty free shops in Singapore (Baker 2016). It is also interesting to note that the tweets (i.e., @BHFWoking Mars recall got you thinking? Time for a #Dechox! #Wokinghour) with #DECHOX (n=38) have received high attention. This can be interpreted as some Twitter citizens have used the massive recall incident to gain publicity, in this case, to promote a campaign to 'have a detox from chocolate'.

From the frequency of appearance analysis in Table 4, the trending words with the highest word count are "BARS", "CHOCLOLATE", "PLASTIC", "COUNTRIES". They are different to that of the hashtags, but they cover the same shocking news titled 'Mars recalls chocolate bars in 55 countries after plastic found in product' (The Guardian 2016). Other high frequency keywords include "MASSIVE", "WIDENS" and "BIGGEST", they highlight the magnitude and severity level of the impact. A list of location is also found which seems to coincide with the analysis of hashtags. They are "GERMANY", "UK", "NETHERLANDS", "EUROPE", and "SINGAPORE". Moreover, some names of the product lines are also extracted. In fact, besides Mars and Snickers (they are the keywords for searching), "MILKY" (Milky Way) and "CELEBRATIONS" are also in the recall list (The Guardian 2016).

When assessing the indicators of the tweets credibility (O'Donovan et al. 2012), most (n=9,487) tweets contain either URLs or have used Mentions (@) when tweeting, only about 12.7% (n=1,443) tweets from the dataset contain information but without mentioning a source (no Mentions and URLs). The top three most mentioned accounts are @MarsGlobal (n=232),

@ITVNews (n=194) and @Haveigotnews (n=151). This could indicate a high credibility of the tweets in the dataset.

The information diffusion is also assessed. The results in Table 6 seem to agree with the previous findings that the spreading of the tweets can link to the use of hashtags and the number of followers (Lee, Agrawal, and Rao 2015). In this study, the most retweeted messages are from the traditional mass media. Many news medias have millions of followers and their broadcasted news messages have been retweeted many times, such as @ITVNews (n=194), @Independent (n=124), @Newsweek (retweet n=109), @AFP (n=89). However, tweets from some (Twitter Verified) celebrities' account have also been retweeted. For instance, a tweet from @Haveigotnews (After issuing a product recall, Mars insist the plastic found in their chocolate is still better than the toys found in Kinder eggs.) has been retweeted 150 times and from @Davidschneider (Mars. Don't recall your Mars Bars. Simply offer any child who finds a "plastic ticket" a free Wonka-style tour of your chocolate factory.) has been retweeted 119 times respectively. These tweets are intended to be funny (Roshan, Warren, and Carr 2016), but risk communication managers are advised to pay attention to this type of tweets, as they also could contain rumour-related information (Branicki and Agyei 2015; Lee, Agrawal, and Rao 2015).

4.2 Content Analysis

Prior to the classic MDS technique, the high frequency words that associated to the "RECALL" and the two affected products "MARS" and "SNICKERS" are compared. These distinctive words are then analysed to identify clusters. Four clusters of words are found to have high co-occurrence. They are further analysed for meaningful prevalent topics.

The focal group of words in the dataset is to provide information about the recall. It contains relevant facts and news broadcasted by the traditional mass media. As seen in the groups 'The Recall' in Table 7, it has popular words like "CHOCOLATE", "BAR", “PLASTIC” and “Netherlands” to convey information about the outbreak of the recall and source of the problem. Other words in this group are used to further explain the impact of the recall such as “BIGGEST” in “HISTORY” and “CHOCCY HORRY”, and the development of the recall: the “MASSIVE” and extended to “55 COUNTIRES”. In group ‘Affected Items and Areas’, it has the names of product lines to be recalled and the affected areas. These topics are most active and have heavily retweeted. It seems that Twitter in this study has been used as a place to find source of information and spread news. This disagrees the finding by Helsloot & Groenendaal (2013, , p182) that ‘Twitter mainly is a channel for sharing speculations, emotions and questions’. A possible reason is that their study was to look at a different type of crisis case (i.e., the Moerdijk fire) which has a smaller scale (in terms of likelihood of that happening and affected location) but more sudden and severe damage. While this study is to investigate a product quality recall which is relatively less catastrophic but has impacted a broader area, hence there is a wider population need to adapt information.

Moreover, some topics are to offer suggestions and give feedback. In group ‘Expected Actions’, it has popular words include “CONTACT”, “CARE” and “TEAM”; “REMOVE” and “SHELVES”. They could imply the Twitter citizens have expected the firm to immediate remove all products with potential risk from shelves and prepare to provide support. In Group ‘Recall Consequence’, the keywords of “CHILD”, “FREE” and “TOUR”, is about a suggestion to offer a free tour for those children who can identify the plastic in the chocolates. However, from the trending words of “COST”, “FIRM”, “MILLIONS”, some Twitter citizens could be behind the pleasure (schadenfreude), as they are even interested in the firm’s financial losses as a result of the product recall. For risk managers, this kind of information could be used to identify the affected customers (when they contact the care team) and understand their needs and expectations (Sommer et al. 2011), hence can improve the preparedness and quality of response (Wendling, Radisch, and Jacobzone 2013). Such interactions with customers could also help to rebuild company reputation and brand image (Ibrahim, Wang, and Bourne 2017).

Tweets to ask questions or intended to make jokes/be funny (Tse et al. 2016; Helsloot and Groenendaal 2013) are also found from the dataset, but their words have relatively low co-occurrence, hence, no major topics can be developed. However, the risk managers may still obtain useful information from these tweets to develop response strategies, particularly from those who have mentioned the organisation's official Twitter account @MarsGlobal, such as '@MarsGlobal Is Switzerland as well affected from the callback in Germany?'; '@MarsGlobal So what do we do if we have eaten some already?!' and '@MarsGlobal, why can't shops refund the recall products? Having to send back seems unfair, too much effort for what it's worth really.' However, not all of these questions are replied in the dataset.

4.3 Sentiment Analysis

Looking at the results of time series analysis in Figure 6, the popularity of the tweets about the Mars plastic scandal peaked on the 23 February with 5,533 posts. This could be the result of the responses to the large scale product recalls announcement made on that day (The Guardian 2016). This was then followed by a downward trend with an erratic pattern, but a sudden increase can be observed on the 25 February. This could be the reactions of another wave of news press release to indicate the recall could also affect countries outside Europe, such as the news to confirm by Singaporean authority (Tan 2016). Therefore, in this study, like that have been mentioned in previous studies (Kwak et al. 2010; Gupta, Lamba, and Kumaraguru 2013) – Twitter is a prominent news source, the exponential growth in the number of tweets may have linked to the news release. However, risk managers are advised to carefully monitor and question the credibility of the widespread form of the news information (Castillo, Mendoza, and Poblete 2011), especially during the emerging crises (Mendoza, Poblete, and Castillo 2010), as false/fake news is more likely to be retweeted and propagated (Vosoughi, Roy, and Aral 2018).

From the results of the SentiStrength classifier, the strongest negative sentiment tweets (-4) are those captured in AM of 24 February 2016 - the day after Mars Inc. announced its globe product recall. the average sentiment value of the Mars Scandal is negative (-0.26169), which is supported by the word pattern categorisation. However, the distribution of sentiment scores falls between the band of circa -1/+1 which can be an indication that some tweets are not very affective (Mostafa 2013). This is consistent with the MDS result, where most of the tweets have been used to spread the news about the recall rather than expressing negative personal feelings. The tweet sentiments are also time sensitive and show temporal patterns, as the scores captured in AM (-0.127) is generally stronger than those in PM (-0.069) over the ten-day period. This result seems to be consistent with previous research that stress and negative emotion can affect tweet sentiments (Wang et al. 2016), and negative sentiments are more likely appeared in the morning possibly due to the morning stress and feelings of early morning anxiety hence suffering mood swings (Cao et al. 2018). Therefore, choose a right time to engage with Twitter citizen and release information could have less impact on the tweet sentiment hence avoid a social media crisis.

4.4 Social-broadcasting Crisis Communication Model

Based on the forgoing results, the proposed model in Figure 1 is revised and named as the Social-broadcasting Crisis Communication (SBCC) Model. As illustrated in Figure 7, the SBCC model has two influential social media creators to broadcast information during the crisis events. They are (a1) the news medias (to broadcast news on social media platforms) and (a2) the social media citizens with a large number of followers (e.g., Social Media Verified celebrities). These are the two main information source risk managers need to carefully monitor, as their information is more likely to be retweeted and propagated. The

SBCC model also contains other less active citizens: (b) the followers who would mainly retweet information from their followees (i.e., a1 and a2); and (c) the inactives who mainly use the platform to obtain information from the organisation or the News Media Webpage. The model highlights the importance of risk communication and engagement between the Organisations and other social media citizens during a crisis event. The Organisation needs to have more interactions with all social media users to not only (1) provide information and (2) reply queries, but also (3) capture expectations and (4) control rumour-related information.

………………………………………………………………..

Insert Figure 7 here.

………………………………………………………………..

5. Conclusions

Social media produces large amounts of data from a variety of sources (e.g., Twitter) making it difficult to grasp and analyse during crisis events. This study proposes a new crisis communication research model - the Social-broadcasting Crisis Communication (SBCC) Model that is based on the previous the SMCC model and the Crisis Response framework to analyse a tweet dataset which contains the 2016 Mars recall information. The new SBCC Model can help to provide insights for organisations to better understand public expectations on social media during crisis events and how risk information is formed and diffused. These insights include key topics and areas and the change of the sentiments during the crisis. In this study, the Twitter citizens are appeared to be rather rational about the Mars recall scandal and the Twitter platform has mainly been used to spread the repetition of information from news media and ask questions. These results agree with some previous studies (Ma, Tse, and Zhang

2017; Tse et al. 2016) that consumers would search for news and convey information on the internet in risk emergence. From the SCCT theory, consumers' expressions are also likely to affect an organisation's reputational assets and have long-term effects, as tweet messages can contain rumour-related information (Branicki and Agyei 2015; Lee, Agrawal, and Rao 2015) and be used for sharing speculations (Helsloot and Groenendaal 2013). The SBCC model help provide useful information on which accounts and content have the most influence. It is significant for organisations to understand the sentiment behind tweets and supervise those of a negative sentiment to avoid propagating negative messages, which is an indispensable to the successful crisis communication.

This study further explores reasons why certain information can spread more widely than others. The study finds that with the use of Hashtags and have large number followers, like the accounts of the news medias and some celebrities, the tweet information is likely read by more followers, thus, the chance of retweeting is also increased. Therefore, these factors play crucial roles in estimating the number of retweets and predicting the spread of information. Managers in public relation and social media department may get insights from our model when they are establishing their risk communication and remedial action during product recall crisis. The above factors are important for organisations to capture and understand public expectations during crisis events and develop proactive strategies and information diffusion models (Wei, Bu, and Liang 2012) to deal with chaos.

However, this study has some limitations, which opens the door for future research agenda. First, only data from one social media platform (i.e., Twitter) is used. Although the framework should be able to apply in other platform like Facebook, but it will be fruitful to further validate the framework and make comparisons to other popular social media platforms (e.g., Facebook, Reddit and Instagram). Second, only one product recall incident and tweets that fell within a particular period of times are employed. In order to reduce the likely errors in generalising to the population, a larger scale tweet dataset to include more incidents from a wider area and a longer time period may produce a longitudinal study. Another limitation observed is that the dataset is limited to only English tweets to reduce research complexity, a dataset to include other languages would help generalise the results. Additional directions for future research include evaluating the validity of the proposed SBCC Model, using other research methods (e.g., focus group, questionnaire, etc.) to collect crises data to assess its practical feasibility and comparing it with other models for crisis responses and communications.

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Figures

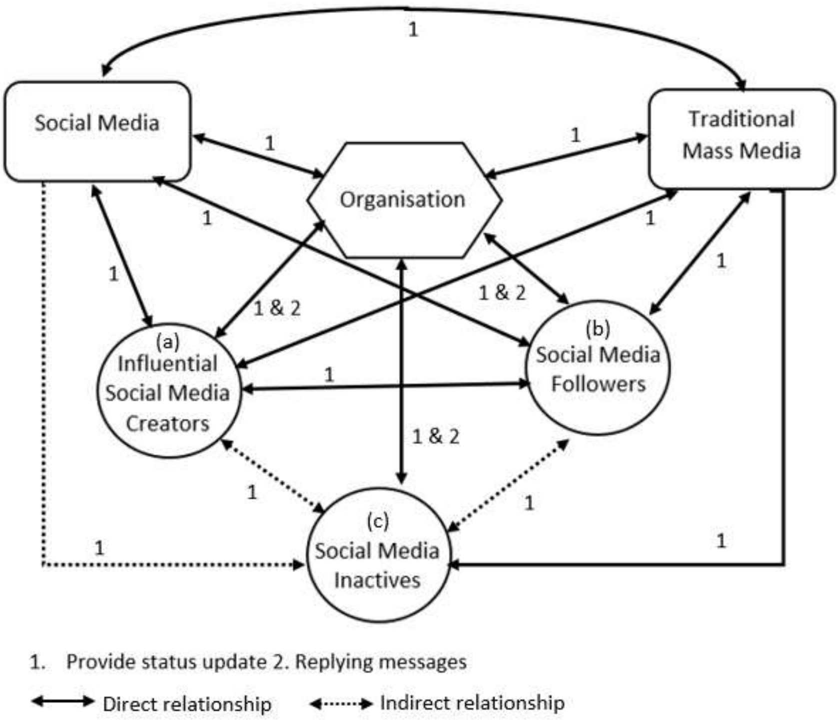

Figure 1. The research model based on the SMCC model (Austin, Fisher Liu, and Jin 2012, p192) and the Crisis Response Framework (Roshan, Warren, and Carr 2016, p, 352)

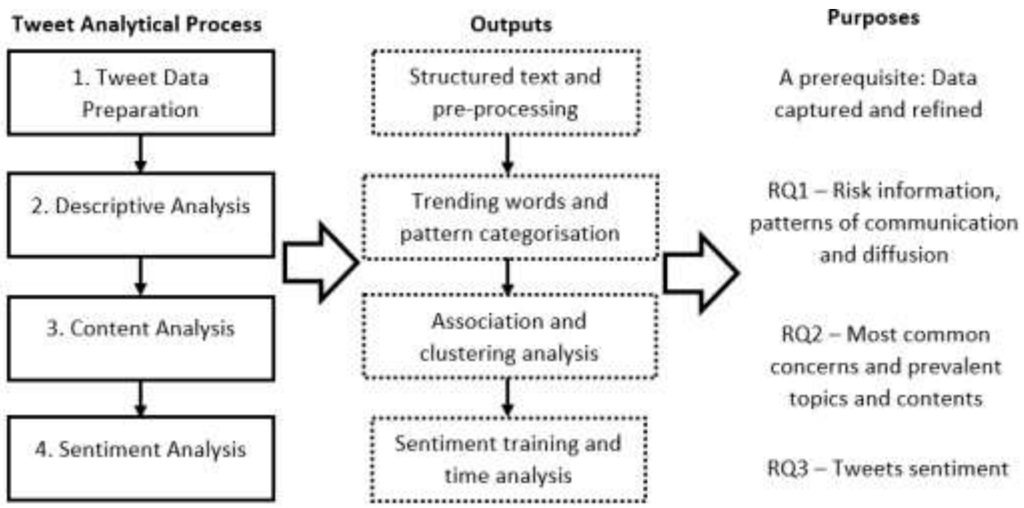

Figure 2. Tweets Analysis Framework

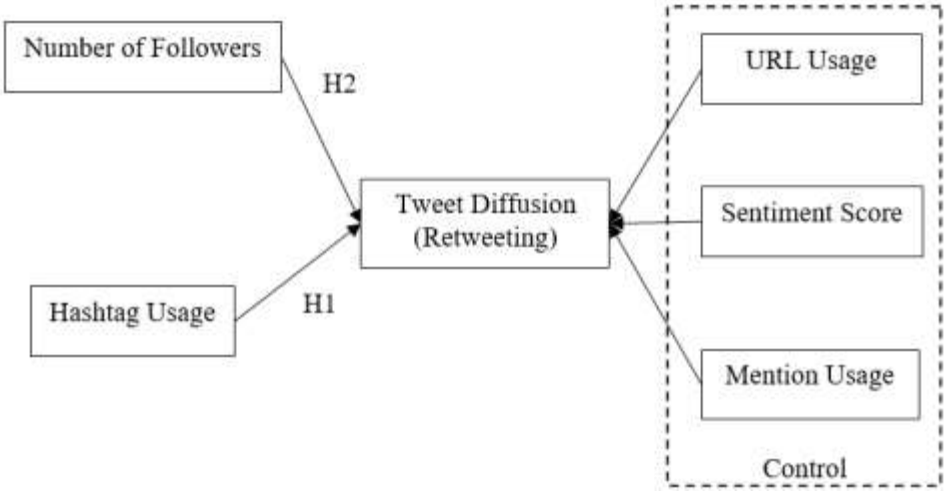

Figure 3. The Hypothesised Model

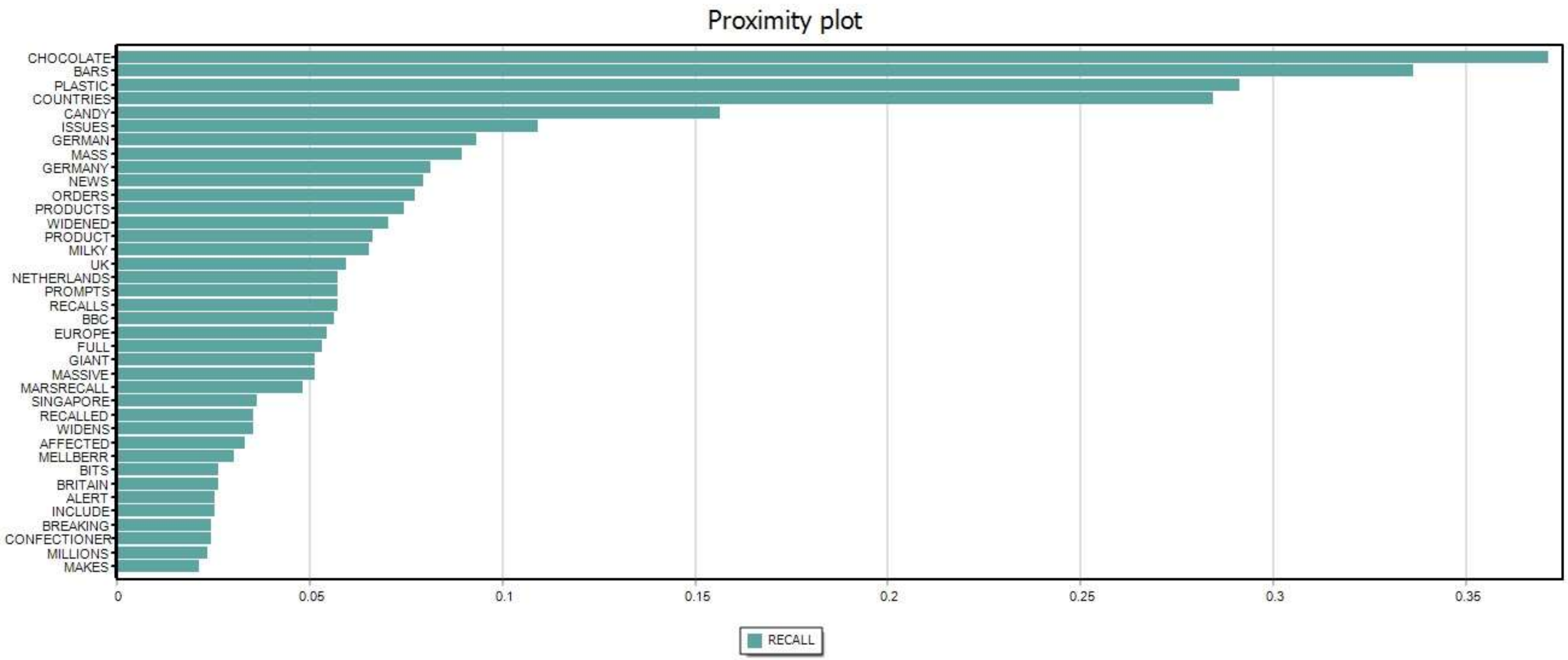

Figure 4. Proximity plot for top frequency words that associated to “RECALL”

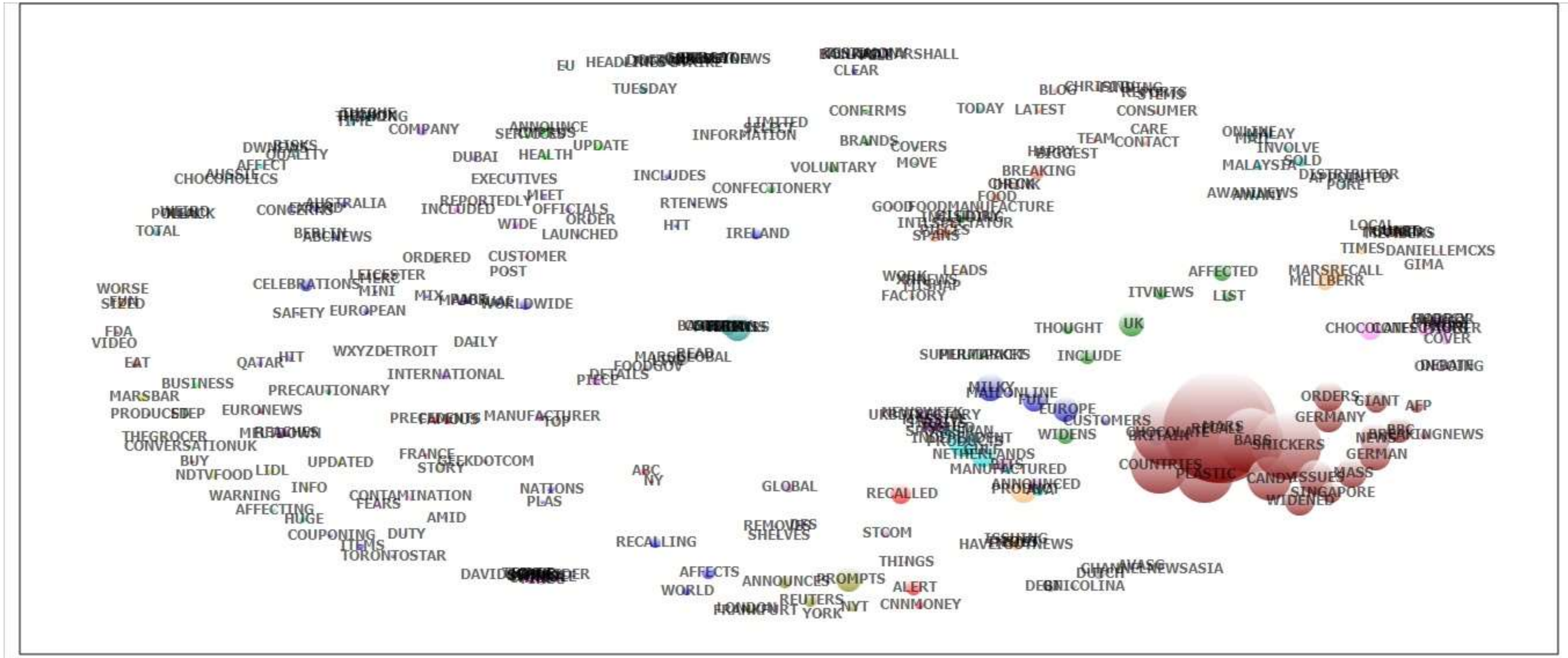

Figure 5. The 2D MDS map

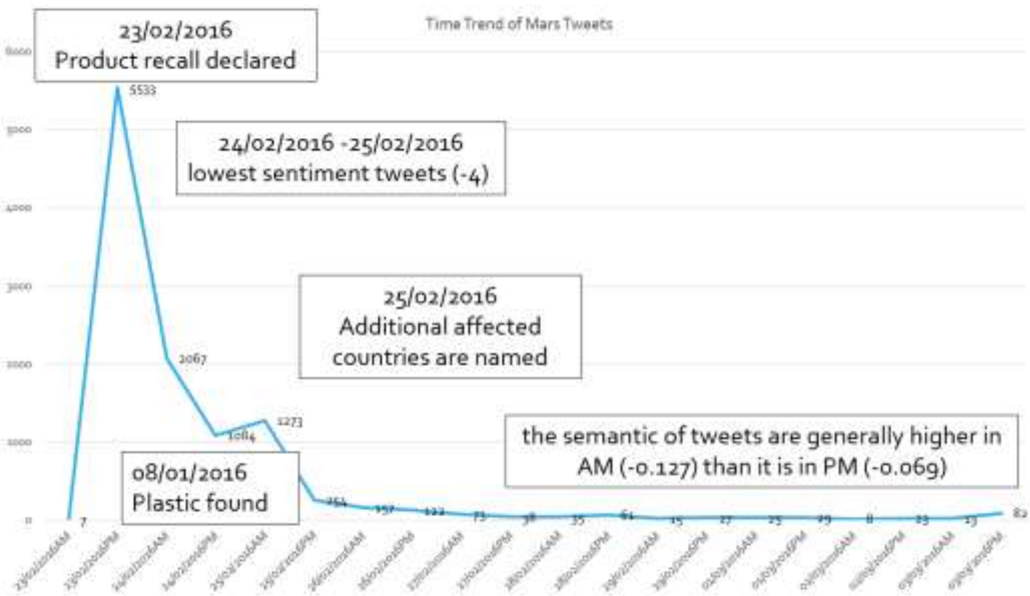

Figure 6. Time trend of Mars Tweets

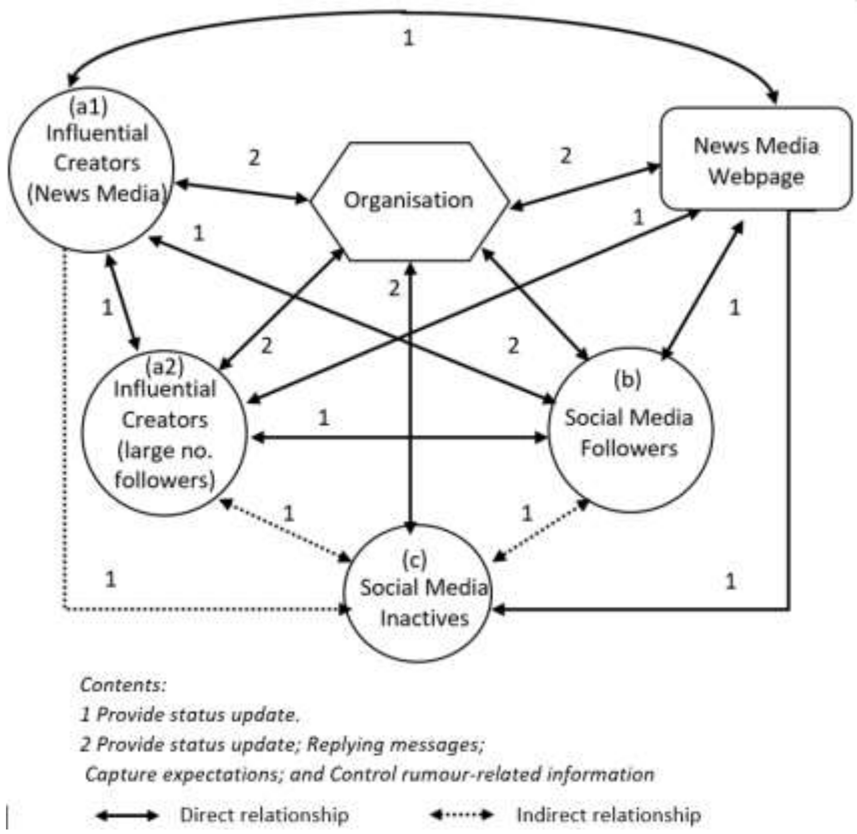

Figure 7. Social-broadcasting Crisis Communication Model

Tables

Total number of Tweets:	*15,930*
Total number of Sentences:	*17,423*
Total number of Words (Token):	*155,507*
Words per Sentence:	*9*
Hashtag (#):	*3,367*
URL:	*9,207*
Mention (@):	*4,648*
Retweet:	*3,725*

Table 1. The tweet dataset statistics

	FREQUENCY	NO. CASES	% CASES
Negative pattern	14693	10388	95.09%
Positive pattern	3458	2956	27.06%
To be ignored	19077	10654	97.53%

Table 2. Word pattern categorisation of the tweet dataset

Numbers	*Top 3 Hashtag (#)*
582	#MarsRecall
407	#Recall
272	#Snickers
	Top 3 Mention (@)
232	@MarsGlobal
194	@ITVnews
151	@Haveigotnews
	Top 3 Retweet
162	RT Chocolate giant Mars orders recall of Mars, Snickers bars in Germany
154	RT Mass recall for Mars in Europe Links
150	RT After issuing a product recall, Mars insist the plastic found in their chocolate is still better than the toys found in Kinder eggs.

Table 3. Top 3 Hashtags Mentions and Retweets

	FREQUENCY	% SHOWN	NO. CASES	% CASES	TF • IDF
CHOCOLATE	4264	6.86%	3995	36.57%	1862.8
BARS	3894	6.26%	3704	33.91%	1829.1
COUNTRIES	3222	5.18%	3123	28.59%	1752.2
PLASTIC	3275	5.27%	3238	29.64%	1729.5
CANDY	1773	2.85%	1736	15.89%	1416.3
ISSUES	1142	1.84%	1135	10.39%	1123.0
GERMAN	974	1.57%	972	8.90%	1023.4
MASS	926	1.49%	926	8.48%	992.5
PRODUCTS	868	1.40%	849	7.77%	963.0
WIDENED	806	1.30%	719	6.58%	952.4
GERMANY	858	1.38%	856	7.84%	948.9
NEWS	845	1.36%	835	7.64%	943.6
ORDERS	804	1.29%	803	7.35%	911.5
RECALLS	746	1.20%	746	6.83%	869.6
PRODUCT	724	1.16%	716	6.55%	856.8
MILKY	702	1.13%	700	6.41%	837.7
UK	646	1.04%	641	5.87%	795.6
NETHERLANDS	625	1.00%	621	5.68%	778.3
MARSRECALL	582	0.94%	505	4.62%	777.0
EUROPE	589	0.95%	569	5.21%	755.8

PROMPTS	594	0.96%	588	5.38%	753.8
BBC	585	0.94%	581	5.32%	745.4
GIANT	549	0.88%	531	4.86%	721.0
FULL	554	0.89%	554	5.07%	717.4
MASSIVE	531	0.85%	530	4.85%	697.8
RECALLED	436	0.70%	435	3.98%	610.4
SINGAPORE	388	0.62%	387	3.54%	562.9
AFFECTED	362	0.58%	361	3.30%	536.1
WIDENS	362	0.58%	362	3.31%	535.6
MELLBERR	314	0.50%	314	2.87%	484.0
BRITAIN	295	0.47%	271	2.48%	473.6
MILLIONS	275	0.44%	263	2.41%	445.1
BITS	277	0.45%	277	2.54%	442.1
INCLUDE	263	0.42%	263	2.41%	425.6
ALERT	260	0.42%	260	2.38%	422.1
BREAKING	252	0.41%	251	2.30%	413.0
CONFECTIONER	250	0.40%	250	2.29%	410.1
PIECES	237	0.38%	237	2.17%	394.3
MAKES	216	0.35%	216	1.98%	368.0
AFP	215	0.35%	214	1.96%	367.2
ANNOUNCED	205	0.33%	205	1.88%	354.0
AFFECTS	205	0.33%	205	1.88%	354.0
HORROR	203	0.33%	203	1.86%	351.4
CHOCCY	203	0.33%	203	1.86%	351.4
ITVNEWS	201	0.32%	201	1.84%	348.8
FRONT	200	0.32%	200	1.83%	347.5
PAGES	192	0.31%	192	1.76%	337.0
REUTERS	180	0.29%	178	1.63%	321.8
ISSUED	177	0.28%	177	1.62%	316.9
ANNOUNCES	173	0.28%	172	1.57%	311.9
CELEBRATIONS	159	0.26%	159	1.46%	292.1

Table 4. Word frequency of the tweet dataset based on TF-IDF

	1	**2**	**3**	**4**	**5**	**6**
1 Followers	1					
2 Retweet	0.034**	1				
3 Hashtag	-0.001	0.142**	1			
4 URL	0.013	-.103**	0.020*	1		
5 Mention	-0.033**	.836**	0.100**	-0.204**	1	
6 SentiScore	-0.012	0.014	0.009	0.012	0.028**	1
**** p<0.05; ** p<0.01***						

Table 5. The Pearson Correlation results

Parameter	**Coefficient**	**S. Errors**	**Wald(df)**	**Sig.**	**Exp(b)**
Followers*	.000	.000	4.022(1)	.042	.800
Hashtag***	.857	.088	93.898(1)	.000	2.356
Mention	22.805	500.765	.002(1)	.964	8015715733.000
URL***	.778	.080	94.337(1)	.000	2.176
Sentiment Score*	-.117	.058	4.076(1)	.043	.890
Constant	-22.239	500.765	.002(1)	.965	.000
Cox-Snell R^2 =0.585, * p<0.05, ** p<0.01, *** p<0.001					

Table 6. The logistic regression results

Group - The Recall: This is the focal group which has the highest frequency words - “CHOCOLATE”, “BARS”, “PLASTIC”, “RECALL”, “GERMAN” – *‘chocolate recall: Mars and Snickers bars in Germany contain plastic.’* “BIGGEST”, “FOOD”, “DRINK”, “HISTORY” – ‘*Mars recall spans 55 countries: is this the biggest food and drink recall in history?’* “CHOCCY”, “HORROR”, “CONFECTIONER” – *‘CHOCCY HORROR, the recall of chocolates by confectioner Mars makes several front pages’* “ANNOUNCED”, “MASSIVE”, “BITS” - ‘*Mars has issued a massive recall of chocolate bars after bits of plastic were found.*’ and ‘*Mars and Snickers just announced a massive recall in 55 countries.*’ “NETHERLANDS”, “PRODUCTS” “MANUFACTURED” – ‘*AVA issues recall of Mars chocolate products manufactured in the Netherlands.’*
Group - Affected Items and Areas: “FUN”, “SIZED”, “WORSE” – *‘the mars candy bar recall is anything but fun-sized...and it just got worse.’* “MILKY”, “SINGAPORE” – ‘*AVAsg issues recall of Dutch-made Mars, Snickers and Milky Way chocolates in Singapore.*’ “WIDENS”, “SUPERMARKET”, “MULTIPACKS”, “UK”– ‘*Mars chocolate recall widens to supermarket multipacks.*’ and ‘*Mars widens recall of chocolate to include UK after plastic found in bars.*’
Group - Expected Actions: “CONTACT”, “CARE”, “HAPPY”, “TEAM”, “GOOD” - ‘*Please check your product if it is labelled with Mars Netherlands, if it is, please contact your local consumer care team.*’ and ‘*Hi Ami, that’s no good! Give our UK chocolate team a call at 800-862-6293. We’d be happy to help you out.*’ “REMOVE”, “SHELVES”, “DFS” – ‘*DFS in Singapore removes Mars products from shelves following global recall.*’ and ‘*Mars, Snickers Milk Way and Celebrations pulled from shelves after plastic found in chocolate.*’
Group - Recall Consequences: “COST”, “FIRM”, MILLIONS” - ‘*Mars, Snickers and Celebrations recall could cost firm millions.*’ “CHILD”, “FINDS”, “FREE” – ‘*Mars, don't recall your Mars Bars, simply offer any child who finds a plastic ticket a free Wonka-style tour of your chocolate factory.’*

Table 7. Meaningful topics from the clustered words

Score	Code	Description
5, 4, 3, 2	Positive	Extreme, strong, moderate and mild positive sentiment
-5, -4, -3, -2,	Negative	Extreme, strong, moderate and mild negative sentiment
-1, 1	No negativity or positivity	No or neutral sentiment

Table 8 Coding scheme in SentiStrength (Ibrahim, Wang, and Bourne 2017; Thelwall et al. 2010)