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Exploring the Public Perception in Social Big Data: An Investigation in 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. Researching into social big data, such as Twitter, can be an effective way to identify public opinions and feelings in risk emergence, as it provides rich sources of data for opinion mining and sentiment analysis. This study aims to investigate and analyse the public perception towards the Mars and Snickers product recall scandal. The study proposes a comprehensive data analysis framework, and utilises the dataset formed of 10,930 Twitter messages over the span of 10-day following the product recall announcement made by Mars Inc., to gauge public attitudes and opinions. The study finds that the overall attitude of Twitter users towards the scandal was negative, and Snickers were the most mentioned product in the 10-day periods after the announcement of the recall. The data analysis highlights that the Tweet diffusion (retweeting) has positive associations with the number of followers and the use of hashtags, hence companies should pay more attention to users who have a large number of followers, as their tweets will be read by a great number of other Twitter users. The findings suggest effective methods for practitioners in crisis management (e.g., how to use social media to disseminate information). The study also presents a progressive tweet-mining framework that can serve as a tool in crisis management to classify the tweet topics, identify and analyse the sentiment and comprehend the changes of the public attitudes.

Keywords: Social media, Crisis management, Twitter mining

1. Introduction

With the advent of social media, the means of creating and sharing information have changed dramatically (Mangold & Faulds, 2009). As mentioned by Neti (2011), social media, or consumer-generated media, can be a new marketing tide like websites and emails. Social media marketing refers to the process of utilising the online platform, such as social networks, Internet communities, blogs, etc., to improve brand awareness and attract new customers. Corporations have benefited from the use of social media (e.g., Twitter) not only as a marketing tool to communicate with customers (Kaplan & Haenlein, 2010), but also an effective way to understand public opinions and feelings, hence it helps to build better relationships with customers (Agnihotri *et al.*, 2012).

Twitter, as a popular social media platform, has a total number of 1.3 billion registered users, with approximately 313 million of them are monthly activated (until 08/2017) and the number is still growing fast. This microblogging platform offers users to search for news and convey real-time information. The data created through the use of Twitter have also attracted increased attention from academics (Townsend, 2013; Veil *et al.*, 2011). This is to some extent inspired by latest excitements over the notion of big data, as the popularity of the platform can offer rich sources of favourable social data to study public behaviour in a non-experimental way. For instance, the Twitter data can comprise information about users' behaviours, emotions and attitudes about a specific product quality (Chae, 2015). Therefore, researchers can utilise such a platform, as part of a useful risk communicating strategy, to identify public opinions and feelings in product quality risk emergence.

The emergence of the social media research demands new approaches, such as the utilisation of text mining (Feldman, 2013), to gain insights by overcoming obstacles in analysing a mass of unstructured texts (Liau & Tan, 2014). Exploring the social big data is promising, but the current Twitter analytics are rather descriptive. Some common text mining methods may include descriptive analytics (e.g., word count analysis) and content analytics (e.g., sentiment analysis). Particularly in the research on crisis events, the development of studying social media and big data is relatively slow and there is little research to further explore the interrelationships between the factors that accompany with a tweet, such as the retweeting behaviour, URL usage, hashtag sage, sentiment value and users' followers etc.

This study aims to identify the principal elements that may demonstrate public sentiments and responses during a product quality crisis. By capturing and analysing the tweets related to the 2016 Mars recall scandal, the study also aims to propose a more progressive tweet-mining framework to include descriptive analytics, content analytics and relationship analytics. Use Twitter as a means to gauge public perception, following three research questions are raised:

- What are they the key topics in the tweets that related to the Mars recall scandal?
- What is users' sentiment towards Mars in the recall?
- What are the significant determinants of users' retweeting behaviour?

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 and 4 presents hypotheses development and the research methodologies. Section 5 explains the study results and implications. Finally, the conclusions and recommendations for future research are presented in Section 6.

2. Literature review

2.1 Social Media and Bid Data

Social media is defined as popular 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 & Ellison, 2007, p219). Web-based messages are explosively transmitted through these platforms and have become a dominant factor affecting public perceptions (Freberg *et al.*, 2011).

Social media makes the world borderless, which to a large extent facilitates the communication of users. This phenomenon enables the world to be more interconnected and accounts for the production of a large amount of data (Rainie and Wellman, 2012). The large pools of data (Boyd & Crawford, 2012) are more readily used for research in various disciplines (Agrawal *et al.*, 2011), such as politics (Shirky, 2011), sociology (O'Keeffe &

Clarke-Pearson, 2011), pedagogy (Dabbagh & Kitsantas, 2012), management (Baird & Parasnis, 2011), and business (Kim & Ko, 2012). 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 & Haenlein, 2010) and academia (Fuchs, 2017).

Manyika et al. (2011) define big data as the large pool of data, which can be collected, saved and analysed. Big data can generate forms of objective facts rather than the previous guesswork, which is recognised by creative practitioners (Agrawal *et al.*, 2011). They are produced directly from the utilisation of social media by individuals, which can be captured from social media site distributors or 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 *et al.*, 2012).

Twitter is a microblogging social media service (Kwak *et al.*, 2010). It provides a popular online platform on mobile and other network devices for users to exchange and share information with other users anytime and anywhere (Thompson, 2011). Common features of Twitter include: 'Twittering' – to share short posts (or tweets) within the 280-character limit (it 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). Because Twitter allows users to follow others and are followed freely (Java *et al.*, 2007), It can yield at an enormous rate of data per day (Claster *et al.*, 2010) and has seen a faster pace of growth since the launch in 2006 (Kwak *et al.*, 2010). Therefore, it provides a rich source for research into people's emotions, which is necessary for deeper understanding of people's behaviours and actions (Ngai *et al.*, 2015; Wang *et al.*, 2012).

2.2 Crisis Management Research 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 (Jin *et al.*, 2014). Technical advance has revolutionised the way of viewing, broadcasting and interacting with communities affected by crisis events, especially for relevant practitioners and researchers (Veil *et al.*, 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. For instance, information derived from Facebook could be easily shared with other users through Google+, Tweeter or other social networks. As an increasing number of people utilise social media for risk and crisis communication (Freberg *et al.*, 2013), many companies have faced huge challengs managing crisis communication (Schultz *et al.*, 2011). Previous studies have been conducted on social media and its impact on crisis communication. Coombs (2007) argues that the evidence-based crisis communication guidance must be integrated into social media in managing crisis. This is supported by some recent studies (Freberg *et al.*, 2013; Gruber *et al.*, 2015; Jin *et al.*, 2014), as they introduce models for social-mediated crisis communication, which address the demand identified by Coombs (2007). In particluar, Gruber et al. (2015) define the leadershiop role in crisis events and prpopose methods in assisting laders to strategically manage the internet communication, such as to collect and handle information during crisis events. Jin et al. (2014) find that emotions of the public such as anger and aversion are increasingly worse when the public receive crisis information through third-party social media platforms, as a result, enterprises should act in time to demonstrate their participation in social media.

In food industry, there are also a growing number of social media studies which have paid attention to crisis events, so that firms involved in food communication can make appropriate response to inquiries and develop strategies to deal with the problems (Rutsaert *et al.*, 2013). As a large amount of fragmented and user generated content is freely available on social media networks (He *et al.*, 2013), the traditional and 'old' strategies are not necessarily working well (Veil *et al.*, 2011) and some new strategies are suggested (Freberg *et al.*, 2013), such as rumour management; channels selection to reach segmented publics; methods to check for information accuracy, follow credible sources and disclose information. Although communicating on the internet is risky due to the inaccuracy, social media is still an ideal choice because of its high efficiency, coverage and accessibility during and after the food crisis events (Shan *et al.*, 2014). Recent studies have addressed social media coverage of food crises (Casey *et al.*, 2011; Chunara *et al.*, 2012). Rutsaert et al. (2013) argue that social media is an appropriate platforming to discuss the risk of food crisis events.

3. Hypotheses Development

In order to determine the significant determinants of users' retweeting behaviour, one of the recent food quality crisis events - the Mar's plastic scandal, is selected in this study. This scandal was a major food recall in 2016. It affected customers from 55 countries and made Mars lose tens of millions of dollars. On Friday, 8 January 2016, a consumer in Germany found a slice 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 are various products affected, such as Milky Way, Snickers, Bars of Mars, Mini Mix and Celebrations,

Since the announcement, consumers have expressed their concern and condemnation about this recall on social media sites. This study uses a dataset formed of public's comments from Twitter to identify the antecedents of users' tweeting behaviour (i.e. retweet). Two hypotheses are formulated and illustrated in the hypothesized model (Figure 1), namely number of followers and hashtag usage could contribute the information diffusion. Furthermore, three control variables are also considered in this study, which are the URL usage, Sentiment Score and Mention Usage.

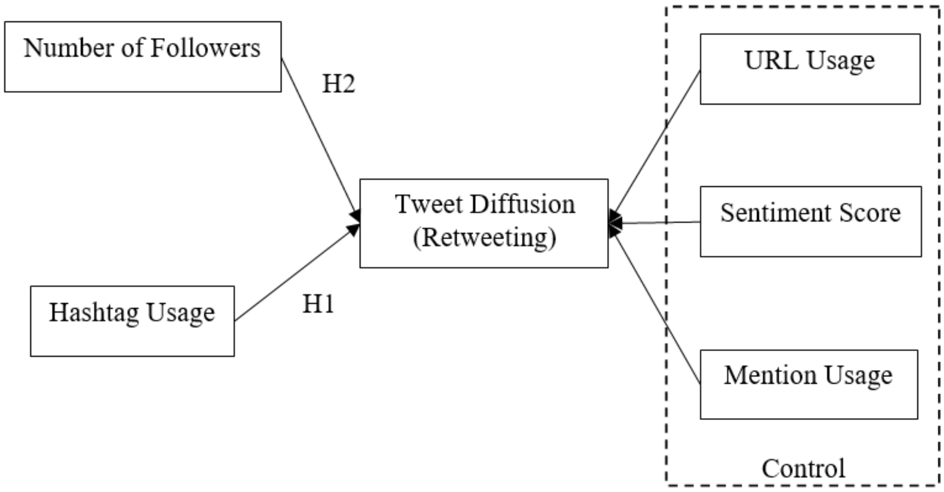

Figure 1. The Hypothesised Model

Use a hash sign (#) to tag a keyword (hence hashtag) is a characteristic in social media like Twitter. The 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 the symbols can help to search for messages more quickly, therefore, it should increase the amount of retweets and help to spread the messages. This study proposes that the use of hashtags may increase the likelihood of diffusing the tweets message. Thus, a hypothesis is represented as follows:

Hypothesis 1: The possibility of spreading messages is positively related to the utilisation of hashtags in tweets during the product recall event.

Followers and followees are two groups of users in Twitter. Followers are users who typically share tweets posted by other users, or followees, who they follow. Followers can freely select other users to follow. As long as a tweet is posted by one user, this tweet message will be spread to followers of this user at once and presented on each follower's Twitter window according to time order (Suh *et al.*, 2010). As a result, the term "Follower" means one user subscribing to other users' tweet while the term "Following" could be seen as those accounts which are subscribed to by others. With the emergence of the social networks, plenty of researches have represented the significance of a great deal of followers for the spread of tweets. As emphasised by Zhou et al. (2010), the structure of followers and following have a crucial impact on diffusing tweets. They also pointed out that, the more the followers one followee has, the bigger the likelihood that the followee's tweet messages are retweeted by others. Furthermore, according to Zaman et al. (2010) and Harvey et al. (2011), it is significant to utilise the quantity of followers for evaluating the quantity of retweeting messages. Nevertheless, to the best of our knowledge, the effect of followers in spreading tweets has not been measured in the context of product-recall. Consequently, the hypothesis of following is developed on the basis of previous research.

Hypothesis 2: The possibility of spreading a message is positively related to the quantity of followers during a product recall event.

4. Methodology

This study develops a Tweets Analysis Framework to capture, analysis the Twitter messages, and test the aforementioned hypotheses. The framework has six steps: tweets collecting, word count analysis, clustering analysis, sentiment analysis, time series analysis and empirical analysis.

In Step One, the Twitter dataset is captured and refined. This study uses Twitter API to capture the relevant tweets over the span of the 10-day period (23/02/2016-03/03/2016) following the product recall announcement made by Mars Inc. Only messages with a hashtag (#) and mentioned (@), and written in English are captured (Thelwall *et al.*, 2010). The final dataset contains 10,930 tweets which are sent from 55 countries. These tweets are then normalised and tokenised (Liau and Tan, 2014) in the QDA Miner software package 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'). Other high frequency but pointless words (e.g., HTTP, HTTPS, RT, etc.) are also removed and common misspellings are corrected (e.g., 'chocolete' instead of 'chocolate').

In Step Two, the QDA Miner is used to generate word count frequency and predict the popular topics from the textual data (Table 1). The software is selected based on it is extensive features on exploring textual data. The major characteristics are also extracted in the proximity plot (Figure 2) (Mostafa, 2013).

	FREQUENCY	SHOWN	PROCESSED	TOTAL	CASES
MARS	12524	15.03%	13.34%	8.72%	43.28%
RECALL	10826	12.99%	11.53%	7.54%	43.93%
SNICKER	4690	5.63%	5.00%	3.27%	18.90%
CHOCOLATE	4263	5.12%	4.54%	2.97%	16.90%
BAR	3893	4.67%	4.15%	2.71%	15.67%
PLASTIC	3275	3.93%	3.49%	2.28%	13.70%
COUNTRIES	3222	3.87%	3.43%	2.24%	13.22%
CANDY	1773	2.13%	1.89%	1.23%	7.35%
ISSUES	1142	1.37%	1.22%	0.80%	4.80%
GERMAN	974	1.17%	1.04%	0.68%	4.11%

Table 1. Word frequency table for the top 10 keywords

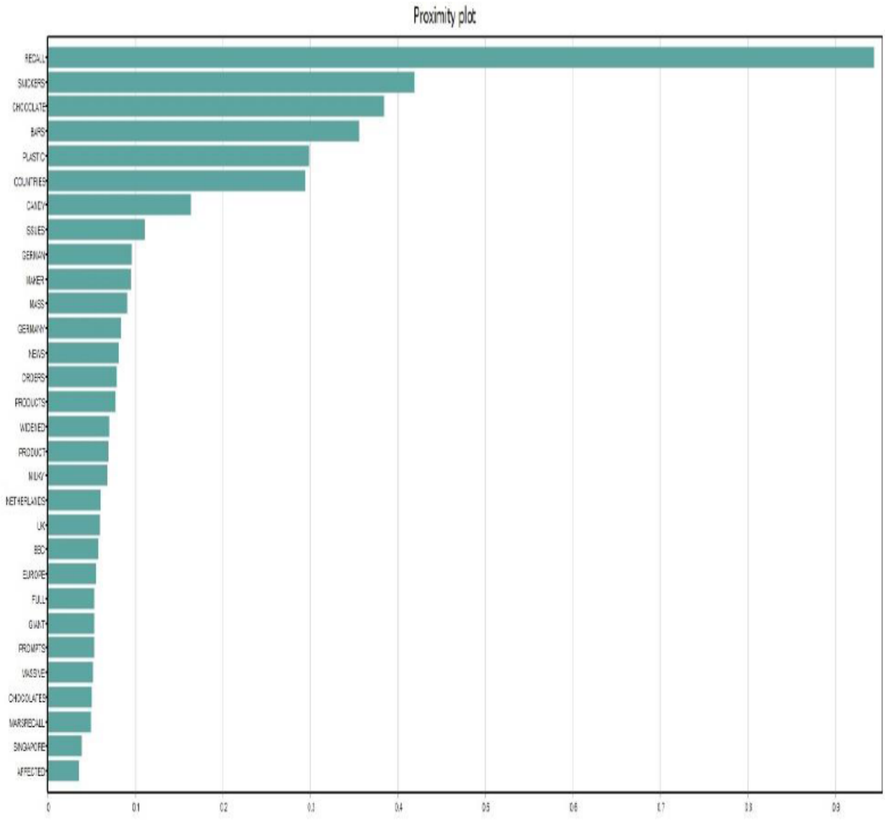

Figure 2. Proximity plot for 'Mars'

In Step Three, the popular topics are further analysed to look for their co-occurrence by using Multi-Dimensional Scaling (MDS) (Péladeau *et al.*, 2017; Taboada *et al.*, 2011). Jaccard's coefficient is applied as the index of co-occurrence. A matrix of distances between the popular topics are illustrated (Figure 3), in which the circles indicate the major topic of the dataset and the closer the circles, the higher the tendency of co-occurrence and vice versa. The lines between the circles indicate the strength of the association.

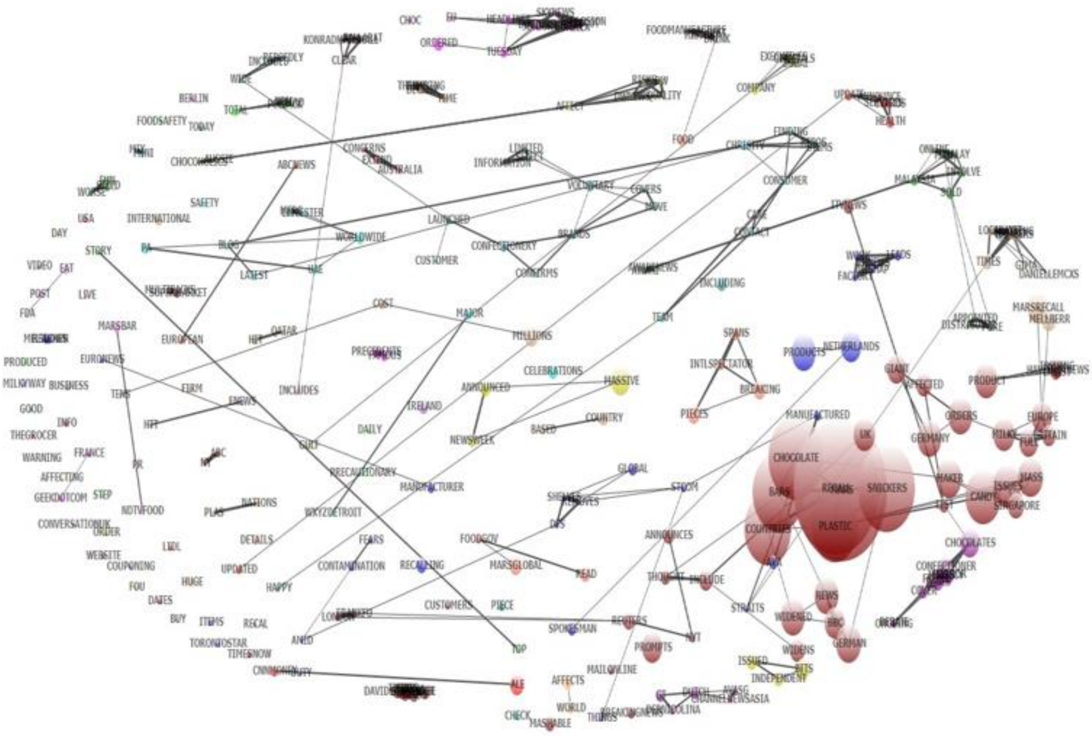

Figure 3. The 2D MDS results

In Step Four, the sentiment analysis is applied to comprehend the motive behind the tweets. This study uses the lexicon-based method to the tweets to measure the semantic orientation. This is one of the popular methods to extract sentiment from text which involves the use of dictionaries to capture polarity (positive or negative sentiment) and explain strength on a scale of 1 (no sentiment) to 5 (very strong sentiment). This study adopts the SentiStrength classifier (Thelwall *et al.*, 2010) and employs Liu's (2010) sentiment lexicon to analyse the sentiment expressed in the tweets.

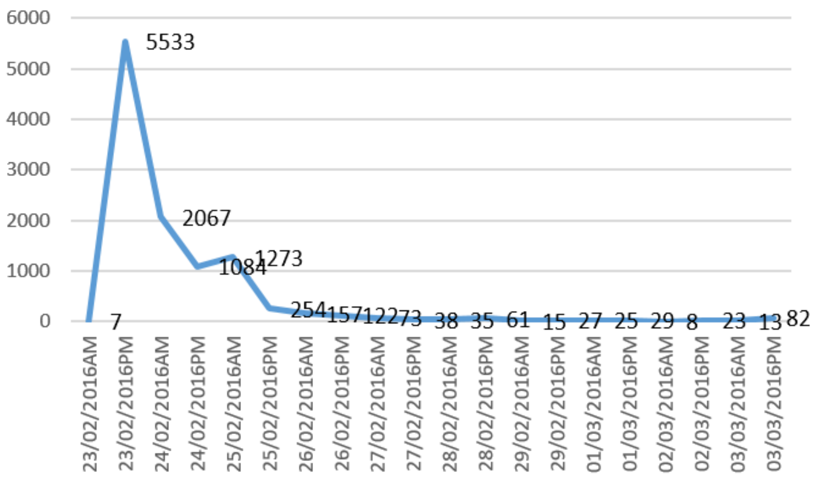

Figure 4. The 2D MDS results

In Step Five, a time series analysis is employed to compare and contrast the sentiment values of the tweets captured in different time. The 10-day period 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 (Figure 4).

In Step Six, the logistic regression is performed to identify the significant antecedents to the retweeting behaviour. In order to test the above hypotheses, the relationship between the independent variables (i.e. hashtags usage and the numbers of followers) and dependent variables (i.e., retweet or not) are examined with controlled variables (i.e., URL usage, mentions and sentiment values).

Parameter	Coefficient	S. Errors	Wald(df)	Sig.	Exp(b)
Hashtag***	.857	.088	93.898(1)	.000	2.356
Followers*	.000	.000	4.022(1)	.042	.800
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 Square=0.585, *p<0.5, **p<0.01, p<0.001					

Table 2. The logistic regression results

5. Results and Implications

From the Table 1, ‘Mars’, ‘Recall’ and ‘Snicker’ have the highest word count frequency during the 10-day product recall period. This can be explained by the Mars recall scandal comes after a customer who found a piece of plastic in a Snickers bar. In Figure 2, the proximity plot uses a single axis to illustrate the most concerned topic and other popular topics. It seems that most tweets are concerned with things such as ‘Recall’, ‘Snicker’, ‘Chocolate’, ‘Bar’ and ‘Plastic’. Twitter users seem to be also concerned with the scandal in ‘Countries’, like ‘Germany’, ‘UK’ and ‘The Netherlands’.

The Figure 3 shows the popular tweets topics and their mutual relationships based on the MDS. In this figure, a pattern of ‘Company Action’ is identified and represented by the topics of ‘Mars’, ‘Snickers’, ‘Recall’, ‘Remove’, ‘Shelves’ and ‘Products’. This could imply that the consumers expect firms to immediate remove all products with potential risk from shelves. In particular, ‘Snickers’ is strongly associated with ‘Mars’ and ‘Recall’, which indicates that the Snickers is the product that consumers were most concerned with during the recall. Another group is the ‘Recall Consequence’ which has the topics of ‘Cost’, ‘Firms’ and ‘Millions’. This may highlight that consumers are actually interested in the firm’s financial losses as a result of the product call.

From the results of the SentiStrength classifier, the average sentiment value of the Mars Scandal tweets is -0.26169 and the distribution of sentiment scores falls between the band of circa -1/+1. These could be an indication that most tweets are not very affective. From the time series analysis in Figure 4, the sentiment scores of the tweets captured in AM (-0.127) is generally stronger than those in PM (-0.069) over the ten-day period. 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 results of the logistic regression can be found in Table 2, the Cox & Shell R-square (i.e. 0.585) indicates a good model fit and the model supports both hypotheses. Thus, the usage of the hashtag (hypothesis 1, $p<0.001$) and the number of followers (Hypothesis 2, $p=0.042<0.05$) are significant drivers of retweet, which suggests that the usage of the hashtag and the number of followers can significantly and positively impact on the retweet behaviour. This study also finds that the sentiment value was negatively associated with the diffusion of tweets ($p<0.05$).

6. Conclusions

This study uses a dataset, which contains 10,930 Twitter messages to gauge public attitudes and opinions. The results of the sentiment analysis agree with some previous studies (Ma *et al.*, 2017; Tse *et al.*, 2016) that consumers would search for news and convey real-time information on the internet in risk emergence. As consumers' expressions are likely to affect a firm's financial performance like sales data and share price (Mostafa, 2013), firms should be active on social network sites and enhance its communication strategy. It is significant for firms to supervise general public's sentiment on social network to avoid propagating the negative message or even the rumour, which is an indispensable factor to the successful crisis communication.

The results of the logistic regression provide insights for firms to better understand social media on how information can be diffused and the reasons why certain information can spread more widely than others. In this study, the numbers of tweet followers and the use of hashtags are two significant factors of retweeting hence, information diffusion. These results are in line with some existing studies (Lee *et al.*, 2015; Suh *et al.*, 2010), as the larger number of tweet followers and the more use of hashtags, the tweets are likely read by more followers, thus, the chance of retweeting is also increased. Therefore, these two factors play crucial roles in estimating the number of retweets and predicting the spread of information. These are important for firms to capture and understand public expectations during crisis events and develop proactive strategies and information diffusion models (Wei *et al.*, 2012) to deal with chaos.

This study also presents a progressive tweet-mining framework the can serve as a tool in crisis management. The framework comprises word count analysis, clustering analysis, sentiment analysis and logistic regression analysis to comprehend Twitter messages. It suggests a promising future direction of research on public perceptions.

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