Analyzing Consumer Behavior from Tweets during Telecommunications Service Outages: Social Media Influence Factors

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Abstract

This paper presents results of analyzing consumer behavior during telecommunications service outages from tweets. Twitter data from a single year during which there were multiple service outages of an Australian telecommunications company were collected with the goal of determining which social media factors influenced consumer behavior during outages of this very widely-used service. The analysis expanded on standard sentiment analysis by focusing on the impact of sarcasm and mockery expressed in tweets as types of sentiments that are both negative and humorous and have been shown in general social influence theories to attract more attention during general human conversations. The data were de-noised and their details and meta-data including time, location, likes, retweets and followers extracted as variables. The de-noised data were then coded for mockery and sarcasm and the celebrity status of the individual as additional variables. Results from using a non-parametric test showed a clear division in significance of negative and non-negative tweets with negative sentiment attracting more likes from consumers. Results show that sarcastic negative tweets attract statistically significant number of higher likes and retweets compared to non-sarcastic negative tweets. This is a novel finding with potential value for decision makers. Through multiple correspondence analysis we were also able to derive the qualitative relationships between the variables. It is postulated that the social media celebrity status of a twitter user and their use of sarcasm and mockery in tweets result in higher engagement in terms of attracting likes and retweets from other users during service outages. These results have implications for modeling of consumer responses to service outages thus develop fast-response service recovery strategies. Moreover, as a long-term impact results enable organizations to form strategies for corporate public relations management and to guide the development of crisis communication schemes.

Keywords: consumer behavior, telecommunications service outage, sarcasm and mockery, social influence

1. Introduction

Billions of consumers embrace social media to share opinions, seek information, manage social relationships and for entertainment (Heinonen, 2011). This has fundamentally transformed the way businesses operate in the modern world. The ubiquitous nature of social media and its user-generated content have created a new channel for consumers to share opinions and influence the decision making of others (Romero, Galuba, Asur, & Huberman, 2011). As a result, the "word-of-mouth" (WOM) online digital marketing channel (Dellarocas, 2003) is further amplified to a socialnomics notion of "world-of-mouth" (Qualman, 2010). Such peer communication in social media has the capability to enhance purchase intentions and product attitudes through influence (Wang, Yu, & Wei, 2012).

The theory of *social influence* (Kelman, 1958) provides a wide spectrum of concepts to explain how individual actions are affected by other people as a result of interactions (Hillmann & Trier, 2013). Social influence theory can be used to explain online social networking activities and interactions such as retweeting, liking, following and sharing others' content (Hillmann & Trier, 2013). There are recent research studies focusing on measuring the causal effect of social influence in social media (Aral & Walker, 2012; Salganik, Dodds, & Watts, 2006). Literature highlights that influence of social media can be used for the betterment of a group of people, by creating awareness during societal problems and crisis situations (Snijders & Helms, 2014). Thus, the role of social media influence has been researched during notable events in politicals context such as elections and protests (Bond et al., 2012; Steinert-Threlkeld, Mocanu, Vespignani, & Fowler, 2015).

Nevertheless, in business and services domains, research on social media influence predominantly concentrates on the role of social media as communication facilitators. For instance, research studies have been carried out to analyze the role of Twitter during railway service disruptions as a real-time news transmitter (Pender, Currie, Delbosc, & Shiwakoti, 2014) and as an emergency information communicator in airlines (Stambaugh, 2013). There is no significant reported research investigating social influence during a failure of a very widely-used service such as telecommunications. This gap in our knowledge provides a research opportunity to examine the influencing factors in social media during a collective event such as a disruption to a very widely-used service to derive insights into changes in consumers' behaviors. Such insight will provide an organization the ability to be proactive in taking appropriate action towards addressing issues of the service disruption as well as counteract any negativity in a timely manner.

In this light, we aim to identify influential factors on social media in the context of an outage of a widely-used service such as Telecommunications and Internet services since the number of frustrated customers can be very large compared to rail and similar service outages. This creates an appropriate scenario to investigate consumer behavior and influential factors. For this research, we select Twitter, both because of its scale and its availability of a large volume of Twitter data (Brandwatch, 2015). In the context of service failures, recent research (Du, Fan, & Feng, 2014) showed the herding phenomenon of consumers' negative sentiments where they can influence fellow consumers, which ultimately contributes to an escalation of collective negativity against service providers. This research was targeted at investigating if this behavior could be observed in the digital world of social media. Thus, we form a research framework in which we analyze the content of Tweets and investigate associations between content, meta-data such as the number of followers, likes and retweets to study the effect of online social influential factors during a service outage. In this regard, we form the following research questions.

1. Does the presence of negative sentiments in tweets influence consumer behavior in social media during a service outage? In particular, do sarcasm and mockery play a role as social media influential factors given that the sarcastic way of presenting criticisms is regarded as a trait attracting and influencing people (Huang, Gino, & Galinsky, 2015).
2. Focusing on users with a large number of followers on Twitter – celebrities – and the associations between other meta-data such as likes and retweets, does social media celebrity status influence fellow customers to change behavior?

Little prior research has been done to explore the social constructs which contribute to online social influence in consumer behavior during a service outage. We particularly focus on the role of sarcasm and mockery in sentiments, as no research has been done to identify their impact as influencing factors in social media. In this research, we conduct analytic studies to investigate the research questions outlined above. The results of this research have the potential to present significant implications in assisting service managers to develop fast-response service recovery strategies. Furthermore, understanding commotions in consumer behavior and sentiments during service outages, enable organizations to form strategies for corporate public relations management and to guide the development of crisis communication schemes.

This paper is organized as follows. The next section presents the theoretical background of the research questions with related literature. Research methodology and data collection are described in Section 3. The analytical methods and their results are presented in Section 4. In Section 5, we discuss the results and implications of key findings followed by a conclusion acknowledging research limitations and envisioning future studies.

2. Theoretical Background

2.1 The role of negative sentiments in social media

Opinions play a central role in many aspects of human life and are prominent influencers of human behavior (Pang & Lee, 2008). Such opinions and reviews act as essential sources of information for marketers and service providers to comprehend the underlying perceptions of their consumers (Ioanăs & Stoica, 2014). The explosive growth of the Web and social media has created a new paradigm for people to exchange opinions, which has created a huge volume of opinionated data recorded in digital form (Pang & Lee, 2008). Online Word-of-Mouth (WOM) contents originated from consumers' attempt to re-balance emotional imbalance and play an important role influencing fellow consumers' decision-making (Ullah, Amblee, Kim, & Lee, 2016). In this regard, sentiment analysis has gained wide interest of researchers. Sentiment analysis is defined as a field of study which analyzes people's opinions, evaluations and reviews towards entities such as products, organizations, events, topics and individuals (Pang & Lee, 2008). There has been a significant amount of research on sentiment analysis in a large variety of domains (Agarwal, Xie, Vovsha, Rambow, & Passonneau, 2011; Fang & Zhan, 2015; Medhat, Hassan, & Korashy, 2014; Prabowo & Thelwall, 2009; Qaisi & Aljarah, 2016; Salehan & Kim, 2016; Villarroel Ordenes, Ludwig, de Ruyter, Grewal, & Wetzels, 2017). Sentiments are normally categorized as positive, neutral or negative (Balahur, 2013). In social media, consumers respond to opinions via interactions (posting likes, retweeting, following others) which enable us to retrieve insights on popular content. Moreover, these insights allow the determination of the factors contributing to the attractiveness in opinions (aka social media influence). Studies show that sentiments which are entertaining, insightful and time sensitive have the ability to attract more people (Cha, Haddadi, Benevenuto, & Gummadi, 2010). Previous research work has identified that positive and negative terms are among a number of features contributing to the predictability of whether a tweet attracts retweets with moderate influence (Naveed, Gottron, Kunegis, & Alhadi, 2011). A subsequent study concluded that tweets with predominantly negative sentiment have a higher retweet probability (Jenders, Kasneci, & Naumann, 2013). This was based on sentiment scores obtained from applying the automatic sentiment analysis algorithm *SentiStrength* (Thelwall, Buckley, Paltoglou, Cai, & Kappas, 2010), which produced inaccurate results largely due to the complexity of sentiment representations and the potential presence of sarcastic tweets. Therefore, the role of sentiment as a social media influence factor needs to be revisited. Service outage is a situation where consumers tend to be agitated and express negative emotions, providing a good context to study impacts of sentiments. Does sentiment play a role in attracting likes and retweets during a service outage and what is the statistical significance of the increase of such likes and retweeting? This study investigates the impact of negative tweets in attracting likes and retweets with the presence of sarcastic and mockery tweets. Human coders were used to review sentiments of the tweets during the service outage to accurately assign sentiment scores followed by non-parametric tests to gauge the significance of the effect of sentiment on social media influence.

2.2 Sarcasm and Mockery in sentiments and their influence

Even though there are research approaches available to determine the impact of positive and negative sentiments in attracting retweets (Jenders et al., 2013; Naveed et al., 2011), there is little reported analysis on sarcasm in tweets and their capacity for attracting likes and retweets. The Cambridge Dictionary defines sarcasm as *"the use of remarks that clearly mean the opposite of what they say, made in order to hurt someone's feelings or to criticize something in a humorous way*". It is apparent that people are attracted to humor (Greengross & Miller, 2011) and as pointed out by (Gibbs, 2000), sarcasm intertwines with mockery with 90% of sarcastic utterances involved mocking. Generally, sarcasm is known as a trait which attracts people since it incorporates creativity and humor with the ability to influence others (Huang et al., 2015). This research investigates if this claim is transferable to the digital world, by investigating the role of sarcasm and mockery in social media influence, to determine if sarcastic and mockery tweets are more likely to attract likes and retweets during service outages. We explain the significance of sarcasm and mockery in consumer online behaviors during a service outage, by performing non-parametric hypothesis tests of distributions in sarcastic/mockery related likes and retweets with those associated with non-sarcastic (and non-mockery) negative tweets. This phenomenon could guide businesses and organizations to engage with and influence their online consumers.

2.3 The role of influential consumers in social media

The mechanism of Electronic Word of Mouth (eWOM) explains how one person's opinions could affect others' decisions and behavior on a digital platform (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). Various metrics have been developed to measure eWOM influence which can promote or demote the behavior of fellow consumers in social network settings (Riquelme & González-Cantergiani, 2016). These metrics range from simple measurement provided by Twitter Application Program Interface (API) to more sophisticated models, e.g., centrality measure and PageRank algorithm. The role of influencers is vital in a time of emergency as their opinions could shape the direction of thoughts and decisions of other consumers. On Twitter, one of the principal components to detect the "celebrity-status" of a user is the number of followers (Hutto, Yardi, & Gilbert, 2013). Contradictive and inconsistent findings (Cha et al., 2010; Hong, Dan, & Davison, 2011; Kwak, Lee, Park, & Moon, 2010; Romero et al., 2011; Suh, Hong, Pirolli, & Chi, 2010) are found by (Naveed et al., 2011) relating to the role of popularity in attracting retweets. It is argued that the inconclusive findings in the likelihood of a tweet to be retweeted are due to the effects of multiple contributing factors in the face of the context of tweets (Naveed et al., 2011). We use a multivariate analytical method and non-parametric hypothesis test to investigate effects of these social media influence characteristics (including celebrity-status, sarcasm and mockery and sentiment) on designated online consumer behaviors (via likes and retweets) during service outages.

3. Research Methodology and Data Analysis

To explore the online consumer behavior during service outages, Twitter responses are collected during a series of service failures that occurred in 2016 for a leading telecommunications provider in Australia. A range of data analysis techniques are used, including descriptive analytics, a multivariate statistical method (MCA – multiple correspondence analysis) and non-parametric hypothese test approach – Kolmogorov-Smirnov test (KS). The research framework (Fig. 1.) encompasses data collection, data pre-processing, data refinement and data analysis studies to investigate the research questions.

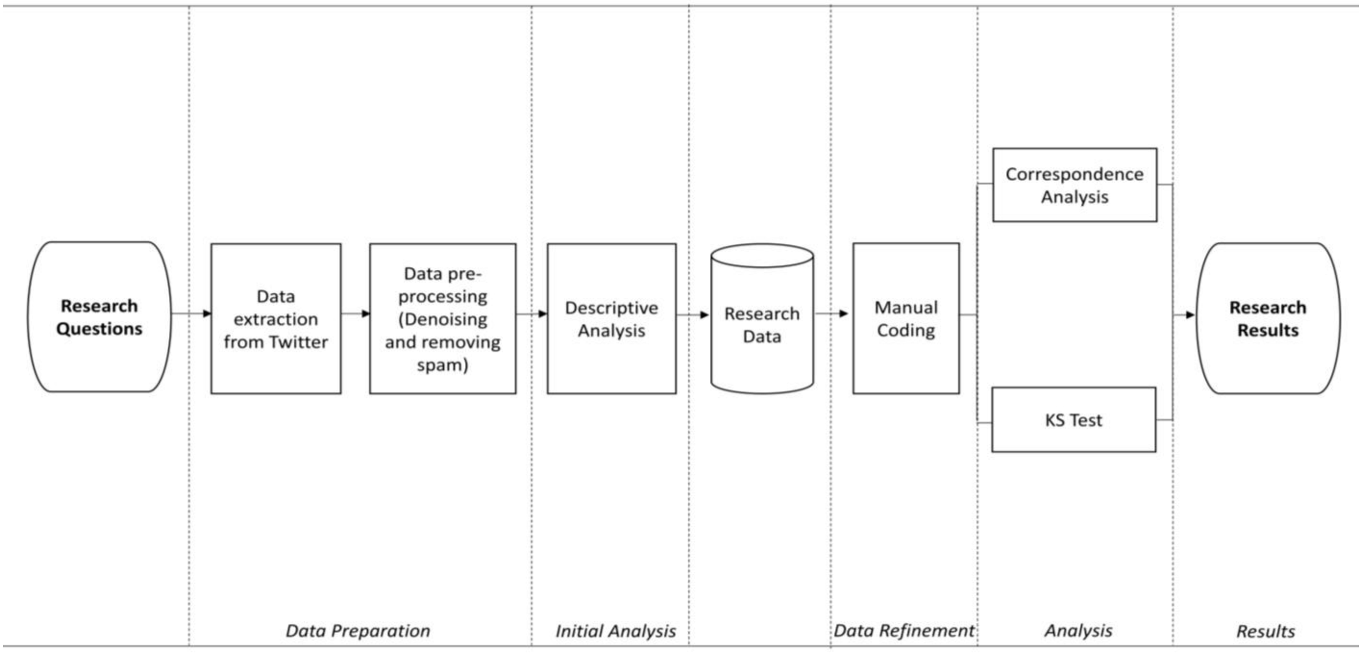


Fig 1. The research framework

3.1 Data collection

We extract Twitter data referring to the case-insensitive mentions of the selected Telco provider over one calendar year during which a series of outages occurred. The Twitter contents and meta-data extracted include:

- time the tweet was sent;
- location the tweet was sent from;
- number of likes the tweet attracted;
- number retweets the tweet was associated with;
- twitter Id;
- number of followers associated with the Twitter Id;
- number of following the Twitter Id was related;
- total number of tweets for the Twitter Id.

The data extraction produced 250,578 rows of these 8 data values. These data are associated with 68,342 unique Twitter Ids which cover a wide scope of categories ranging from news feeds attitude and opinion sharing to online advertisements. The trends of the daily aggregated number of tweets and Twitter Ids are shown in Fig. 2. where peaks indicate the strong effects from events including service outages.

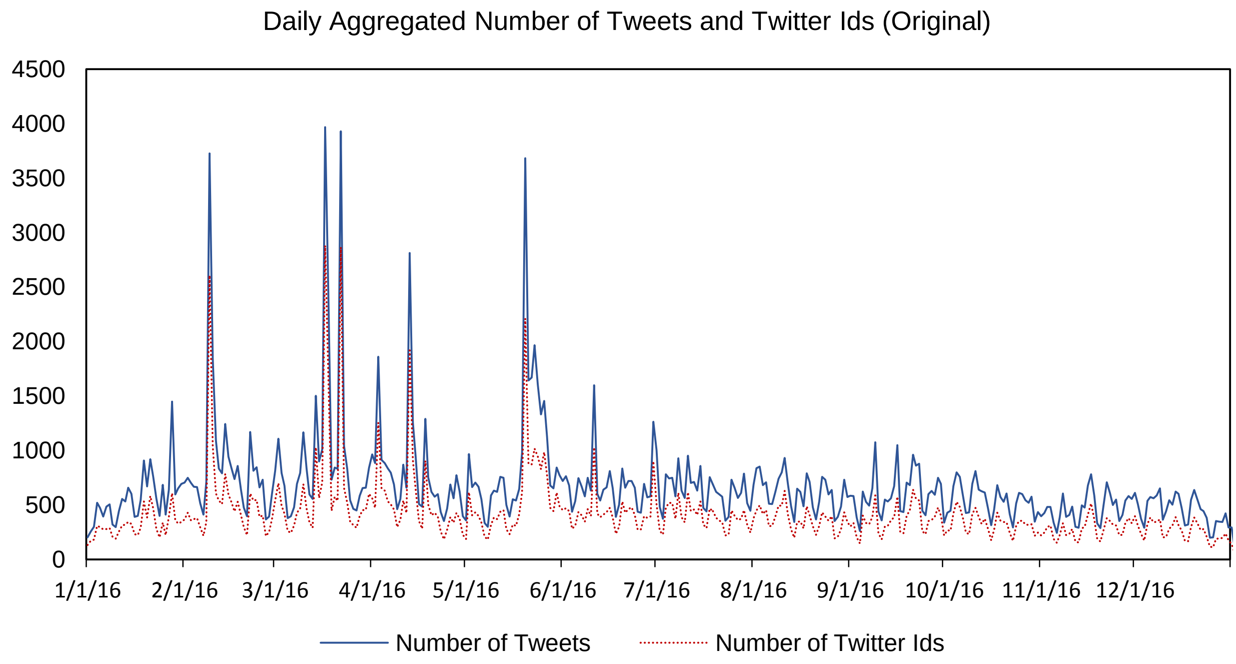


Fig 2. Daily aggregated tweets and tweet Ids

3.2 Data pre-processing

In order to remove noisy (irrelevant and redundant) data a data pre-processing phase is conducted. It is observed that a large number of tweets are created by people around the world to share news related to service outage by the selected Telco company. In addition, some tweets are online advertisement spam created by e-vendors or robotic accounts. For example, a robotic account spammed a small amount of news every few hours every day repetitively over the year. These noisy data accounting for approximately 36% of the total number of tweets had to be removed from the study as we focus on exploring consumer behaviors. De-noising has been performed by a semi-automatic approach in which a pattern shared by news feeds are identified and consequently removed by scripts with a final inspection manually removing advertisements and tweets created by robotic accounts. The data cleaning process produced a sample of 160,773 tweets originated by 48,583 unique Twitter Ids.

Fig. 3. illustrates the trend of the daily aggregated tweets and Twitter Ids for the clean data, which is aligned with the trend and pattern observed in Fig. 2. The highly fitted (with $R^2 > 0.93$) linear regression lines between date series before and after the de-noising show a consistent result. The final inspection indicates the de-noising process is successful with major events and responses from consumers to these events preserved.

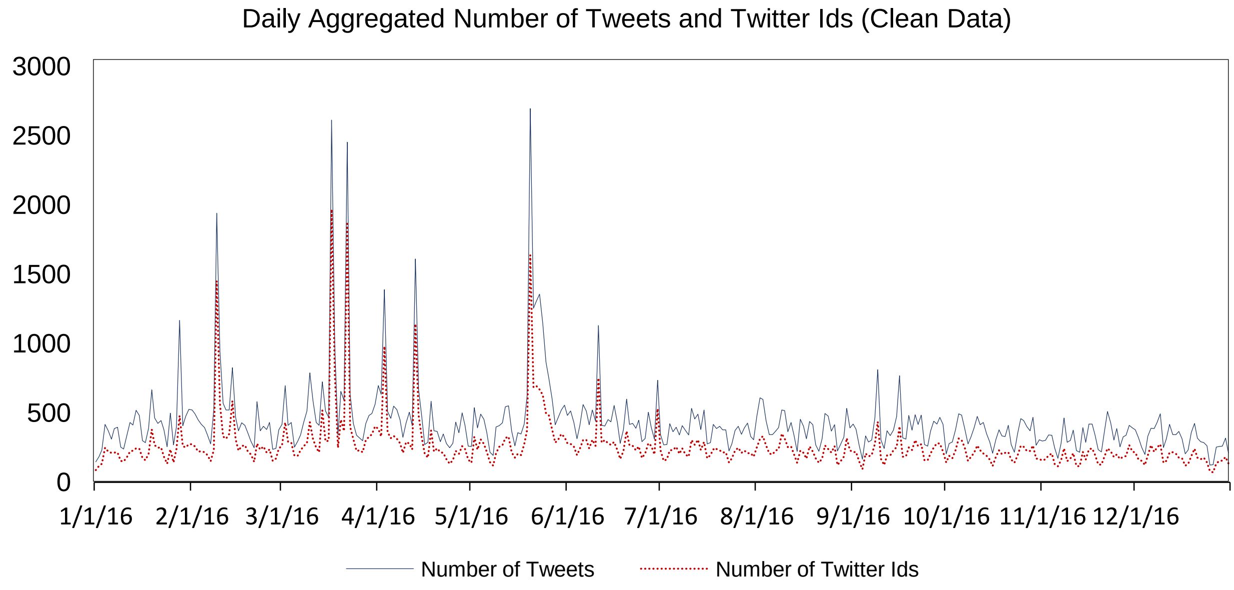


Fig. 3. Daily aggregated tweets and tweet Ids after de-noising

Twitter data captured during the service outage are irregular time series data with a non-constant time interval for observations. These data are transformed into regular time series by placing data into various scales at hourly, daily and at individual Twitter Id level to aid the analysis. For example, studying distributions of tweets per Twitter Id requires an aggregation of the number of tweets at Id level, whereas comparing the correlation of variables ‘Likes’ and ‘Retweets’ requires an aggregation at hourly or daily scale. Mapping continuous data into nominal values (binning) is done in order to support interpretations and improve visualization of the underlying patterns. For example, the continuous value of likes is mapped into a nominal variable (‘Likes’) with values ‘Likes_None’ and ‘Likes_Not_None’ based on if a tweet attracts a like or not. This is performed to identify different types of tweets which attract interactions such as likes from other users. Data collected from one of the outage days are used to evaluate this phenomenon and the results are given in the Table 1.

Table 1

'Likes' variable descriptions – Data collected from one of the outage days

Likes	**Description**	**Volume (No. of Tweets)**	**Percentage**
Likes_None	when a tweet attracts 0 likes	1000	54.41%
Likes_Not_None	when a tweet attracts the number of likes is greater than 0	838	45.59%

3.3 Pre-analytical study using descriptive statistics

This study is conducted to produce an overview of consumer responses over time and investigate significant correlations among meta-data such as the number of users, tweets, retweets and likes. Descriptive statistical methods are used to present the 4 variables expressed through hourly and daily aggregation of tweets (Table 2). A plot indicating heavy-tailed distributions for data from the year 2016 is presented in Fig. 4.

Table 2

Summary statistics of hourly and daily aggregated responses

Variable	**Mean**		**Maximum**		**Minimum**		**Standard Deviation**	
	hourly	daily	hourly	daily	hourly	daily	hourly	daily
Number of users	13.81	263.12	670	1968	0	71	19.68	193.68
Number of tweets	18.30	438.52	850	2696	0	125	24.93	279.60
Number of retweets	3.99	95.54	1514	2183	0	4	23.77	198.61
Number of likes	10.66	255.57	1746	5015	0	21	48.16	480.82

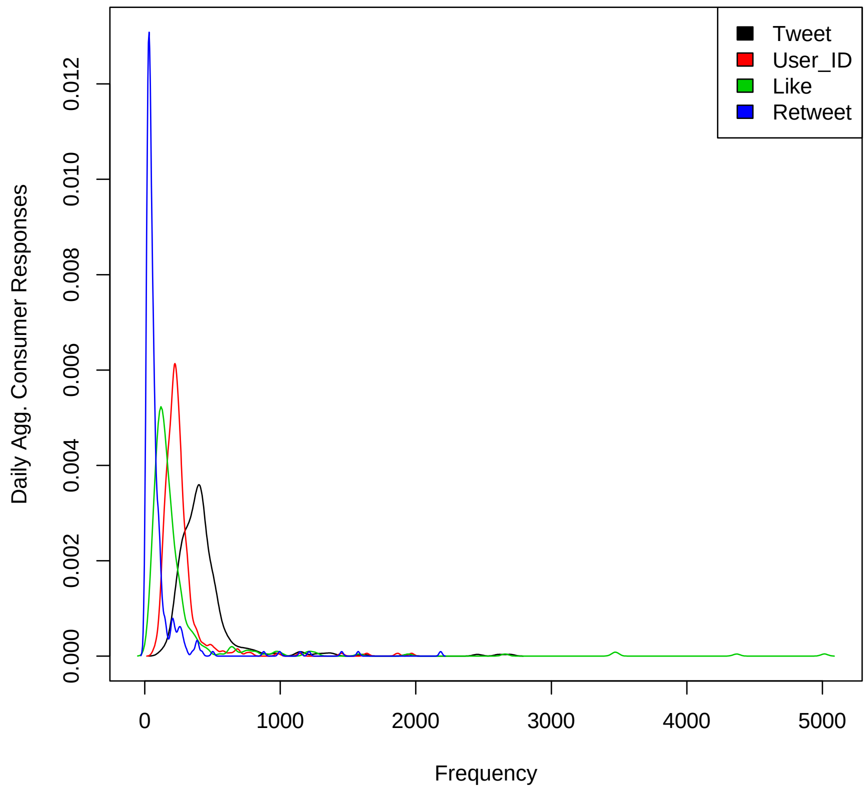


Fig. 4. Density plots for daily aggregation of consumer responses from tweets.

Cross-sectional correlation of daily and hourly responses is carried out to analyze the associations between the variables. Spearman correlation is selected as the most appropriate technique since this behavior does not meet the Pearson correlation requirements of normality of variables and linearity. As expected, it is observed that the number of Twitter users has a strong positive correlation with the number of tweets. This is clear in both daily (Correlation: 0.95) and hourly (Correlation: 0.99) analyses showing a significant association where the number of tweets has increased with the number of Twitter users during this time period.

The relationship between likes and retweets has a strong positive association in both daily (Correlation: 0.65) and hourly (Correlation: 0.73) analyses. In addition, it can be seen that the variables tweet and likes are also positively correlated where the number of likes grows with the number of tweets on both daily and hourly basis. Studies show that likes can be denoted as an activity measure and a measure of gratification (Blau & Neuthal, 2012). In this context, an increase in the number of tweets and likes serves as a cue to understanding the active engagement of people. Thus, a comparison is done to determine the engagement of people on Twitter during the outage days and other normal days of the year. It can be observed that there is a significantly higher interaction on Twitter during the days of the outage. The analysis showed that:

- the average number of Twitter users on outage days is seven times greater than that on normal days;
- the average number of tweets is six times greater and “Likes”;

“Retweets” too have increased in a larger proportion during the outage days, proving a higher interaction among consumers (Table 3).

Table 3

Comparison of Twitter engagement on the days of the outage and normal days of the year

	No. of Users (Average)	**No. of Tweets (Average)**	**No. of Likes (Average)**	**No. of Retweets (Average)**
Twitter activity - Usual Days	246	415	219	83
Twitter activity - Outage Days	1731	2427	3493	1173
Ratio between outage day Twitter activity and normal day Twitter activity	7:1	6:1	16:1	14:1

Given the large volume of Twitter data generated during the outage days, we subsequently analyzed data from one of the outages to disclose the activity and engagement on Twitter. For this purpose, we plotted the number of tweets with the manually coded sentiments in tweets to analyze the hourly trends during the day (Fig. 5).

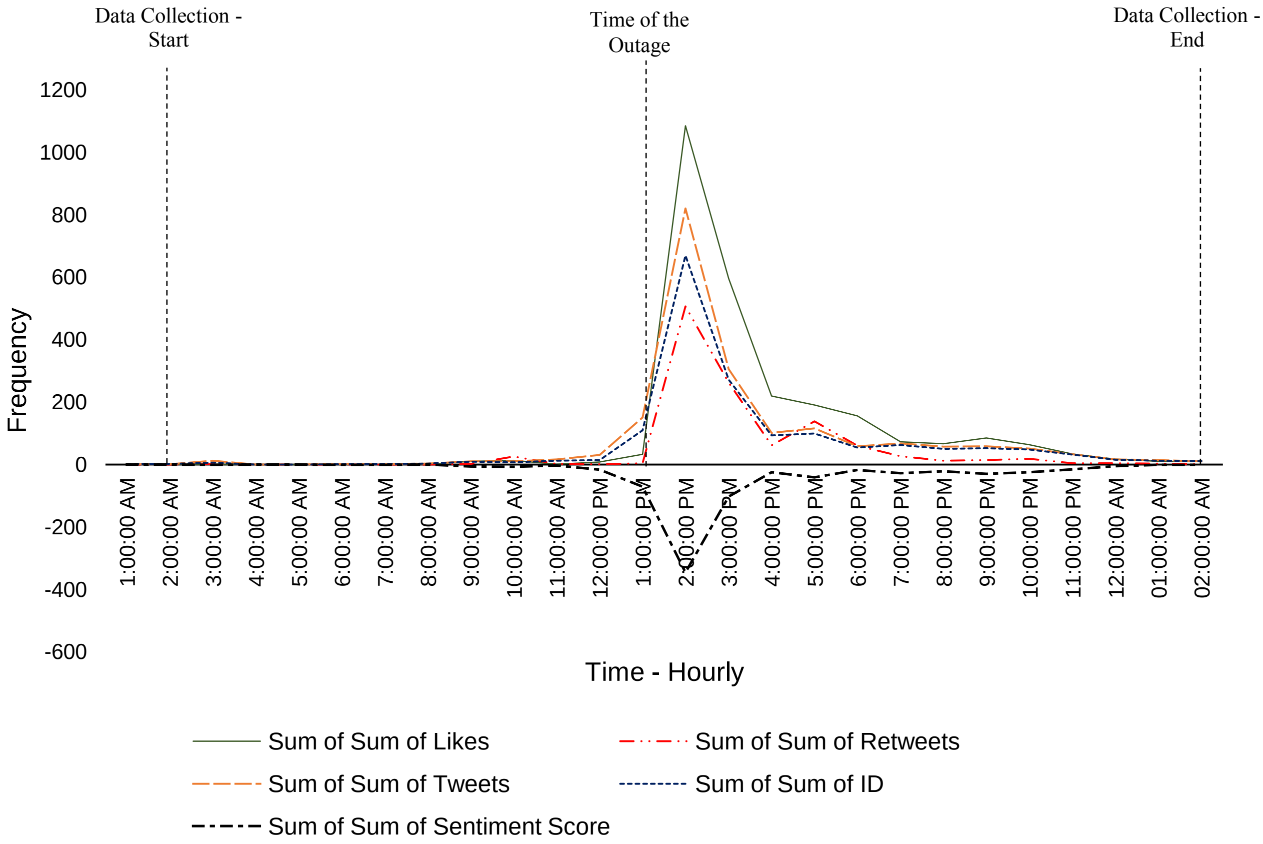


Fig. 5. Hourly trend of tweet measurements on the day of an outage

There is a significant rise in Twitter activity indicating a resonance on Twitter during the outage which is occurred around 2.00 pm on this particular day. It can be observed that during the time when the aggregated Twitter activity was positively peaked, the aggregated sentiment score[1] was negatively peaked concurrently. The response data followed the service outages lay the foundation for us to study consumer social influence behavior. A research data set is collected focusing on 24 hours' data from the moment of the outages to this end.

3.4 Data refinement with content tagging

To scrutinize consumers' responses in tweet contents for service outage events, a research data set was generated from the data for the 24 hours after a major event (Fig. 5). This data set

[1] Aggregated sentiment scores: 13:00: (-71), 14:00: (-346), 15:00: (-103), 16:00: (-25). A negative tweet has a sentiment score '-1' and the scores for a positive tweet and a neutral tweet are "1" and "0" respectively.

captured the response to a major service outage on an hourly basis. A Lexicon-based automatic sentiment classification function has been implemented using R ‘syuzhet’ library (Jockers, January 28, 2015/2017) where a number of recent sentiment dictionaries were included. The accuracy of applying automatic sentiment classification to Tweet content is not high with a testing performance of approximately 53% due to the presence of many sarcastic and mockery valences. Therefore, human coders were used to review and manually assign sentiment categories (‘negative’, ‘positive’ and ‘neutral’) to improve the accuracy of sentiment annotation. A coding procedure is also performed to identify sarcastic and mockery tweets. The annotations are performed by a research assistant and subsequently reviewed by two researchers independently to produce the final coded data. Table 4 describes a new nominal variable (Coding) derived from this review process.

Table 4

Coding examples of mockery-sarcastic (‘MSResp_Neg’), not mockery-sarcastic (‘N_MSResp_Neg’) negative tweets and not mockery-sarcastic none-negative tweets (‘N_MSResp_N_Neg’).

Coding	Description	Examples
MSResp_Neg	a mockery or sarcastic negative comment	*… never been a better time to be a <Telco name> customer …*
N_MSResp_Neg	Negative but not a mockery or sarcastic comment	*… paying a lot for no service <Telco name> …*
N_MSResp_N_Neg	None-negative and not a mockery or sarcastic comment	*… we've just experienced a nation-wide <Telco name> mobile outage. But it seems we're back online now …*

To investigate a hypothesis that Twitter users are likely to be attracted by users with a certain degree of followers, a nominal variable Celeb is produced to reflect their celebrity status. Table 5 presents the results of coding for Celeb-based on a threshold of 500 followers for a medium to high celebrity (‘Celeb_MH’). A user is coded as low (‘Celeb_L’) if they are below the 500-follower threshold.

Table 5

Celeb variable descriptions – research data set

Celeb	Description	Volume	Percentage
Celeb_MH	Twitter ID with number of followers >= 500	992	53.97%
Celeb_L	Twitter ID with number of followers less than 500	846	46.03%

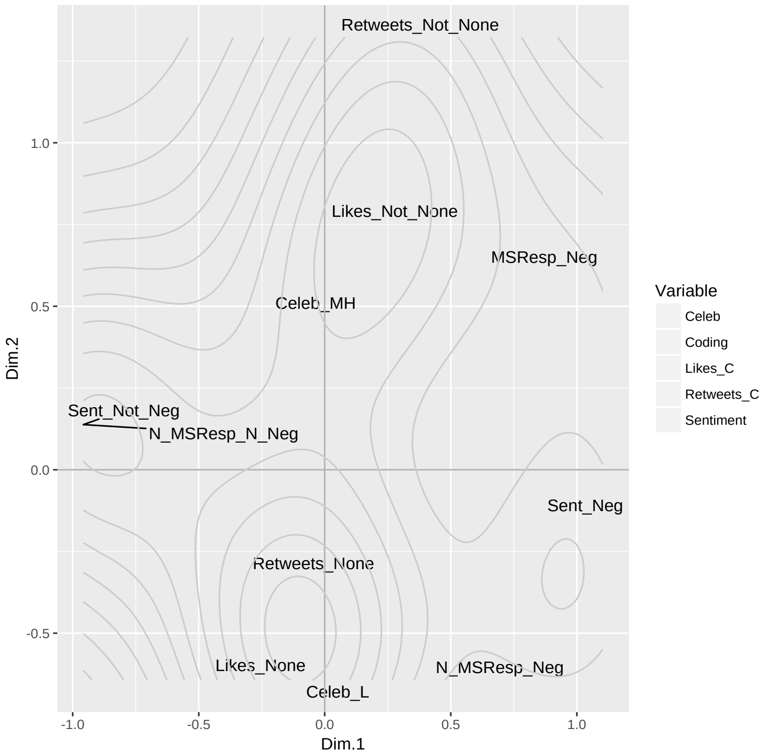
4. Results

Based on the insights obtained from a pre-analytics study using descriptive statistics, we drill down to a research data set to examine the relationship between the influential nature of tweets and sentiments expressed in the Tweet contents. The role of negativity, sarcasm and mockery as influential factors is investigated. This study also explores the role of celebrity status on Twitter as an influential factor during service outages.

4.1 Data analysis using Multiple Correspondence Analysis

This study focuses on finding behavior patterns among consumers' response to service outage via analyzing coded tweet text contents. We aim to identify if negativity, sarcasm and mockery could be regarded as influential factors by using Correspondence Analysis (CA). CA (Costa et al., 2013; Doey & Kurta, 2011; Greenacre, 2007; Hair et al., 2007) is a multivariate statistical technique that is used to explore the key underlying dimensions and perceptual locality of variables in this dimensional space.

Multiple correspondence analysis (MCA) extends the scope of CA to three or more categorical variables. In practice, the number of dimensions to be retained in the solutions is based on a moderate degree (>0.2) of inertia (eigenvalues) or research objectives (Hair et al., 2007). The unique benefits of CA are its abilities to represent instances (rows) and attributed (columns) in joint perceptual space thus providing a novel means of visualizing patterns of relationships among dependent variables. The R library "factoextra" (Kassambara & Mundt, 2017) is applied to the Twitter responses after service outage data (after 13:00) on a specific day (Fig. 5, Fig. 6 (a)) – the study group from research data set. MCA is subsequently applied to an independent validation data set (the validation group) for another outage day to validate the patterns (Fig. 6 (b)). It is observed that only 5.6% of distinctive IDs appeared in both data sets indicating the responses for the study group and the validation group are independent.



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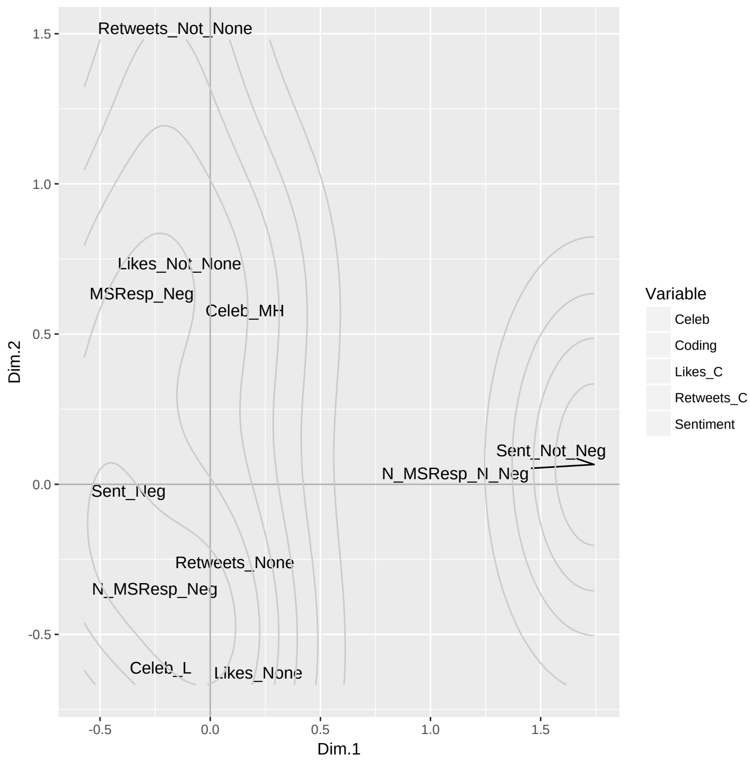


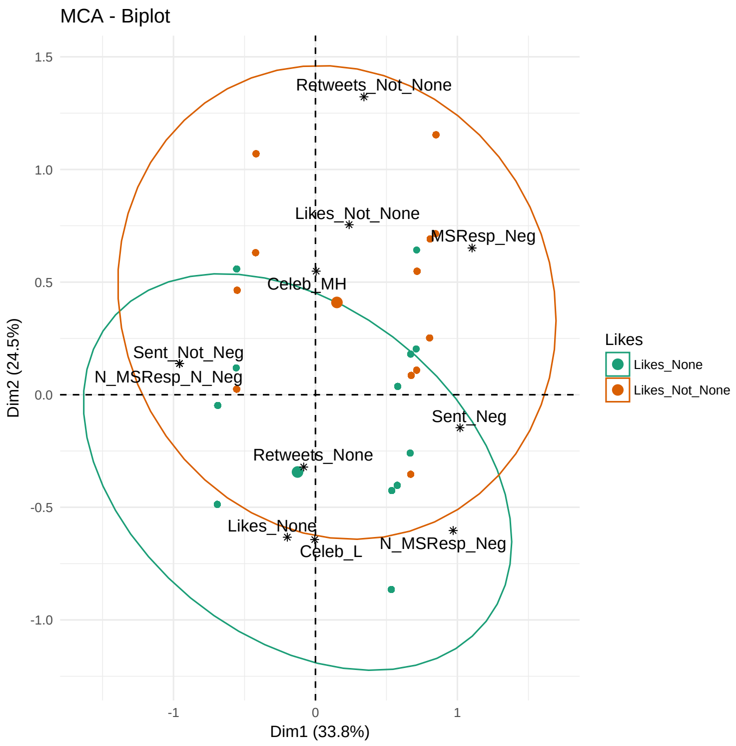
(b)

Fig. 6. Results of MCA for (a) the dataset from one outage as study group, and (b) from a second unrelated outage as validation data. Similar patterns can be observed from these perceptual maps. The contours from 2D density estimations show the mass of data. The perceptual maps show clear patterns of relationships among variables.

'Likes_None' is close to 'N_MSResp_Neg' (none sarcastic or mockery negative tweets), 'Celeb_L' and 'Retweets_None' from a perceptual map created from MCA for both outage data and the validation data. On the other hand, 'Likes_Not_None' is strongly associated with 'MSResp_Neg' (sarcastic and mockery negative tweets), 'Celeb_MH' and 'Retweets_Not_None' on both maps based on their relative proximity. The patterns of above relationships indicate the significant roles of sarcasm and celebrity status in social media influence on both perceptual maps with dimensions 1 and 2 accounting for 58.3% and 57.9% variances respectively for outage data and validation data. The role of negative sentiments ('Sent_Neg') is inconclusive from MCA due to its existence[2] in both sarcastic-mockery tweets

[2] The ratio non-sarcastic-mockery tweets to sarcastic-mockery tweets is 1.9 for the study group and 2.2 for the validation group.

and non-sarcastic-mockery tweets. The effect of overlaying data points relating to the variable likes and retweets to all variables are shown in the perceptual maps of Fig. 7.



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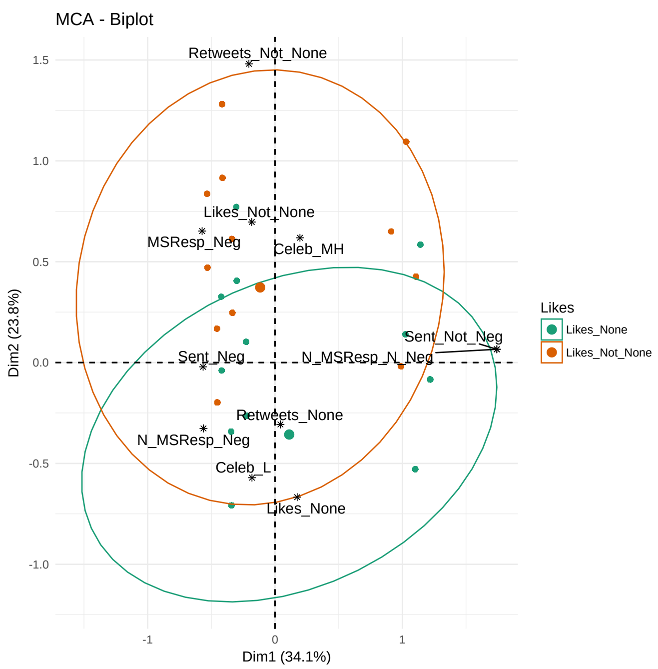

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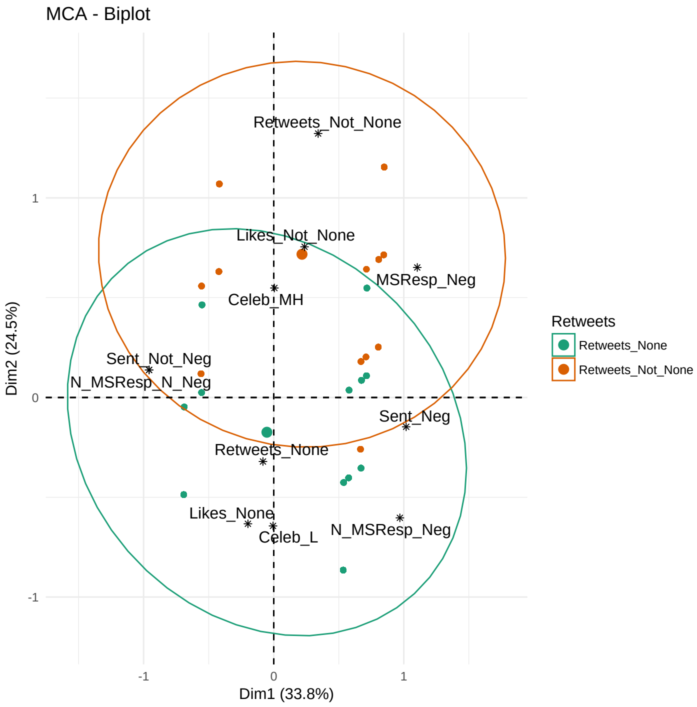

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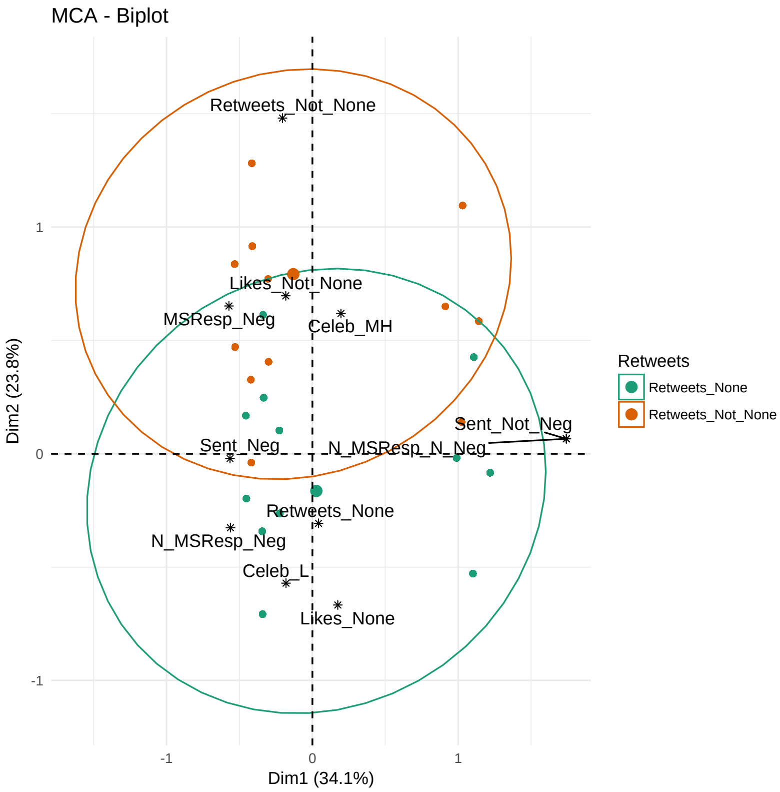

(d)

Fig. 7. Biplots for likes and retweets. (a) and (b) relate variables for study group and validation group to likes and (c) and (d) relate variables to retweets relating to study and validation groups. The biplot from overlaying data points of ‘Retweets’ to variables in perceptual maps. The ellipses represent the 0.95 confidence boundary approximation of data points with the same ‘Retweets’ value

(‘Retweets_None’, ‘Retweets_Not_None’). Data points are colored dots and the black stars represent variables.

These biplots clearly demonstrate that an underlying structure may exist to differentiate whether a tweet attracts a like/retweet or not. It is postulated that based on a Twitter user’s celebrity status, whether he or she utilizes sarcastic or mockery tweets, their tweet sentiment will lead to better engagements in terms of attracting likes and retweets from other users during service outages. A non-parametric test (Kolmogorov-Smirnov) is performed multiple times over the number of likes and retweets associated with variables Sentiment, Coding and Celeb. For example, the empirical cumulative distribution (ecd) of the number of likes associated with a negative sentiment tweet (‘Sent_Neg’) is tested against the number of likes relating to a non-negative sentiment tweet (‘Sent_Not_Neg’). The series of KS test is performed for the data set for the outage day and the validation data set. Table 6 presents the results of a series KS test on various variables for the outage and validation data set respectively.

Table 6

KS tests result for variables influence on engagements. The *p*-values which indicate a lack of significance are denoted in bold. Significance level: $\alpha = 0.05$.

Variables	**Likes**		**Likes**		**Retweets**		**Retweets**	
	Outage Day Data		Validation Data		Outage Day Data		Validation Data	
	D	*p*	D	*p*	D	*p*	D	*p*
Sent_Neg vs	0.14	0.00	0.15	0.00	0.04	**0.35**	0.03	**0.64**
Sent_Not_Neg	**Confirmed**: The distribution of ‘Likes’ associated with negative sentiment tweets are significantly different to that for non-negative tweets. The level of supports of negative tweets for ‘Retweets’ is not significant							
MSResp_Neg vs	0.25	0.00	0.15	0.00	0.15	0.00	0.07	0.02

N_MSResp_Neg	**Confirmed**: Distributions of ‘Likes’ and ‘Retweets’ associated with sarcastic negative tweets are significantly different to those for non-sarcastic negative tweets							
Celeb_MH vs Celeb_L	0.22	0.00	0.16	0.00	0.11	0.00	0.11	0.00
	Confirmed: Distributions of ‘Likes’ and ‘Retweets’ associated with ‘Celeb_MH’ users are significantly different to those for ‘Celeb_L’ (< 500 followers) users. The threshold level of 500 is taken from the experimental results to identify the most differentiating celebrity value to classify if a Twitter user is able to attract likes and retweets							

From the results of empirical cumulative distribution studies demonstrate that negative sentiment of the tweets has an influence on attracting more likes from consumers during the service outage. The results also denote that a higher level of engagements can be ascribed to the influence of sarcastic-mockery tweets. This reveals that attractive and influencing nature of sarcasm and mockery is observed in social media as well.

Furthermore, it can be seen that a user’s celebrity status is capable of attracting likes and retweets from other consumers during service outages. On Twitter, retweeting is the most prominent indicator of influence as users tend to broadcast their favorite tweets to their followers (Xu & Yang, 2012). This behavior in these results provides further evidence that consumers with a large number of followers are more influential in spreading information during a critical time like an outage of a very widely-used service and that their information is well received by other consumers.

5. Discussion and Conclusion

Digitization is infused into every facet of today's business and has become an inseparable component of managing customer relationships. A study on customer delight, defines customer satisfaction as "profoundly positive emotional experience" (Oliver, Rust, & Varki, 1997), highlighting the relationship between customer experience and the longevity of the business. This emphasizes the need to learn the consumer behavior and to identify the influential factors affecting customers' decisions and behavior. This necessity is particularly imperative during a time of a failure or a disruption (Janet R. McColl-Kennedy & Amy K. Smith, 2006). Our study contributes to consumer behavior research from a novel dimension by analyzing social media influence factors based on Twitter content and metadata in response to a group crisis situation such as an outage of a very widely-used service. There appears to be no significant research studying the role of sarcasm and mockery in social media influence during a crisis situation such as a service outage.

This research has resulted in three key findings. First, by studying sentiments during service outages we confirm that tweets with negative sentiments attract more attention of fellow consumers, supporting the influential nature of negative opinions during a group service failure. Second, as previous research on sentiments predominantly focuses on positive, negative and neutral sentiments, we bring an innovation by revealing the role of sarcasm and mockery in sentiments as a social media influencer. We found that sarcasm and mockery contribute to the popularity of a tweet during service outages based on the experimental results revealing that sarcastic negative tweets have attracted statistically significant higher number of likes and retweets compared to non-sarcastic negative tweets. This novel finding emphasizes the role of negative sarcasm as a dominant influencer in social media which affects consumer behavior during a crisis situation such as a service outage. Third, we studied the role of celebrity status in social media influence during service outages. It was identified that a Twitter Id having 500 or more followers is likely to attract more likes and retweets during service outage. This confirms that consumers with a larger audience are able to better engage fellow consumers via their tweets during an event such as a service outage. Thus, by exploring tweets and related meta-data, we designed and contributed an approach that can be used to identify the influential factors on Twitter during service outages.

The findings have potential significant managerial implications to form strategies for customer and public relationship management which are crucial at a time of a service outage. The social influence factor analysis and the analytical approaches conducted in this study enable service recovery managers to promptly react to consumers' opinions via negative valence. While service outages are inevitable, a good service recovery can convert frustrated customers into loyal ones (Miller, Craighead, & Karwan, 2000). Mitigating negative word of mouth and converting disgruntled consumers into brand advocates remain a principal challenge. A recent study on influence theory in the context of social media reveals that the positive effects of recovery success will be significantly higher due to virtual presence of fellow consumers (Schaefers & Schamari, 2016). Thus, service recovery managers may proactively identify and engage with influential fellow consumers via social media to strategically foster positive customer relationships. Our findings on social influencer factors provide evidence for organizations to classify influencers among their online customers. There are over 30% of negative tweets which are sarcastic or mocking in nature and these sarcastic-mockery comments significantly attract likes and retweets. Specially, given that the negative sarcasm has emerged as a prominent influence factor it is recommended that service managers should pay attention to consumers disseminating these tweets. Resources should be allocated to research and development work in automatic sarcasm detection for social media data.

Public relationship management is the focal point for an organization to effectively manage brand values. This is particularly important in a time of service failure. Crisis communication serves as a prominent aspect among the public relationship management disciplines (Grunig, 2010). Studies highlight that social media should be incorporated into crisis communication strategies given the emerging trends in the digital world (Jin, Liu, & Austin, 2014). Based on the findings from this research, we suggest that a company's crisis communication scheme needs to incorporate a tailored strategy targeting social influencers distributing sarcastic negative valence.

One of the limitations of this study is the data source constraint in which consumer data is only collected from Twitter, hence the study is limited to those who express their opinions via Twitter. To address this limitation data collection could be extended to other social media resources which are publicly available. This study focuses on a particular series of service outages by a Telco company. Based on this scenario, it provides good internal validity for the research. However, there could be possible issues when generalizing results of this study to a wider industry domain. Future research may extend the study to other industry domains. The cultural preferential variance towards sarcasm and mockery is an area for further research since the consumer data collected are predominantly from people with an Australian cultural background. A future extension may focus on the roles of sarcasm and mockery for social media influence in situations with heterogeneous cultural and linguistic backgrounds. Another future research direction of this study would be to study the consumer behavior in response to recurrent service outages to gauge the related time variant effects.

References

Agarwal, A., Xie, B., Vovsha, I., Rambow, O., & Passonneau, R. (2011). Sentiment Analysis of Twitter Data. In *Proceedings of the Workshop on Languages in Social Media* (pp. 30–38). Stroudsburg, PA, USA: Association for Computational Linguistics. Retrieved from http://dl.acm.org/citation.cfm?id=2021109.2021114

Aral, S., & Walker, D. (2012). Identifying influential and susceptible members of social networks. *Science (New York, N.Y.)*, *337*(6092), 337–341. https://doi.org/10.1126/science.1215842

Balahur, A. (2013). Sentiment Analysis in Social Media Texts. In *WASSA@ NAACL-HLT* (pp. 120–128). Retrieved from https://www.aclweb.org/anthology/W/W13/W13-16.pdf#page=132

Blau, I., & Neuthal, T. (2012). Tweeting educational technology: a tale of professional community of practice. *International Journal of Cyber Society and Education*, *5*(1), 75.

Bond, R. M., Fariss, C. J., Jones, J. J., Kramer, A. D. I., Marlow, C., Settle, J. E., & Fowler, J. H. (2012). A 61-million-person experiment in social influence and political mobilization. *Nature*, *489*(7415), 295–298. https://doi.org/10.1038/nature11421

Brandwatch Report on Social Insights of the Telecommunication Industry, , https://www.brandwatch.com/wp-content/uploads/2015/11/Telecommunication-Report.pdf, Accessed 28.04.2017

Cha, M., Haddadi, H., Benevenuto, F., & Gummadi, K. P. (2010). Measuring User Influence in Twitter: The Million Follower Fallacy. In *Fourth International AAAI Conference on Weblogs and Social Media*. Retrieved from https://aaai.org/ocs/index.php/ICWSM/ICWSM10/paper/view/1538

Costa, P., Soares, C., Santos, N. C., Cunha, P., Cotter, J., & Sousa, N. (2013). The Use of Multiple Correspondence Analysis to Explore Associations between Categories of

Qualitative Variables in Healthy Ageing [Research article]. https://doi.org/10.1155/2013/302163

Dellarocas, C. (2003). The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms. *Management Science*, *49*(10), 1407–1424. https://doi.org/10.1287/mnsc.49.10.1407.17308

Doey, L., & Kurta, J. (2011). Correspondence analysis applied to psychological research. *Tutorials in Quantitative Methods for Psychology*, *7*(1), 5–14.

Du, J., Fan, X., & Feng, T. (2014). Group Emotional Contagion and Complaint Intentions in Group Service Failure: The Role of Group Size and Group Familiarity. *Journal of Service Research*, *17*(3), 326–338. https://doi.org/10.1177/1094670513519290

Fang, X., & Zhan, J. (2015). Sentiment analysis using product review data. *Journal of Big Data*, *2*, 5. https://doi.org/10.1186/s40537-015-0015-2

Gibbs, R. W. (2000). Irony in Talk Among Friends. *Metaphor and Symbol*, *15*(1–2), 5–27. https://doi.org/10.1080/10926488.2000.9678862

Greengross, G., & Miller, G. (2011). Humor ability reveals intelligence, predicts mating success, and is higher in males. *Intelligence*, *39*(4), 188–192. https://doi.org/10.1016/j.intell.2011.03.006

Grunig, J. E. (2001). The Role of Public Relations in Management And Its Contribution to Organizational and Societal Effectiveness, Speech deleivered in Taipei, Taiwan, 12 May 2001.

Hair JF, Black B, Babin B, Anderson RE, Tatham RL (2007) Multivariate Data Analysis. Toronto: Prentice Hall.

Heinonen, K. (2011). Consumer activity in social media: Managerial approaches to consumers' social media behavior. *Journal of Consumer Behaviour*, *10*(6), 356–364. https://doi.org/10.1002/cb.376

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, *18*(1), 38–52. https://doi.org/10.1002/dir.10073

Hillmann, R., & Trier, M. (2013). Influence And Dissemination Of Sentiments In Social Network Communication Patterns. *ECIS 2013 Completed Research*. Retrieved from http://aisel.aisnet.org/ecis2013_cr/52

Hong, L., Dan, O., & Davison, B. D. (2011). Predicting Popular Messages in Twitter. In *Proceedings of the 20th International Conference Companion on World Wide Web* (pp. 57–58). New York, NY, USA: ACM. https://doi.org/10.1145/1963192.1963222

Huang, L., Gino, F., & Galinsky, A. D. (2015). The highest form of intelligence: Sarcasm increases creativity for both expressers and recipients. *Organizational Behavior and Human Decision Processes*, *131*, 162–177. https://doi.org/10.1016/j.obhdp.2015.07.001

Hutto, C. J., Yardi, S., & Gilbert, E. (2013). A Longitudinal Study of Follow Predictors on Twitter. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 821–830). New York, NY, USA: ACM. https://doi.org/10.1145/2470654.2470771

Ioanăs, E., & Stoica, I. (2014). Social Media and its Impact on Consumers Behavior. *International Journal of Economic Practices and Theories*, *4*(2), 295–303.

Janet R. McColl-Kennedy, & Amy K. Smith. (2006). Chapter 10 Customer Emotions in Service Failure and Recovery Encounters. In *Individual and Organizational Perspectives on Emotion Management and Display* (Vol. 2, pp. 237–268). Emerald Group Publishing Limited. https://doi.org/10.1016/S1746-9791(06)02010-4

Jenders, M., Kasneci, G., & Naumann, F. (2013). Analyzing and Predicting Viral Tweets. In *Proceedings of the 22Nd International Conference on World Wide Web* (pp. 657–664). New York, NY, USA: ACM. https://doi.org/10.1145/2487788.2488017

Jin, Y., Liu, B. F., & Austin, L. L. (2014). Examining the Role of Social Media in Effective Crisis Management: The Effects of Crisis Origin, Information Form, and Source on Publics' Crisis Responses. *Communication Research*, *41*(1), 74–94. https://doi.org/10.1177/0093650211423918

Jockers, M. L. (2017). *syuzhet: An R package for the extraction of sentiment and sentiment-based plot arcs from text*. HTML. Retrieved from https://github.com/mjockers/syuzhet (Original work published January 28, 2015)

Kassambara, A., & Mundt, F. (2017). factoextra: Extract and Visualize the Results of Multivariate Data Analyses (Version 1.0.4). Retrieved from https://cran.r-project.org/web/packages/factoextra/index.html

Kelman, H. C. (1958). Compliance, identification, and internalization three processes of attitude change. *Journal of Conflict Resolution*, *2*(1), 51–60. https://doi.org/10.1177/002200275800200106

Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a Social Network or a News Media? In *Proceedings of the 19th International Conference on World Wide Web* (pp. 591–600). New York, NY, USA: ACM. https://doi.org/10.1145/1772690.1772751

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113. https://doi.org/10.1016/j.asej.2014.04.011

Miller, J. L., Craighead, C. W., & Karwan, K. R. (2000). Service recovery: a framework and empirical investigation. *Journal of Operations Management*, *18*(4), 387–400. https://doi.org/10.1016/S0272-6963(00)00032-2

Naveed, N., Gottron, T., Kunegis, J., & Alhadi, A. C. (2011). Bad News Travel Fast: A Content-based Analysis of Interestingness on Twitter. In *Proceedings of the 3rd International Web Science Conference* (p. 8:1–8:7). New York, NY, USA: ACM. https://doi.org/10.1145/2527031.2527052

Oliver, R. L., Rust, R. T., & Varki, S. (1997). Customer delight: Foundations, findings, and managerial insight. *Journal of Retailing*, *73*(3), 311–336. https://doi.org/10.1016/S0022-4359(97)90021-X

Pang, B., & Lee, L. (2008). Opinion Mining and Sentiment Analysis. *Foundations and Trends® in Information Retrieval*, *2*(1–2), 1–135. https://doi.org/10.1561/1500000011

Pender, B., Currie, G., Delbosc, A., & Shiwakoti, N. (2014). Social Media Use during Unplanned Transit Network Disruptions: A Review of Literature. *Transport Reviews*, *34*(4), 501–521. https://doi.org/10.1080/01441647.2014.915442

Prabowo, R., & Thelwall, M. (2009). Sentiment analysis: A combined approach. *Journal of Informetrics*, *3*(2), 143–157. https://doi.org/10.1016/j.joi.2009.01.003

Qaisi, L. M., & Aljarah, I. (2016). A twitter sentiment analysis for cloud providers: A case study of Azure vs. AWS. In *2016 7th International Conference on Computer Science and Information Technology (CSIT)* (pp. 1–6). https://doi.org/10.1109/CSIT.2016.7549473

Qualman, E. (2010). *Socialnomics: How Social Media Transforms the Way We Live and Do Business*. John Wiley & Sons.

Riquelme, F., & González-Cantergiani, P. (2016). Measuring user influence on Twitter: A survey. *Information Processing & Management*, *52*(5), 949–975. https://doi.org/10.1016/j.ipm.2016.04.003

Romero, D. M., Galuba, W., Asur, S., & Huberman, B. A. (2011). Influence and Passivity in Social Media. In *Proceedings of the 20th International Conference Companion on*

World Wide Web (pp. 113–114). New York, NY, USA: ACM. https://doi.org/10.1145/1963192.1963250

Salehan, M., & Kim, D. J. (2016). Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics. *Decision Support Systems*, *81*, 30–40. https://doi.org/10.1016/j.dss.2015.10.006

Salganik, M. J., Dodds, P. S., & Watts, D. J. (2006). Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market. *Science*, *311*(5762), 854–856. https://doi.org/10.1126/science.1121066

Schaefers, T., & Schamari, J. (2016). Service Recovery via Social Media: The Social Influence Effects of Virtual Presence. *Journal of Service Research*, *19*(2), 192–208. https://doi.org/10.1177/1094670515606064

Snijders, R., & Helms, R. W. (2014). Analyzing Social Influence through Social Media: A Structured Literature Review [Part of book]. Retrieved from http://dspace.library.uu.nl/handle/1874/306129

Stambaugh, C. (2013). Social Media and Primary Commercial Service Airports. *Transportation Research Record: Journal of the Transportation Research Board*, *2325*, 76–86. https://doi.org/10.3141/2325-08

Steinert-Threlkeld, Z. C., Mocanu, D., Vespignani, A., & Fowler, J. (2015). Online social networks and offline protest. *EPJ Data Science*, *4*(1), 19. https://doi.org/10.1140/epjds/s13688-015-0056-y

Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). Want to be Retweeted? Large Scale Analytics on Factors Impacting Retweet in Twitter Network. In *2010 IEEE Second International Conference on Social Computing* (pp. 177–184). https://doi.org/10.1109/SocialCom.2010.33

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010). Sentiment in Short Strength Detection Informal Text. *J. Am. Soc. Inf. Sci. Technol.*, *61*(12), 2544–2558. https://doi.org/10.1002/asi.v61:12

Ullah, R., Amblee, N., Kim, W., & Lee, H. (2016). From valence to emotions: Exploring the distribution of emotions in online product reviews. *Decision Support Systems*, *81*, 41–53. https://doi.org/10.1016/j.dss.2015.10.007

Villarroel Ordenes, F., Ludwig, S., de Ruyter, K., Grewal, D., & Wetzels, M. (2017). Unveiling What Is Written in the Stars: Analyzing Explicit, Implicit, and Discourse Patterns of Sentiment in Social Media. *Journal of Consumer Research*, *43*(6), 875–894. https://doi.org/10.1093/jcr/ucw070

Wang, X., Yu, C., & Wei, Y. (2012). Social Media Peer Communication and Impacts on Purchase Intentions: A Consumer Socialization Framework. *Journal of Interactive Marketing*, *26*(4), 198–208. https://doi.org/10.1016/j.intmar.2011.11.004

Xu, Z., & Yang, Q. (2012). Analyzing User Retweet Behavior on Twitter. In *Proceedings of the 2012 International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2012)* (pp. 46–50). Washington, DC, USA: IEEE Computer Society. https://doi.org/10.1109/ASONAM.2012.18

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