Examining customer perception and behaviour through social media research – an empirical study of the United Airlines overbooking crisis

Abstract

Airlines have been adopting yield management to optimise the perishable seat control problem and overbooking is a commoon strategy. This study outlines the connections between yield management, crises, and crisis communication. Using big data captured on a social media platform, this study aims to combine traditional yield management with emerging social big data analytics. As part of this, we use the twitter data on the 2017 United Airline (UA) to analyse the overbooking crisis. Our findings shed light on the importance of a more effective orchestration of yield management to avoid the escalation of crises during crisis communication phases.

Highlights

- UA had two image repair phases over the 24-hour apology tour.
- The UA's insincere rhetorical apologies, and 'mortification' shown by their defensive posture was a main contributor to their crisis management failure.
- Information on social media is propagated and spread rapidly and globally, which introduces new stakeholders into the conversation.
- New stakeholders are difficult to define and target, thus making it hard to alter their perceptions and repair image.

Keywords: Social media big data, Customer behaviour, Image repair, Crisis communication Twitter mining

1.Introduction

Revenue management and yield management have long been an interest in the airline industry (Belobaba, 1987; Chiang et al., 2007) and have been investigated widely by practitioners and academics (Alderighi et al., 2015; Smith et al., 1992; Terciyanlı and Avşar, 2019). A main implication drawn from theoretical models (Tse and Poon, 2017; Wang and Fung, 2014) and empirical research is that overbooking can effectively minimise the loss of revenue due to passenger no-shows and late cancellations (Camilleri, 2018; Shlifer and Vardi, 1975). The practice of intentionally overbooking is an important strategy for airlines to manage their perishable seats; yet, it remains a challenge to balance the possible consequences of spoilage and denied boarding. Ineffective and poorly executed overbooking situations could be costly, as the loss includes not only financial penalties but also customer goodwill. This could be further undermined if negative reviews are communicated on social media platforms, thus representing a possible self-induced crisis.

Recent literature in big data analytics has focused on managing crisis communication (Houston et al., 2015; Tse et al., 2018; Veil et al., 2011). In particular, this growing body of literature has focused on the role of big data in spreading disaster information

(Palen, 2008), with a particular focus on stakeholder-centred response dynamics. This research stream concludes that social media data can be used to search for keywords, diffuse information (Aula, 2010; Houston et al., 2015) and spread rumours (Tse et al., 2016). However, despite these critical insights, very little research has focused on how firms can utilise big data to repair post crisis damaged images and impressions. To the best of our knowledge, this is the first study that aims to explore the use of social big data in the airline industry for managing risks associated to overbooking and crisis communication. Using big data captured on a social media platform, this study aims to combine traditional yield management with emerging social big data analytics. As part of this, we will use social big data on the 2017 United Airline (UA) to analyse the overbooking crisis.

On the 9th of April 2017, UA's United Express flight #3411 was booked to the capacity but would need to make room to transport four crew members. After failing to seek out enough volunteers willing to give up seats, the flight attendant decided to forcedly remove a passenger and brought in airport security officials for assistance. Multiple video footages then captured and shared the moment of a paying passenger was violently dragged off the seat and removed from the plane. This footage went viral over the realm of the online social media and the incident escalated. Hours later, the parent company UA responded to the incident with a series of apologetic tweets aimed at explaining the overcapacity situation and legitimising the removal of an unwilling passenger. These apologies were deemed as insincere. A second round of, even bigger, criticism against the company was then sparked. The concern was not just focused on the controversial overbooking strategy, but also on the company's attitude on shirking responsibility and justifying any perceived wrongdoing.

This study outlines the connections between yield management, crises, and crisis communication. Based on the understanding that yield management, when orchestrated ineffectively, can lead to crises and stakeholder dissatisfaction, the primary focus of this study is to critically assess UA's post crisis management using Benoit's (2018) approach. In doing so, the present study will use social media big data analytics to empirically compare the image repair discourse used by the company against the theoretical strategies proposed by Benoit (1997) and Coombs (2000). The study chooses the data from Twitter for four important reasons: 1, Twitter, as a popular social media platform(Kwak et al., 2010), can yield at an enormous rate of data per day (Claster et al., 2010). 2, Twitter allows users to capture and create social surplus for research (Manyika et al., 2011). 3, Twitter, as a useful repository, can play an important role in crisis communication (Heverin and Zach, 2010). 4. In this study, the infamous video footage that later went viral was first shared on Twitter. Based on the above, the following research questions underpin this study:

RQ1 What dominant image repair strategies were used by UA's during the 2017 overbooking incident?

RQ2 What information was shared by Twitter citizens in response to UA's apologies? Were there any prevalent topics or contents?

RQ3 What was the sentiment towards the overbook incident? Were there any patterns of information diffusion?

The study is organised as follows: Section 2 reviews the literature on crisis communication and the image repair theory. 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 Overbooking policy

Over the years, airlines have been adopting yield management systems (Chiang et al., 2007) that are based on probabilistic dynamic fare management models (Subramanian et al., 1999; Suzuki and Review, 2002). The aim of these systems is to optimise the highly perishable seat inventory control problem (Bilotkach et al., 2015). One common characteristic is to oversell available seats based on predictions concerning the probability distributions of the number of passengers likely to not attend the flight (Chua et al., 2016). As the booking decisions are repeated time and time again, the risk-neutral probabilities can be justified (McGill and Van Ryzin, 1999), hence an optimal overbooking extent can be estimated (Huang et al., 2011; Suzuki and Review, 2006). The primary objective of overbooking the seats is to hedge against the risk of cancellations and no-shows (Gallego et al., 2004), but it also offers cheaper fares for customers (Wang et al., 2019; Weatherford and Bodily, 1992) and is accepted by the IATA ever since the industrial deregulation in the 1970s (Fu et al., 2011; IATA, 2017).

While overbooking seemingly provides a mutually beneficial scenario for the industry and customers (Chua et al., 2016), such a risk-based strategy also poses other challenges which should form a new research agenda. Knowing that denying boarding could damage customer goodwill, studies looking at overbooking should also account for long-term customer behavioural effects (McGill and Van Ryzin, 1999; Wangenheim and Bayón, 2007). One such effect is the use of word-of-mouth to spread messages conveying the negative experiences incurred with respect to overbook situations. In conjunction with technological advancement associated with the widespread adoption and use of social media, these messages are more likely to be shared and trigger a bigger crisis, with the implications of damaging brand reputations and disseminating rumours (Alexander and ethics, 2014; Garrow et al., 2011). Therefore, crisis response and communication strategies should be actively integrated within the yield management approaches adopted in the airline industry.

2.2 Social Media and Twitter

The emerging concept of social media is top of many business management research agenda in recent years (Kaplan and Haenlein, 2010; Singh et al., 2018). Social media is a popular web-based platform for users with whom they share a connection (Henderson and Bowley, 2010) to articulate views, share contents, exchange information and make interactions (Boyd and Ellison, 2007; Choi, 2016). It enables the world (Troisi et al., 2018) to be more interconnected and accounts for the production of social big data (Govindan et al., 2018; Malita, 2011; Rainie and Wellman, 2012).

Social big data are defined as the ‘data sources which can be characterised by their

different formats and contents, their very large size, and the online or streamed generation of information' (Bello-Orgaz et al., 2016. p2). They can generate forms of objective facts rather than the previous guesswork (Agrawal et al., 2011) and be captured from social media site distributors or collected manually (Tufekci, 2014). The large pools of data (Boyd and Crawford, 2012) are more readily used for research in various disciplines (Agrawal et al., 2011). In contrast with some other conventional data collection methods (e.g., interview and survey) (Boyd and Crawford, 2012), this is an more effective method to generate bigger impacts (Chen et al., 2012).

Twitter is a microblogging social media service (Kwak et al., 2010) which can yield at an enormous rate of data per day (Claster et al., 2010). It provides a popular online platform on mobile and other network devices (Thompson, 2011) for users to exchange and share crisis information (Houston et al., 2015; Veil et al., 2011). In particular, this growing body of literature has focused on the role of big data in spreading disaster information (Palen, 2008), with a particular focus on stakeholder-centred response dynamics. For instance, many have used Twitter to disseminate information (Roshan et al., 2016; Stewart and Wilson, 2016), search for keywords (Houston et al., 2015) and spread rumours (Tse et al., 2016).

2.3 Crisis communication

Crisis communication is defined as 'the collection, processing, and dissemination of information required to address a crisis situation' (Coombs and Holladay, 2011, p20). The recent prevalence of social media platforms has created a new channel for crisis negotiation and communication (Austin et al., 2012; Freberg et al., 2013), as they provide more direct, up-to-date and relatively credible information (Procopio and Procopio, 2007) for the stakeholders (Sedereviciute and Valentini, 2011).

However, such platforms are complex and interconnected, it would be difficult for the main organisations to effectively identify all stakeholders and manage their dyadic relationships (Wan et al., 2015). In addition, as everyone can actively participating in sharing information online, stakeholders and their relationships could be redefined (Himelboim et al., 2014): the main organisations are no longer the only influencers (Freberg et al., 2013), rather, there are peripheral stakeholders that can gain legitimacy and become new influencers by creating and propagating crisis information (Sedereviciute and Valentini, 2011). The contents of the information are also become less manageable and controllable (Aula, 2010). The large amount of fragmented, user generated (He et al., 2013) second-hand (word-of-mouth) contents (Coombs and Holladay, 2007) can easily spread false rumour (Oh et al., 2013; Tse et al., 2018), anger and aversion emotions to disrupt social orders and affect the interactions of stakeholders (Schultz et al., 2011), hence, further worsen the crisis (Jin et al., 2014). Many organisations have found it challenging to develop responses during crisis events (Freberg et al., 2013; Schultz et al., 2011).

Over the years, strategies have been developed to manage the interrelationships between stakeholders and guide the crisis communication (Birkland, 1997; Fishman, 1999; Schultz et al., 2011). Benoit (1997) and Coombs (2000) also considered strategies to protect reputational assets and tried to develop theoretical links between crises and crisis response strategies. For instance, the Situational Crisis

Communication Theory (SCCT) (Coombs, 2007; Coombs and Holladay, 2002) and the Social Mediated Crisis Communication (SMCC) Model (Jin et al., 2014) are the classic but effective evidence-based frameworks to understand the formation of crisis information, model the negative behavioural intentions in different crises, and highlight strategies to maximise protection of reputational image affected by post-crisis communication (Tse et al., 2016).

2.4 The Image repair theories

At the core of crisis communication (Smudde and Courtright, 2008), protecting and repairing reputations during the course of and after, the crisis has become more urgent (Cameron and Cheng, 2017). Image is defined as 'the perceptions of the rhetor held by the audience, shaped by the words and deeds of that rhetor, as well as by the actions of others'(Brinson and Benoit, 1996, p30). Therefore, repairing the image is to rebuild the perceptions of the audience (Benoit, 1995a) in order to re-acknowledge the legitimacy (Boyd, 2000).

Following pervious work on image restoration at the individual-level(Kruse, 1981; Ware and Linkugel, 1973), Benoit (1995b, 2000) formulated a theory for image repair (or previously restoration) which works also for organisations. This theory is based on 'goal-directed' persuasion (Burns and Bruner, 2000; Coombs and Schmidt, 2000),which can guide a set of rhetoric (Harlow et al., 2011) to effectively 'improve images tarnished by criticism and suspicion' (Benoit, 2014, p3). The rhetoric is a group of persuasive discourse to maintain positive images and respond to potential threads or suspicious words (Benoit and Henson, 2009) thereby bolstering one's face and reputation (Muralidharan et al., 2011). According to Benoit (1995b, 2000), the image repair discourse consists of five emerging strategies, namely as, denial *(simple denial* or *shifting blame)*, evade responsibility *(provocation, defeasibility, accident,* or *good intentions)*, reduce offensiveness *(bolstering, minimisation, differentiation, transcendence, attack accuser* or *compensation)*, corrective action and mortification. They are seldom used in isolation (Holtzhausen and Roberts, 2009) but could work separately (Coombs and Schmidt, 2000).

However, Benoit (1997) also realised that these strategies cannot always assure success and have limitations, such as the premise that powers of persuasion are limited. Hence, a unitary set of repairing strategies could fail, if not backfire, and could present obstacles to a company restoring their image to a pre-crisis state. Other parallel studies include receiver-oriented and theme-oriented image repair theories (Moffitt, 1994; Sproule, 1988). Despite the noted limitations, the image repair theories and their strategies have received positive fine-turnings and suggestions (Burns and Bruner, 2000; Liu and Fraustino, 2014). In recent years, they started to be used in the realm of social media (Cheng, 2018) to help develop understanding of post-crisis image repair and restoration approaches (Hambrick et al., 2015; Moody, 2011; Muralidharan et al., 2011).

This study aims to follow Benoit's (2018) recent study to compare UA's tweets against the image repair theory. As he stated, UA has made some attempts to response to the online negative comments and hashtags (e.g. #newunitedairlinesmotto and #boycottUnitedAirlines) which can be viewed as corrective action in crisis

communication to repair corporate images.

3. Research method

3.1 Descriptive information

This study is designed in three steps: tweet word counts analysis (to classify trendy keywords); tweet topic development (to identify dominant image repair strategies and prevalent crisis topics); and tweet sentiment analysis (to identify the tweet sentiments and the pattern of information diffusion).

The tweet dataset used in this study is captured within the 24-hour window following the UA incident on 09/04/2017. In order to capture tweets originated from all countries (Takahashi et al., 2015), while avoiding complications related to multilingual analysis (Thelwall et al., 2011), English tweets containing United Airline or UA are used. The dataset is then tokenised and normalised to stem and remove stop words (Tse et al., 2016; Yee Liau and Pei Tan, 2014). To analyse the strategies used by UA to repair their image, as well as the twitter citizens' behaviour during the crisis, the dataset is divided into two sub datasets, namely the Rhetorical dataset by the UA and the Crisis dataset by Twitter citizens.

The Rhetorical dataset contains tweets only sent by the UA (@united) between the first video footage tweeted (at 6:24pm on 09/04/2017) and United CEO Oscar Munoz's apology tweeted (at 2:10pm on 11/04/2017). There are 387 tweets in total, in which 46 of them are direct replies, or content related to video footage, and two of them are United CEO Oscar Munoz's statement about the incident.

The Crisis dataset consists of tweets by Twitter citizens between the timeframe of Oscar Munoz' tweets (the approximately 24 hours period between 4:27pm 10/04/2017 and 4:27pm 11/04/2017). The final Crisis dataset contains 55,083 tweets and which are sent from 61 countries. Summary statistics and top hashtags for the Crisis dataset are presented in Table 1.

Total number of Tweets:	*55,083*
Total number of Tweet accounts:	*40,560*
Total number of Sentences:	*61,905*
Total number of Words (Token):	*1,074,270*
Hashtags (#):	*15,114*
Mentions (@):	*18,893*
URL:	*42,597*

Table 1. The Crisis dataset statistics

3.2 Word counts analysis

This study adopts the TF-IDF to measure the frequency of word appearance in the two datasets (O'Leary, 2011). 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) (Sohrabi and Akbari, 2016). This method weights a word's importance if it appears many times in a tweet. The trending words may help to analyse the text in the corpus, discover themes and construct latent topics of the incident (Anthes, 2010; Blei, 2012).

For the Rhetorical dataset, only the 46relevant tweets are analysed, and the top 10 keywords are illustrated in Table 2. The meaningful trending words which are related to the incident include asking for ‘FLIGHT’ ‘NUMBER’ and ‘DETAILS’ via ‘DM’ (direct message), making ‘APOLOGIZES’ or stating ‘REGRET’ to ‘HEAR’ the ‘TROUBLE’ and offering ‘ASSISTANCE’.

	FREQUENCY	%SHOWN	NO. CASES	%CASES	TF -IDF
DM	11	5.57%	11	24.44%	6.7
FLIGHT	7	3.57%	7	15.56%	5.7
DETAILS	6	3.06%	6	13.33%	5.3
HEAR	6	3.06%	6	13.33%	5.3
APOLOGIZE	5	2.55%	5	11.11%	4.8
DAVID	4	2.04%	4	8.89%	4.2
NUMBER	4	2.04%	4	8.89%	4.2
REGRET	3	1.53%	3	6.67%	3.5
ASSISTANCE	3	1.53%	3	6.67%	3.5
TROUBLE	3	1.53%	3	6.67%	3.5

Table 2. Word frequency of the Rhetorical dataset based on TF-IDF

In the Crisis dataset, the top 10 keywords are shown in the Table 3. The top most meaningful trending words include ‘PASSENGER’, ‘FLIGHT’, ‘DRAG’, ‘CEO’, and ‘OVERBOOK’. In particular, the three trending words of ‘OVERBOOK’, ‘DRAG’ and ‘CEO’ provide key information sent by the Twitter citizens in the incident: ‘an overbooked UA flight’, ‘a passenger was dragged off’ and ‘a shocking statement from the CEO of UA’.

	FREQUENCY	%SHOWN	NO. CASES	%CASES	TF -IDF
PASSENGER	21111	6.62%	20946	38.03%	8864.9
FLIGHT	20462	6.42%	20063	36.42%	8975.1
DRAG	16681	5.23%	16630	30.19%	8676.2
CEO	12959	4.06%	12633	22.93%	8287.4
OVERBOOK	11917	3.74%	11852	21.52%	7951.3
PLANE	10965	3.44%	10904	19.80%	7713.1
MAN	10269	3.22%	10175	18.47%	7532.1
FORCIBLY	6645	2.08%	6619	12.02%	6114.9
VIDEO	6611	2.07%	6495	11.79%	6137.9
REMOVED	6534	2.05%	6508	11.81%	6060.7

Table 3. Word frequency of the Crisis dataset based on TF-IDF

In order to establish general knowledge of how these keywords were penetrated and transferred over the 24-hour focal period, a Pearson correlation is performed to measure the proportion of tweets containing the five trending words. From the result shown in Figure 1, the numbers of tweets containing ‘PASSENGER’ has not changed significantly, indicating that tweets about the passenger remained important throughout the time period. The number of tweets including ‘OVERBOOK’, ‘FLIGHT’ and ‘DRAG’ dropped respectively, thus suggesting that tweets focused on circulating information about UA’s overbooked flight and a passenger being dragged off became less popular after a few hours. While, on the other hand, tweets containing ‘CEO’

increased in a significant linear fashion, indicating a steady but significant rise on information diffusion on the United CEO.

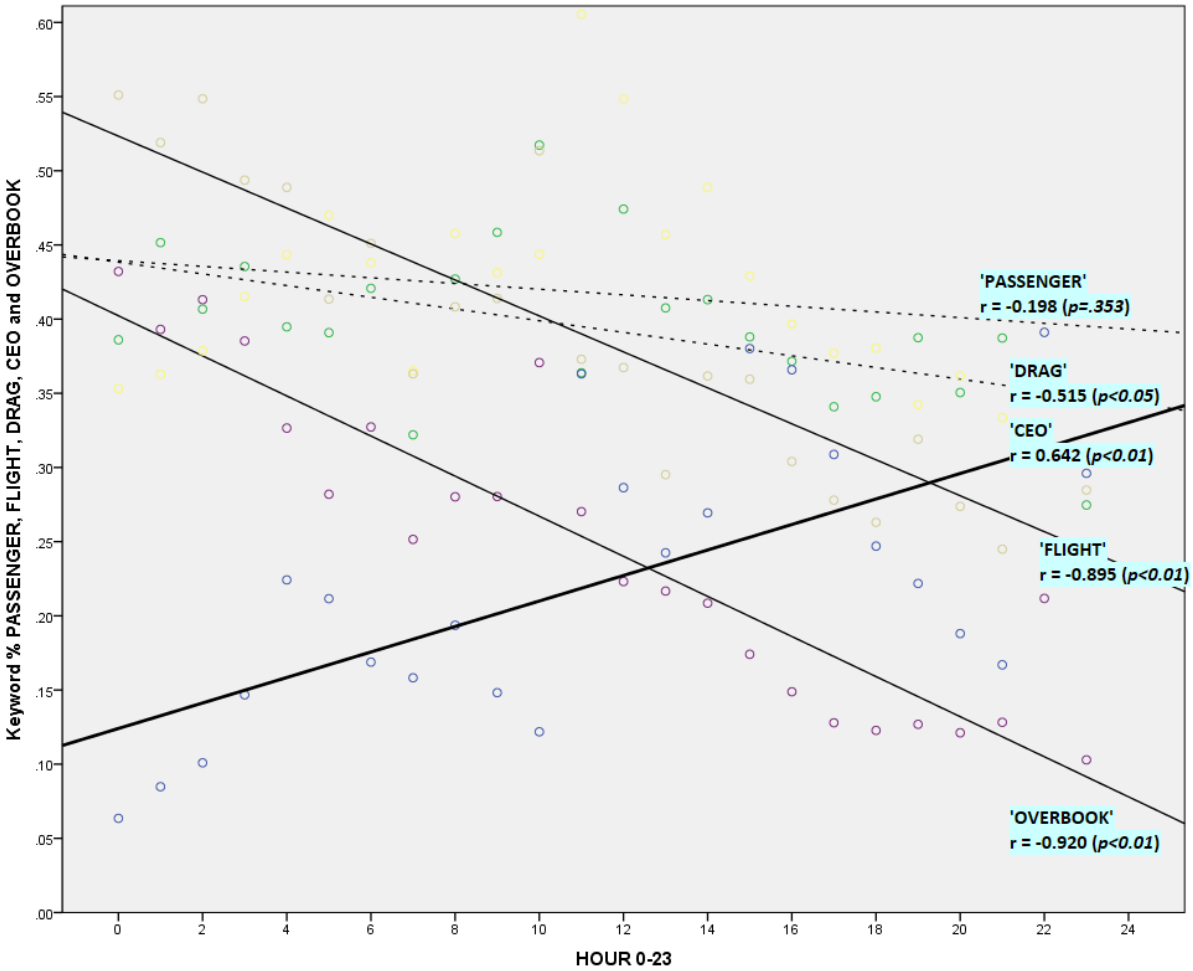

Figure 1. Scatterplot of the Top 5 keywords and time from the Crisis dataset

3.3 Topics in the Rhetorical dataset

The two tweet datasets are then analysed to identify their relevant topics. The 46 tweets in the Rhetorical dataset are associated to Benoit's (1995b, 2000) persuasive strategies. As shown in Table 4, the Rhetorical dataset contains tweets in topics of 'Denial' (n=2), 'Evade Responsibility' (n=1), 'Corrective Action' (n=2) and 'Mortification' (n=10). In addition, the results show that the dataset contains a topic on 'Require Information', which are tweets sent to require information about the incident/video footage (n=4). In addition, 'Exploiter' tweets emerged as a topic which were not prevalent at the beginning of the incident but emerged later as Twitter citizens exploited the incident for unrelated, individual purposes (n=26). The study also finds that a tweet to show United CEO's response to the incident has a 'Hybrid' meaning to include mortification, corrective action and requirement information (n=1).

Tweet Types	Meaning	Examples tweets
1. Denial (shift blame)	Someone else did it	*'flight 3411 from Chicago to Louisville was overbooked. After our team looked for volunteers, one customer refused to leave MD'*

2.Evade Responsibility (provocation)	We did it, but were provoked	*'the aircraft voluntarily and law enforcement was asked to come to the gate. ^MD'*
3. Corrective Action	We will fix the problem	*'Thanks for letting us know. We're always looking to improve. ^RD'* *'Hey Jayse, if you weren't able to get on your flight, please DM us. We can help get you re-booked. ^JR'*
4. Mortification	We admit responsibility or ask for forgiveness	*'We apologize for the setback. Let us know if you have any questions along the way. ^RD'* *'We're sorry to hear that, Jim. If you need any assistance, please DM us. ^TY'* *"United CEO Oscar Munoz: I'm sorry. We will fix this"*
5. Require Information	Asked for information about the incident	*'Tyler, this is very concerning. Can you please provide the flight number and details via DM? Thank you. ^AD'* *'Hello Gordan, can you DM us more details on what happened?^MD'*
6. Exploiter	Retweeted and linked	*'We understand your frustration and dislike the trouble it caused. We expect travel to be easy on passengers. ^JR'*
7.Reduce offensiveness (Hybrid)	Offense less serious than it appears	*'This is an upsetting event to all of us here at united. I apologize for having to re-accommodate these customers. Our team is moving with a sense of urgency to work with the authorities and conduct our own detailed review of what happened. We are also reaching out to this passenger to talk directly to him and further address and resolve this situation.'*

Table 4. Topic group in the Rhetorical dataset

3.4 Topics in the Crisis dataset

The 55,083 tweets in the Crisis dataset are also grouped to identify topics. Based on the identified trending words, the Multi-Dimensional Scaling (MDS), a classic dimensional reduction technique (Kruskal, 1964), is applied to discern structure (Clarke et al., 2009) and test their co-occurrence to construct latent topics (Péladeau et al., 2017; Tse et al., 2016) . Jaccard's Coefficient of Similarity (Dunn and Everitt, 2012) is used as the index of co-occurrence to identify underlying dimensions (Luchman et al., 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.

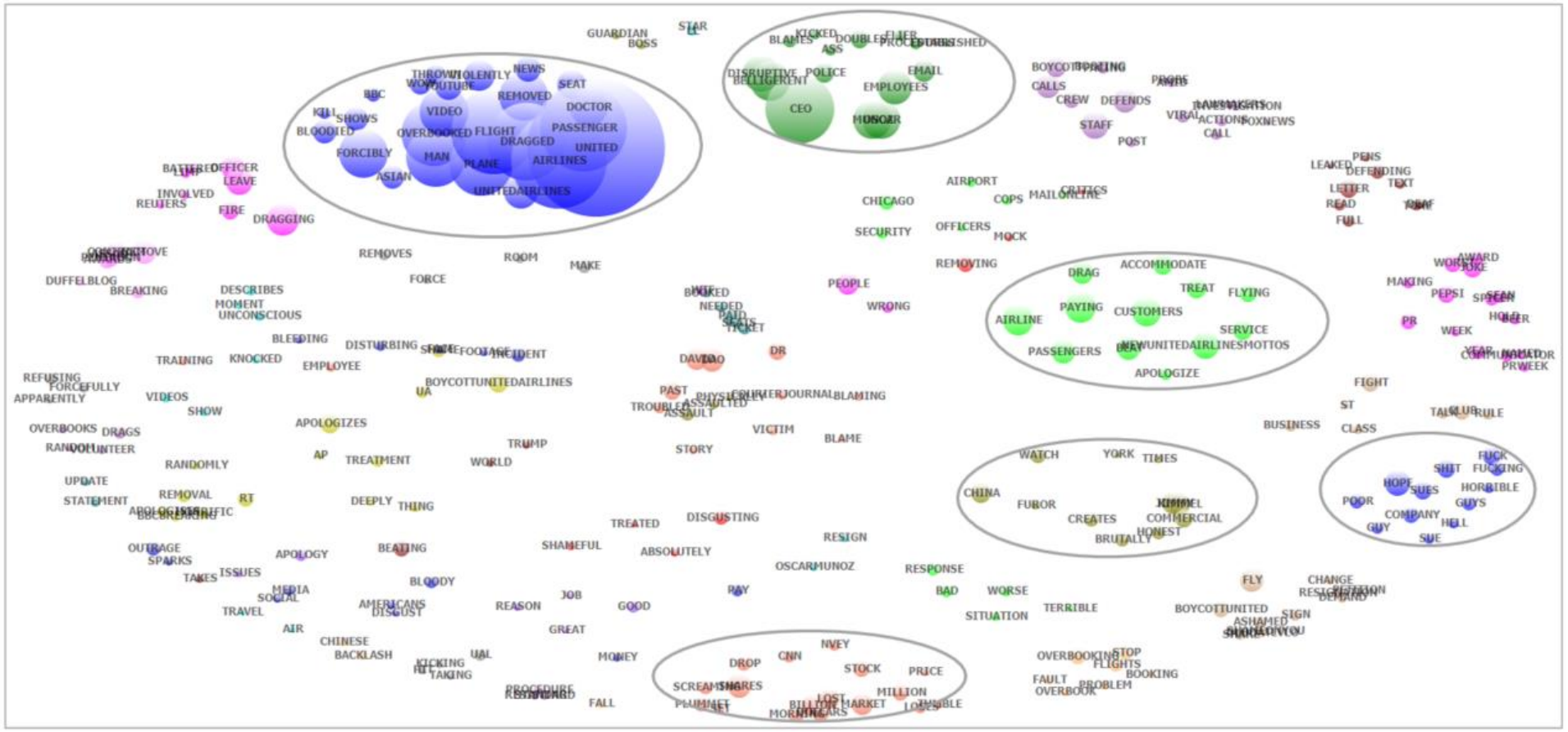

Figure 2. The 2D MDS matrix map

The result of the MDS is displayed in a matrix map illustrated in Figure 2, in which the circles indicate the clustered major keywords of the dataset, whereas the distances between the circles indicate the strength of the association. From the matrix map, six clusters of words are found to have high co-occurrence; hence six key topic groups are identified. Meaningful names are given to these six topic groups. They are listed in the topic group clouds in Figure 3 to indicate key words. Table 5 provides further explanation of these clouds and presents example tweets.

Figure 3. The topic group clouds

Topic Group	Example Keywords	Example Tweets
1 Event Description	'PASSENGER' 'FLIGHT' 'OVERBOOK' 'DRAG'	*'United DRAGGING a PASSENGER from OVERBOOKED FLIGHT was lesson in stupidity - LA Times'* *'That PASSENGER DRAGGED Off That FLIGHT'* *'MAN gets DRAGGED off of United Airlines just bc FLIGHT was OVERBOOKED & no one voluntarily got off so they picked a guy and DRAGGED him out'*
2 Comments to CEO	'CEO' 'MUNOZ' 'EMAIL' 'DISRUPTIVE' 'BELLIGERENT'	*'@united CEO OSCAR MUNOZ issued a LETTER defending his EMPLOYEES, saying the passenger was being ???DISRUPTIVE and BELLIGERENT. Seriously?'* *'@Mikel_Jollett @united CEO MUNOZ CALLS him "DISRUPTIVE AND BELLIGERENT" in EMAIL TO EMPLOYEES #LIAR RESIGN NOW! #united3411 #wtf #cnn'* *'MUNOZ is a moron United CEO DEFENDS ACTIONS of STAFF in VIRAL video, as lawmakers CALL for investigation'*
3 Disappointed Messages	'NEWUNITEDAIR-LINESMOTTOS' 'PAYING' 'CUSTOMER'	*'#NEWUNITEDAIRLINESMOTTOS FLY United - Now with a free, priority DRAG off SERVICE randomly available to all PAYING PASSENGERS'* *'Non-PAYING #United Airlines employees more important than PAYING CUSTOMERS. FLY with #United and get ASSAULTED. The not so*

	'FRIENDLY' 'SKIES'	*FRIENDLY SKIES.'* *'FLY the FRIENDLY SKIES...on Some Other AIRLINE. #NEWUNITEDAIRLINESMOTTOS'*
4 Blame	'HOPE' 'SUE' 'FXXK' 'SXXT' 'FXXKING' 'HXXL'	*'I'm absolutely disgusted, @united! I HOPE that POOR man will SUE the HXXL out of the COMPANY. #unitedAIRLINES #disgusting'* *'@united HOPE you get the SXXT sued out of your COMPANY, FXXKING disrespectful degenerates. FXXK you and your employees #neverflyunited'* *'I HOPE HE SUES THE HXXL OUT OF THIS FXXK AXS AIRLINE'*
5 Company Lost	'STOCK' 'MARKET' 'LOST' 'MILLION'	*'United Airlines LOST some $250 MILLION in STOCK MARKET value TODAY by #CNN via @c0NVEY'* *'UnitedAirlines has LOST about a BILLION DOLLARS in MARKET value this MORNING'*
6 Joke	'JIMMY' 'KIMMEL' 'COMMERCIAL'	*'Unbelievable. "Reaccommodate?" WATCH: JIMMY KIMMEL created a brutally honest COMMERCIAL for United Airline'* *'I had to share this. Too funny last night! United Airlines COMMERCIAL (JIMMY KIMMEL LIVE)'*

Table 5 Topic group in the Crisis dataset

These topic groups consist of 49,742 tweets which account for 90.3% of the total tweets (n=55,083). The spread of the tweets in the 24-hour focal time is illustrated in Table 6. Topic Group 1 'Event Description' is the focal group, as it contains the greatest number of the tweets (55.53%), followed by Topic Group 2 to express 'Comments to CEO' (17.2%). 9.25% of tweets are identified as Topic Group 3 to send 'Disappointed Messages' to UA, while others including Topic Groups of 'Blame' UA (2.98%), 'Company Lost' (3.31%) and 'Joke' (2.01%).

From the Table 6, the proportion of 'Event Description' tweets (Topic Group 1) has decreased from 70.3% to 41.62% over the 24-hour period, while the numbers of tweets about 'CEO' (Topic Group 2) and 'Company Lost' (Topic Group 5) have become more popular and increased from 2.62% to 20.17% and 0.19% to 11.74% respectively. In addition, there was an evident upward trend with tweets used to express a 'Joke' (Topic Group 6), and a downward trend on tweets sending 'Disappointed Messages' (Topic Group 3) and 'Blame' (Topic Group 4), although they are still relatively moderate.

	Topic Group 1	**Topic Group 2**	**Topic Group 3**	**Topic Group 4**	**Topic Group 5**	**Topic Group 6**	**Total**
Hour 0 *(n=1606)*	1129 (70.3%)	42 (2.62%)	178 (11.08%)	76 (4.73%)	3 (0.19%)	0	*1428* *(88.92)*
Hour 1 *(n=2819)*	1977 (70.13%)	67 (2.38%)	300 (10.64%)	167 (5.92%)	3 (0.11%)	0	*2514* *(89.18)*
Hour 2 *(n=2348)*	1656 (70.53%)	114 (4.86%)	274 (11.67%)	163 (6.94%)	4 (0.17%)	0	*2211* *(94.17)*
Hour 3 *(n=2767)*	1901 (68.7%)	291 (10.52%)	274 (9.90%)	144 (5.2%)	4 (0.14%)	0	*2614* *(94.46)*
Hour 4 *(n=2404)*	1463 (60.86%)	403 (16.76%)	267 (11.11%)	130 (5.41%)	3 (0.12%)	0	*2266* *(94.26)*
Hour 5 *(n=2387)*	1467 (61.46%)	395 (16.55%)	279 (11.69%)	126 (5.28%)	7 (0.29%)	0	*2274* *(95.27)*
Hour 6 *(n=2044)*	1306 (63.89%)	287 (14.04%)	230 (11.25%)	109 (5.33%)	1 (0.05%)	1 (0.05%)	*1934* *(94.61)*
Hour 7 *(n=1972)*	989 (50.15%)	256 (12.98%)	226 (11.46%)	77 (3.9%)	1 (0.05%)	1 (0.05%)	*1550* *(78.59)*
Hour 8 *(n=1663)*	978 (58.81%)	249 (14.97%)	224 (13.47%)	60 (3.61%)	0	8 (0.48%)	*1519* *(91.34)*
Hour 9 *(n=1505)*	972 (64.58%)	189 (12.56%)	186 (12.36%)	53 (3.52%)	0	1 (0.07%)	*1401* *(93.09)*
Hour 10 *(n=1330)*	925 (69.55%)	138 (10.38%)	151 (11.35%)	41 (3.08%)	2 (0.15%)	2 (0.15%)	*1259* *(94.66)*
Hour 11	738	483	128	24	1	18	*1392*

(n=1432)	(51.54%)	(33.73%)	(8.94%)	(1.68%)	(0.07%)	(1.26%)	*(97.22)*
Hour 12 *(n=1470)*	833 (56.67%)	340 (23.13%)	136 (9.25%)	30 (2.04%)	5 (0.34%)	81 (5.51%)	*1425 (96.94)*
Hour 13 *(n=1860)*	896 (48.17%)	266 (14.3%)	165 (8.87%)	22 (1.18%)	6 (0.32%)	29 (1.56%)	*1384 (74.4)*
Hour 14 *(n=2038)*	1165 (57.16%)	438 (21.49%)	183 (8.98%)	38 (1.86%)	10 (0.49%)	31 (1.52%)	*1865 (91.5)*
Hour 15 *(n=2562)*	1221 (47.66%)	791 (30.87%)	217 (8.47%)	50 (1.95%)	18 (0.7%)	74 (2.89%)	*2371 (92.54)*
Hour 16 *(n=2796)*	1230 (43.99%)	903 (32.3%)	268 (9.59%)	58 (2.07%)	27 (0.97%)	122 (4.36%)	*2608 (93.28)*
Hour 17 *(n=2986)*	1349 (45.18%)	776 (25.99%)	261 (8.74%)	41 (1.37%)	82 (2.75%)	138 (4.62%)	*2647 (88.65)*
Hour 18 *(n=2810)*	1337 (47.58%)	565 (20.11%)	239 (8.51%)	37 (1.32%)	237 (8.43%)	115 (4.09%)	*2530 (90.04)*
Hour 19 *(n=3012)*	1592 (52.86%)	572 (18.99%)	203 (6.74%)	38 (1.26%)	232 (7.7%)	130 (4.32%)	*2767 (91.87)*
Hour 20 *(n=2542)*	1244 (48.94%)	397 (15.62%)	217 (8.54%)	33 (1.3%)	267 (10.5%)	115 (4.52%)	*2273 (89.42)*
Hour 21 *(n=2270)*	1178 (51.89%)	307 (13.52%)	182 (8.02%)	33 (1.45%)	208 (9.16%)	79 (3.48%)	*1987 (87.52)*
Hour 22 *(n=3089)*	1644 (53.22%)	528 (17.09%)	138 (4.47%)	31 (1%)	306 (9.91%)	73 (2.36%)	*2720 (88.05)*
Hour 23 *(n=3371)*	1403 (41.62%)	680 (20.17%)	170 (5.04%)	61 (1.81%)	396 (11.74%)	93 (2.76%)	*2803 (83.15)*
Total *(n=55083)*	*30593 (55.53%)*	*9477 (17.2%)*	*5096 (9.25%)*	*1642 (2.98%)*	*1823 (3.31%)*	*1111 (2.01%)*	*49742 (90.3%)*

Table 6 The spread of the Crisis dataset tweets in the 24-hour focal time

3.5 The relationship of the topics

As shown in Figure 4, the Rhetorical dataset contains seven topics over the 24-hour period. On 10/04, 'Mortification', 'Denial', 'Evade Responsibility', 'Reduce Offensiveness' and 'Corrective Action' are the main topics, they are the image repair strategies used by UA. 'Require Information' is another main topic, as UA had the initial objective to obtain information (by asking 'DM' or direct message) about the incident. On 11/04, there is only one topic left to indicate the image repair strategy 'Mortification'. This result suggests that UA had two phases of image repair discourse.

In comparisons, the topic numbers in the Crisis dataset are not hugely different, although the proportion is changed. There are five on 10/04 including 'Event Description', 'Comments to CEO', 'Disappointed Messages', 'Blame' and 'Company Lost'' and six on 11/04, the additional one is 'Joke'.

It is also interesting to note that during this period, the Rhetorical dataset has a group of tweets with the topic 'Exploiter'. These were tweets originally used by UA to respond to customers' queries, but were exploited to link to the incident to send irony tweets.

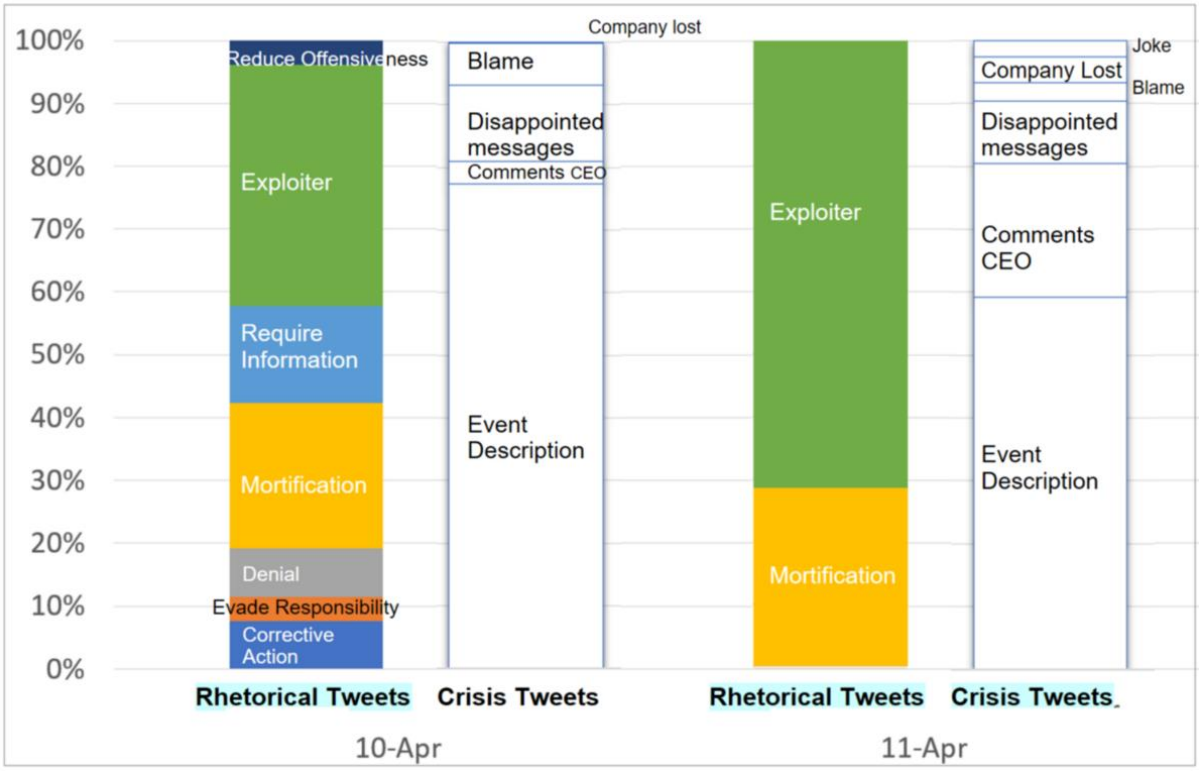

Figure 4 A timeline of tweet topics during the crisis

3.6 Sentiment analysis

The sentiment analysis is applied to the six topics from the Crisis dataset. The study adopts the SentiStrength classifier (Thelwall et al., 2010) and employs Hu & Liu's (2004) sentiment lexicon to calculate the sentiment. As illustrated in Table 7, the SentiStrength analysis captures polarity (positive or negative sentiment) and explains strength on a scale of 1 (no sentiment) to 4 (very strong sentiment). This sentiment analysis has been previously tested (Gilbert, 2014; Tse et al., 2016) and successful applied in recent studies (Gao et al., 2015; Ibrahim et al., 2017).

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 7 Coding scheme in SentiStrength (Ibrahim et al., 2017; Thelwall et al., 2010)

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

- '*We are not afraid to show you great customer service!????????'* [sentence: 1, -1], [scale result: 1]
- '*Horrible!!!!Passenger dragged off overbooked United flight*' [sentence: 1, -5], [scale result: -4]
- '@united is a failing airline. Poor customer service. Sad!' [sentence: 1, -5], [scale result: -4]

In the first example, the rationale is: *we are not afraid* [-4] *to show you great* [3] *customer service!????????*[+1 punctuation emphasis] [sentence: 4,-4],therefore, [result: 0 (sum of sentence max positive and negative scores)][overall result = 1 as

positive >-negative]. In the second example, the rationale is: *Horrible* [-4] *!!!!*[-1 punctuation emphasis] [sentence: 1, -5] *Passenger dragged off overbooked United* [proper noun] flight [sentence: 1,-1], hence [sentence max: 1, -5] [scale result: -4 (sum of sentence max positive and negative scores)]. In the third example, the rationale is: *@united is a failing* [-3] *airline* [sentence: 1,-3].*Poor* [-2] *customer service* [sentence: 1,-2] *Sad* [-4] *!*[-1 punctuation emphasis], hence [sentence max: 1,-5], [scale result: -4 (sum of sentence max positive and negative scores)].

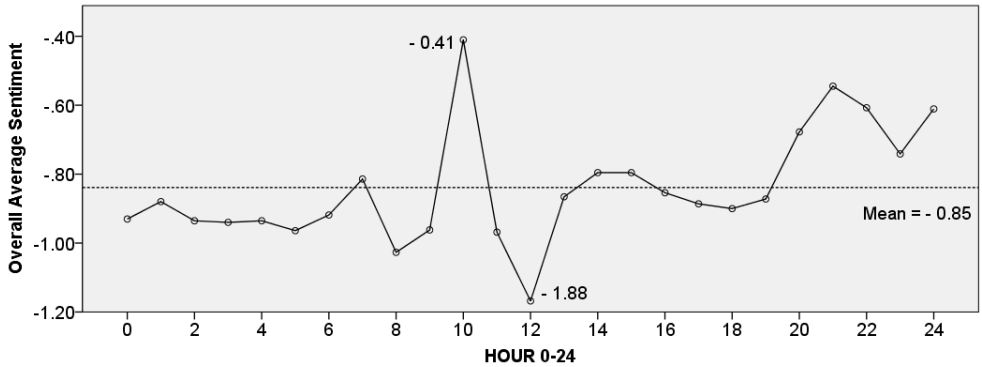

Figure 5 Time trend of the average sentiment of the Crisis dataset

From the results of the SentiStrength classifier illustrated in Figure 5, the overall average sentiment scores of the Crisis dataset is between -0.41 (10th hour) and -1.88 (12th hour), and the mean score is -0.85 which indicates a mild to moderate negative overall attitude towards the incident. 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, there are significantly more tweets to spread the overbook news and comment to CEO's defensive attitude (Topic Group 1 and 2) than expressing negative personal feelings (Topic Group 3 and 4).

The strongest negative sentiment tweets in the Crisis dataset are those captured between 8 and 12 hours after the first United CEO's apology tweet. With a closer look at Figure 6, they are associated to the high proportion of negative tweets in the same time period. These could be the reactions to United CEO's first wave of insincere apologies.

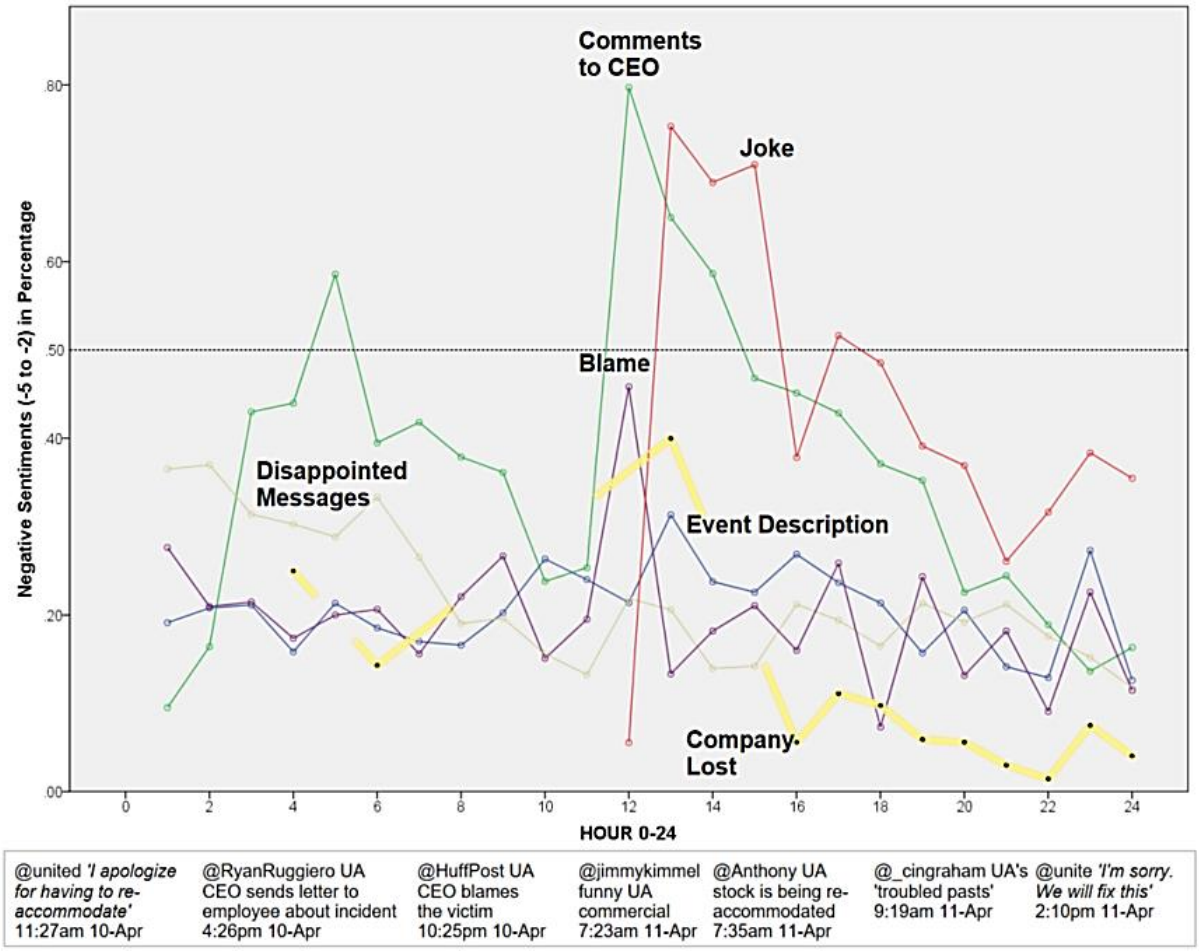

Figure 6 Time trend of negative sentiments percentage and linked tweets

The average sentiments of the six topics are then analysed. Figure 6 shows the percentage of tweets with negative sentiments over the 24-hour period and their relevant tweets. Most topic groups contain less than 50 percent of negative sentiment across the focal time period. For instance, tweets about 'Disappointed Messages' and 'Event Description' remained steady at around 20 percent, 'Blame' fluctuated and peaked in the 11th hour but mostly fall between the 20 percent and 40 percent boundaries, whereas tweets from the topic group of 'Company Lost' largely fall below 20% for the study hours. In contrast, the topic groups relating to 'Comments to CEO' peak between the 10th and 14th hour, with a high negative sentiment of approximately 80% in the 11th hour. The topic group concerning 'Joke' follows a similar pattern and peaks at over 70 percent at between the 12th and 14th hour.

4. Discussion and managerial implications

Findings from this study will assist airlines in understanding the emergence and evolution of crises post boarding denial incidents, and will also assist in the search and development of a more effective crisis communication system. From the topics identified in the Rhetorical dataset, UA had chosen to apply a combination of image repair strategies over the 24-hour apology tour. This finding supports the study by Benoit (2018), as the strategies used can be mainly divided into two phases (Figure 4).The company publicly admitted the responsibility (Mortification) of the 'overbook', but meanwhile, also had tweets crafted to rhetorically justify the situation, such as to

deny (Shift Blame) the cause of delay, evade the responsibility (Provocation) to the uncooperative passenger, and reduce the perceived offensiveness (Minimisation and Differentiation) of the violent removal of the 'uncooperative passenger'. Hence, UA had a clear defensive posture in the first phase of the image repair discourse. Therefore, not all defensive strategies are appropriate, nor legitimate, and caution should be given to their use in overbook crises. Although it is a natural tendency to use defensive strategies in the initial stage of the crisis continuum (Benoit, 1995b; Coombs, 1998), some defensive strategies might not work well (Holtzhausen and Roberts, 2009), as Coombs (1998) also argued, they are only useful when crisis responsibility is weak.

In the Crisis dataset, six main topics were identified, as shown in Figure 3 and Table 5. These topics provide crucial crisis information about the incident. For instance, the focal group Topic Group 1 – Event Description and the Topic Group 5 – Company Lost, both contain relevant information, general perceptions and broadcasted news about the 'overbook'. This is a useful method and can be used to collect guiding information related to managing the crisis (Coombs and Holladay, 2002), while also improving the preparedness for image repair discourse (Wendling et al., 2013). However, false/fake news is also likely to be propagated (Vosoughi et al., 2018), and therefore credibility of the widespread form of news information should be carefully monitored (Castillo et al., 2011).

The Crisis dataset also has three other topic groups, Topic Group 2 - Comments to CEO, topic Group 3 - Disappointed Messages and Topic Group 4 - Blame, to share comments, expectations and ask questions. This confirms the finding by Helsloot & Groenendaal (2013, p182) that 'Twitter mainly is a channel for sharing speculations, emotions and questions'. This information hence, provide opportunities for the airlines to understand the stakeholders' influences, needs and reactions to the crisis incident (Sommer et al., 2011; Yuen et al., 2017). According to Coombs (2007) and Ibrahim et al. (2017), these are crucial attributes in the crisis situation model of SCCT, as they help developing crisis responding strategies. Tweets intended to make jokes or included jokey language (Helsloot and Groenendaal, 2013) also formed a topic: Topic Group 6 – Joke, in the dataset. Although the number of these tweets could be relatively lower, they still have potential to worsen the crisis situation, such as spread rumours (Tse et al., 2016) and express irony and sarcasm (Kelsey and Bennett, 2014).

The multiple topic groups in the Crisis dataset, however, could have also fostered new stakeholders to emerge. This study confirms that UA tried various methods to manage crisis communication (Seeger, 2006; Veil et al., 2011), such as creating a venue to listen to the public concern, responding to queries for dialogic conversations, and demanding for 'DM' (one-to-one) to pitch the conversions. However, this could have also created a new environment to introduce new stakeholders, plus the fast spread of information on the interconnected social media platform (Hornik et al., 2015), the most salient influencers and relevant audiences could be hard to define and target for image repairing. Plus, different stakeholders could have also tweeted for other purposes, such as news media to express information and increase coverage, competitors to blame for wrongdoing (schadenfreude), social media influencer to increase publicity and so on. In the Rhetorical dataset, there were even tweets that

were originally used by UA to respond to customers' queries for other matters but were later retweeted and exploited to link to the incident to express critiques. Therefore, focusing on consumer-generated contents could help airlines to better understand the overbooking crisis, but if the defensive practices are unfavourable for some new, unknown, and undiscovered stakeholders and audiences, creating more communication channels could only further escalate critiques and negative messages.

Furthermore, it is interesting to note that the keywords of 'OVERBOOK', 'FLIGHT' and 'DRAG' are rated the top 5 in appearance (Table 3), but their numbers have a significant downward trend (Figure 1) and their associated tweets (Topic Group 1 – Event Description) have a relatively low proportion of negative sentiment tweets compared to all other topic groups (Figure 6). This may highlight that the Twitter citizens had less negative perceptions and reactions to the 'overbook' situation, as the flight, in fact, was not 'overbooked', but only needed four seats to transport four crew members for a later flight. However, the use of violent behaviour to remove a legitimate passenger and UA's subsequent defensive attitude caused a huge public backlash (Chi, 2017) and reputational damage (Benoit, 2018), This seems to provide confirmation to Slavic's (1999) work, in that risk is socially constructed. When overbook is less offensive, the general perception could be less negative and emotional, and therefore could be quickly replaced by other more serious offensive tweets, such as attempts to justify any perceived wrongdoing. Therefore, it can be argued that overbooking is not the biggest downside, but, rather, the subsequent handling and defensive attitude could be a source that triggers more negative emotions and words. Thus, sparking a bigger crisis for the focal company.

5. Conclusion

Overselling is a common strategy used by many airlines in yield management, with the primary aim of offsetting losses due to passenger' no-shows and late cancellations. However, the negative reviews incurred with respect to the overbook could cause not only damage of goodwill, but also a huge financial loss and company crisis. Using the twitter datasets captured within the 24-hour window following the UA overbooking crisis on 09/04/2017, this study was driven by an underpinning motivation to encourage research aimed at integrating yield management insights with the emergence of social big data analytics. As an initial step in addressing this integration, this study has analysed crisis response and communication in the context of an overbook situation. From this, our findings shed light on the importance of a more effective orchestration of yield management and stakeholder analysis to avoid the escalation of crises during crisis communication phases.

As the findings suggest that the poor stakeholder analysis and image repair discourse in the crisis management protocols were the main reasons behind the escalation of the incident. Therefore, at least four contributing factors have been identified: first, insincere rhetorical apologies, which did not take on a tone that accepted mistakes and responsibility, together with 'mortification' shown by their defensive posture. Second, the new and dynamic stakeholders that emerged because of the complex social medial platforms were hard to define and target. Three, the spread of uncontrolled user-generated contents was propagated rapidly and globally. Four, the

spread could have even been faster for negatively worded information, hence, it was harder to develop rhetorical messages to alter their perceptions and repair image.

This study also captures demands for a 'cultural shift' on the controversial airline practice of overbooking from airliners and policy makers. These demands include a better seat capacity planning procedure to reduce overbooking, higher incentives for voluntarily rescheduling, and more importantly paid customers should never be removed (e.g., @Katie_Lovelyy *And if the flight IS overbooked, offer whatever incentives necessary to change flights. You don't forcibly remove PAYING travellers #united*). They also suggest that compensations should be offered to volunteers at the gate, before they are boarded and seated (e.g., @TheLindseyCraze *You should know that a flight is overbooked BEFORE people are seated on the place. If they don't volunteer???*).

To the authors' best knowledge, this is the first study that aims to use social big data in the airline industry for managing risk associated to overbooking and crisis communication. However, the study has some limitations, which opens the door for future research. The first limitation observed is that this study has concentrated on the content of information and sentiment analysis, it would be also fruitful to apply stakeholder analysis (Sedereviciute and Valentini, 2011) to map those new and undiscovered stakeholders network (Elshendy and Fronzetti Colladon, 2017) in order to suggest effective ways to responding to overbooking crises. Second, the study only used data from one social media platform (i.e., Twitter), therefore future studies could include data from other social media platforms (e.g., Facebook, YouTube and Instagram) to make comparisons. Third, only tweets that fell within the 24-hour window (4:27pm 10/04/2018 – 4:27pm 11/04/2018) are employed. However, these tweets are purposely captured between the two United CEO's statements on twitter. Four, the dataset is limited to only English tweets to reduce research complexity, a dataset to include other languages would help generalise the results.

References

Agrawal, D., Bernstein, P., Bertino, E., Davidson, S., Dayal, U., Franklin, M., Gehrke, J., Haas, L., Halevy, A., Han, J., 2011. Challenges and Opportunities with big data 2011-1.

Alderighi, M., Nicolini, M., Piga, C.A.J.R.o.E., Statistics, 2015. Combined effects of capacity and time on fares: insights from the yield management of a low-cost airline. 97(4), 900-915.

Alexander, D.E.J.S., ethics, e., 2014. Social media in disaster risk reduction and crisis management. 20(3), 717-733.

Anthes, G., 2010. Topic models vs. unstructured data. *Communications of the ACM* 53(12), 16-18.

Aula, P., 2010. Social media, reputation risk and ambient publicity management. *Strategy & Leadership* 38(6), 43-49.

Austin, L., Fisher Liu, B., Jin, Y., 2012. How audiences seek out crisis information: Exploring the social-mediated crisis communication model. *Journal of Applied Communication Research* 40(2), 188-207.

Bello-Orgaz, G., Jung, J.J., Camacho, D., 2016. Social big data: Recent achievements and new challenges. *Information Fusion* 28, 45-59.

Belobaba, P.P., 1987. Survey Paper—Airline yield management an overview of seat inventory control. *Transportation science* 21(2), 63-73.
Benoit, W.L., 1995a. *Accounts, Excuses, and Apologies: A Theory of Image Restoration Strategies*. State University of New York Press.
Benoit, W.L., 1995b. Sears' repair of its auto service image: Image restoration discourse in the corporate sector. *Communication Studies* 46(1-2), 89-105.
Benoit, W.L., 1997. Image repair discourse and crisis communication. *Public relations review* 23(2), 177-186.
Benoit, W.L., 2000. Another visit to the theory of image restoration strategies. *Communication Quarterly* 48(1), 40-43.
Benoit, W.L., 2014. *Accounts, Excuses, and Apologies, Second Edition: Image Repair Theory and Research*. State University of New York Press.
Benoit, W.L., 2018. Crisis and Image Repair at United Airlines: Fly the Unfriendly Skies. *Journal of International Crisis and Risk Communication Research* 1(1), 2.
Benoit, W.L., Henson, J.R., 2009. President Bush's image repair discourse on Hurricane Katrina. *Public Relations Review* 35(1), 40-46.
Bilotkach, V., Gaggero, A.A., Piga, C.A.J.T.M., 2015. Airline pricing under different market conditions: Evidence from European Low-Cost Carriers. 47, 152-163.
Birkland, T.A., 1997. *After disaster: Agenda setting, public policy, and focusing events*. Georgetown University Press.
Blei, D.M., 2012. Probabilistic topic models. *Communications of the ACM* 55(4), 77-84.
Boyd, D., Crawford, K., 2012. Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, communication & society* 15(5), 662-679.
Boyd, D.M., Ellison, N.B., 2007. Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication* 13(1), 210-230.
Boyd, J., 2000. Actional legitimation: No crisis necessary. *Journal of Public Relations Research* 12(4), 341-353.
Brinson, S.L., Benoit, W.L., 1996. Dow Corning's image repair strategies in the breast implant crisis. *Communication Quarterly* 44(1), 29-41.
Burns, J.P., Bruner, M.S., 2000. Revisiting the theory of image restoration strategies. *Communication Quarterly* 48(1), 27-39.
Cameron, G., Cheng, Y., 2017. The Status of Social-Mediated Crisis Communication (SMCC) Research: An Analysis of Published Articles in 2002–2014, *Social Media and Crisis Communication*. Routledge, pp. 29-40.
Camilleri, M.A., 2018. Pricing and revenue management, *Travel Marketing, Tourism Economics and the Airline Product*. Springer, pp. 155-163.
Castillo, C., Mendoza, M., Poblete, B., 2011. Information credibility on twitter, *Proceedings of the 20th international conference on World wide web*. ACM, pp. 675-684.
Chen, H., Chiang, R.H., Storey, V.C., 2012. Business intelligence and analytics: From big data to big impact. *MIS quarterly* 36(4).
Cheng, Y., 2018. How social media is changing crisis communication strategies: Evidence from the updated literature. *Journal of Contingencies and Crisis Management* 26(1), 58-68.
Chi, L., 2017. Not so friendly skies: United Airlines' public relations disaster. BBC, Online.
Chiang, W.-C., Chen, J.C., Xu, X.J.I.j.o.r.m., 2007. An overview of research on revenue management: current issues and future research. 1(1), 97-128.
Choi, T.M., 2016. Incorporating social media observations and bounded rationality into fashion

quick response supply chains in the big data era ☆. *Transportation Research Part E Logistics & Transportation Review* 114, S1366554516301806.
Chua, G.A., Lim, W.S., Yeo, W.M.J.E.J.o.O.R., 2016. Market structure and the value of overselling under stochastic demands. 252(3), 900-909.
Clarke, B., Fokoue, E., Zhang, H.H., 2009. *Principles and theory for data mining and machine learning*. Springer Science & Business Media.
Claster, W.B., Cooper, M., Sallis, P., 2010. Thailand--Tourism and conflict: Modeling sentiment from Twitter tweets using naïve Bayes and unsupervised artificial neural nets, *Computational Intelligence, Modelling and Simulation (CIMSiM), 2010 Second International Conference on*. IEEE, pp. 89-94.
Coombs, T., Schmidt, L., 2000. An empirical analysis of image restoration: Texaco's racism crisis. *Journal of Public Relations Research* 12(2), 163-178.
Coombs, W.T., 1998. An analytic framework for crisis situations: Better responses from a better understanding of the situation. *Journal of public relations research* 10(3), 177-191.
Coombs, W.T., 2007. Protecting organization reputations during a crisis: The development and application of situational crisis communication theory. *Corporate reputation review* 10(3), 163-176.
Coombs, W.T., Holladay, S.J., 2002. Helping crisis managers protect reputational assets: Initial tests of the situational crisis communication theory. *Management Communication Quarterly* 16(2), 165-186.
Coombs, W.T., Holladay, S.J., 2007. The negative communication dynamic: Exploring the impact of stakeholder affect on behavioral intentions. *Journal of Communication Management* 11(4), 300-312.
Coombs, W.T., Holladay, S.J., 2011. *The Handbook of Crisis Communication*. Wiley.
Dunn, G., Everitt, B.S., 2012. *An Introduction to Mathematical Taxonomy*. Dover Publications, Mineola, New York.
Elshendy, M., Fronzetti Colladon, A., 2017. Big data analysis of economic news: Hints to forecast macroeconomic indicators. *International Journal of Engineering Business Management* 9, 1847979017720040.
Fishman, D.A., 1999. ValuJet Flight 592: Crisis communication theory blended and extended. *Communication Quarterly* 47(4), 345-375.
Freberg, K., Palenchar, M.J., Veil, S.R., 2013. Managing and sharing H1N1 crisis information using social media bookmarking services. *Public Relations Review* 39(3), 178-184.
Fu, X., Dresner, M., Oum, T.H., 2011. Effects of transport service differentiation in the US domestic airline market. *Transportation Research Part E Logistics & Transportation Review* 47(3), 297-305.
Gallego, G., Phillips, R.J.M., Management, S.O., 2004. Revenue management of flexible products. 6(4), 321-337.
Gao, B., Berendt, B., Vanschoren, J., 2015. Who is more positive in private? Analyzing sentiment differences across privacy levels and demographic factors in Facebook chats and posts, *Advances in Social Networks Analysis and Mining (ASONAM), 2015 IEEE/ACM International Conference on*. IEEE, pp. 605-610.
Garrow, L.A., Kressner, J., Mumbower, S.J.J.o.A.T.M., 2011. Is increasing airline denied boarding compensation limits the answer? Factors that contribute to denied boardings. 17(5), 271-277.
Gilbert, C.H.E., 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text, *Eighth International Conference on Weblogs and Social Media (ICWSM-14). Available at (20/04/16) http://comp. social. gatech. edu/papers/icwsm14. vader. hutto. pdf*.

Govindan, K., Cheng, T.C.E., Mishra, N., Shukla, N., 2018. Big data analytics and application for logistics and supply chain management. *Transportation Research Part E: Logistics and Transportation Review* 114, 343-349.
Hambrick, M.E., Frederick, E.L., Sanderson, J., 2015. From yellow to blue: Exploring Lance Armstrong's image repair strategies across traditional and social media. *Communication & Sport* 3(2), 196-218.
Harlow, W.F., Brantley, B.C., Harlow, R.M., 2011. BP initial image repair strategies after the Deepwater Horizon spill. *Public Relations Review* 37(1), 80-83.
He, W., Zha, S., Li, L., 2013. Social media competitive analysis and text mining: A case study in the pizza industry. *International Journal of Information Management* 33(3), 464-472.
Helsloot, I., Groenendaal, J., 2013. Twitter: An underutilized potential during sudden crises? *Journal of Contingencies and Crisis Management* 21(3), 178-183.
Henderson, A., Bowley, R., 2010. Authentic dialogue? The role of "friendship" in a social media recruitment campaign. *Journal of Communication Management* 14(3), 237-257(221).
Heverin, T., Zach, L., 2010. *Microblogging for crisis communication: examination of Twitter use in response to a 2009 violent crisis in the Seattle-Tacoma, Washington, area*. ISCRAM.
Himelboim, I., Golan, G.J., Moon, B.B., Suto, R.J., 2014. A social networks approach to public relations on Twitter: Social mediators and mediated public relations. *Journal of Public Relations Research* 26(4), 359-379.
Holtzhausen, D.R., Roberts, G.F., 2009. An investigation into the role of image repair theory in strategic conflict management. *Journal of Public Relations Research* 21(2), 165-186.
Hornik, J., Satchi, R.S., Cesareo, L., Pastore, A., 2015. Information dissemination via electronic word-of-mouth: Good news travels fast, bad news travels faster! *Comput. Hum. Behav.* 45, 273-280.
Houston, J.B., Hawthorne, J., Perreault, M.F., Park, E.H., Goldstein Hode, M., Halliwell, M.R., Turner McGowen, S.E., Davis, R., Vaid, S., McElderry, J.A.J.D., 2015. Social media and disasters: a functional framework for social media use in disaster planning, response, and research. 39(1), 1-22.
Hu, M., Liu, B., 2004. Mining and summarizing customer reviews, *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, pp. 168-177.
Huang, K., Chang, K.-C.J.J.o.R., Management, P., 2011. A model for airline seat control considering revenue uncertainty and risk. 10(2), 161-171.
IATA, 2017. Position-paper-flight-overbooking. The IATA, online.
Ibrahim, N.F., Wang, X., Bourne, H., 2017. Exploring the effect of user engagement in online brand communities: Evidence from Twitter. *Comput. Hum. Behav.* 72, 321-338.
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.
Kaplan, A.M., Haenlein, M., 2010. Users of the world, unite! The challenges and opportunities of Social Media. *Business horizons* 53(1), 59-68.
Kelsey, D., Bennett, L., 2014. Discipline and resistance on social media: Discourse, power and context in the Paul Chambers 'Twitter Joke Trial'. *Discourse, Context & Media* 3, 37-45.
Kruse, N.W., 1981. The scope of apologetic discourse: Establishing generic parameters. *Southern Journal of Communication* 46(3), 278-291.
Kruskal, J.B., 1964. Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. *Psychometrika* 29(1), 1-27.

Kwak, H., Lee, C., Park, H., Moon, S., 2010. What is Twitter, a social network or a news media?, *Proceedings of the 19th international conference on World wide web*. ACM, pp. 591-600.
Liu, B.F., Fraustino, J.D., 2014. Beyond image repair: Suggestions for crisis communication theory development. *Public Relations Review* 40(3), 543-546.
Luchman, J.N., Bergstrom, J., Krulikowski, C., 2014. A motives framework of social media website use: A survey of young Americans. *Comput. Hum. Behav.* 38, 136-141.
Malita, L., 2011. Social media time management tools and tips. *Procedia Computer Science* 3, 747-753.
Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., Byers, A.H., 2011. Big data: The next frontier for innovation, competition, and productivity.
McGill, J.I., Van Ryzin, G.J.J.T.s., 1999. Revenue management: Research overview and prospects. 33(2), 233-256.
Moffitt, M.A., 1994. Collapsing and Integrating Concepts of" Public" and" Image" into a New Theory. *Public Relations Review* 20(2), 159-170.
Moody, M., 2011. Jon and Kate Plus 8: A case study of social media and image repair tactics. *Public Relations Review* 37(4), 405-414.
Mostafa, M.M., 2013. More than words: Social networks' text mining for consumer brand sentiments. *Expert Systems with Applications* 40(10), 4241-4251.
Muralidharan, S., Dillistone, K., Shin, J.-H., 2011. The Gulf Coast oil spill: Extending the theory of image restoration discourse to the realm of social media and beyond petroleum. *Public Relations Review* 37(3), 226-232.
O'Leary, D.E., 2011. Blog mining-review and extensions:"From each according to his opinion". *Decision Support Systems* 51(4), 821-830.
Oh, O., Agrawal, M., Rao, H.R., 2013. Community intelligence and social media services: A rumor theoretic analysis of tweets during social crises. *Mis Quarterly*, 407-426.
Palen, L.J.E.Q., 2008. Online social media in crisis events. 31(3), 76-78.
Péladeau, N., Dagenais, C., Ridde, V., 2017. Concept mapping internal validity: A case of misconceived mapping? *Evaluation and Program Planning* 62, 56-63.
Procopio, C.H., Procopio, S.T., 2007. Do you know what it means to miss New Orleans? Internet communication, geographic community, and social capital in crisis. *Journal of Applied Communication Research* 35(1), 67-87.
Rainie, L., Wellman, B., 2012. *Networked: The New Social Operating System*. MIT Press.
Roshan, M., Warren, M., Carr, R., 2016. Understanding the use of social media by organisations for crisis communication. *Comput. Hum. Behav.* 63, 350-361.
Schultz, F., Utz, S., Göritz, A., 2011. Is the medium the message? Perceptions of and reactions to crisis communication via twitter, blogs and traditional media. *Public relations review* 37(1), 20-27.
Sedereviciute, K., Valentini, C., 2011. Towards a more holistic stakeholder analysis approach. Mapping known and undiscovered stakeholders from social media. *International Journal of Strategic Communication* 5(4), 221-239.
Seeger, M.W., 2006. Best practices in crisis communication: An expert panel process. *Journal of Applied Communication Research* 34(3), 232-244.
Shlifer, E., Vardi, Y.J.T.S., 1975. An airline overbooking policy. 9(2), 101-114.
Singh, A., Shukla, N., Mishra, N., 2018. Social media data analytics to improve supply chain management in food industries. *Transportation Research Part E: Logistics and Transportation Review* 114, 398-415.
Slovic, P., 1999. Trust, emotion, sex, politics, and science: Surveying the risk-assessment

battlefield. *Risk analysis* 19(4), 689-701.
Smith, B.C., Leimkuhler, J.F., Darrow, R.M.J.i., 1992. Yield management at American airlines. 22(1), 8-31.
Smudde, P.M., Courtright, J.L., 2008. Time to get a job: Helping image repair theory begin a career in industry. *Public Relations Journal* 2(1).
Sohrabi, M.K., Akbari, S., 2016. A comprehensive study on the effects of using data mining techniques to predict tie strength. *Comput. Hum. Behav.* 60, 534-541.
Sommer, S., Schieber, A., Hilbert, A., Heinrich, K., 2011. Analyzing customer sentiments in microblogs–A topic-model-based approach for Twitter datasets, *Proceedings of the Americas conference on information systems (AMCIS)*.
Sproule, J.M., 1988. The new managerial rhetoric and the old criticism. *Quarterly Journal of Speech* 74(4), 468-486.
Stewart, M.C., Wilson, B.G., 2016. The dynamic role of social media during Hurricane# Sandy: An introduction of the STREMII model to weather the storm of the crisis lifecycle. *Comput. Hum. Behav.* 54, 639-646.
Subramanian, J., Stidham Jr, S., Lautenbacher, C.J.J.T.s., 1999. Airline yield management with overbooking, cancellations, and no-shows. 33(2), 147-167.
Suzuki, Y.J.T.R.P.E.L., Review, T., 2002. An empirical analysis of the optimal overbooking policies for US major airlines. 38(2), 135-149.
Suzuki, Y.J.T.R.P.E.L., Review, T., 2006. The net benefit of airline overbooking. 42(1), 1-19.
Takahashi, B., Tandoc Jr, E.C., Carmichael, C., 2015. Communicating on Twitter during a disaster: An analysis of tweets during Typhoon Haiyan in the Philippines. *Comput. Hum. Behav.* 50, 392-398.
Terciyanlı, E., Avşar, Z.M., 2019. Alternative risk-averse approaches for airline network revenue management. *Transportation Research Part E: Logistics and Transportation Review* 125, 27-46.
Thelwall, M., Buckley, K., Paltoglou, G., 2011. Sentiment in Twitter events. *Journal of the Association for Information Science and Technology* 62(2), 406-418.
Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., Kappas, A., 2010. Sentiment strength detection in short informal text. *Journal of the Association for Information Science and Technology* 61(12), 2544-2558.
Thompson, R.L., 2011. Radicalization and the use of social media. *Journal of strategic security* 4(4), 167.
Troisi, O., D'Arco, M., Loia, F., Maione, G., 2018. Big data management: The case of Mulino Bianco's engagement platform for value co-creation. *International Journal of Engineering Business Management* 10, 1847979018767776.
Tse, T.S., Poon, Y.-T.J.J.o.f.b.r., 2017. Modeling no-shows, cancellations, overbooking, and walk-ins in restaurant revenue management. 20(2), 127-145.
Tse, Y.K., Loh, H., Ding, J., Zhang, M., 2018. An investigation of social media data during a product recall scandal. *Enterprise Information Systems*, 1-19.
Tse, Y.K., Zhang, M., Doherty, B., Chappell, P., Garnett, P., 2016. Insight from the horsemeat scandal: Exploring the consumers' opinion of tweets toward Tesco. *Industrial Management & Data Systems* 116(6), 1178-1200.
Tufekci, Z., 2014. Big Questions for Social Media Big Data: Representativeness, Validity and Other Methodological Pitfalls. *ICWSM* 14, 505-514.
Veil, S.R., Buehner, T., Palenchar, M.J., 2011. A work-in-process literature review: Incorporating social media in risk and crisis communication. *Journal of contingencies and crisis management*

19(2), 110-122.
Vosoughi, S., Roy, D., Aral, S., 2018. The spread of true and false news online. *Science* 359(6380), 1146-1151.
Wan, S., Koh, R., Ong, A., Pang, A., 2015. Parody social media accounts: Influence and impact on organizations during crisis. *Public Relations Review* 41(3), 381-385.
Wang, T., Xing, Z., Hu, H., Qu, X.J.T.R.P.E.L., Review, T., 2019. Overbooking and delivery-delay-allowed strategies for container slot allocation. 122, 433-447.
Wang, X., Fung, R.Y.K., 2014. An option-based hedging mechanism for managing the risk of overbooking in parallel airline alliances. *Transportation Research Part E: Logistics and Transportation Review* 70, 146-162.
Wangenheim, F.v., Bayón, T.J.J.o.M., 2007. Behavioral consequences of overbooking service capacity. 71(4), 36-47.
Ware, B.L., Linkugel, W.A., 1973. They spoke in defense of themselves: On the generic criticism of apologia. *Quarterly Journal of speech* 59(3), 273-283.
Weatherford, L.R., Bodily, S.E.J.O.r., 1992. A taxonomy and research overview of perishable-asset revenue management: Yield management, overbooking, and pricing. 40(5), 831-844.
Wendling, C., Radisch, J., Jacobzone, S., 2013. The use of social media in risk and crisis communication.
Yee Liau, B., Pei Tan, P., 2014. Gaining customer knowledge in low cost airlines through text mining. *Industrial Management & Data Systems* 114(9), 1344-1359.
Yuen, K.F., Wang, X., Wong, Y.D., Zhou, Q., 2017. Antecedents and outcomes of sustainable shipping practices: The integration of stakeholder and behavioural theories. *Transportation Research Part E: Logistics and Transportation Review* 108, 18-35.