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#DeleteUber: Hashtag Crises and Chaos

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#DeleteUber: Hashtag Crises and Chaos

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#DeleteUber: Hashtag Crises and Chaos

Abstract

Social media backlash against companies is part of daily news headlines. What makes the #DeleteUber event particularly unique from other crises is the event's duration which lasted for more than 100 consecutive days. Such an extensive time period led many publications to refer to the event as *chaos*. This paper employs chaos theory to answer - *is a social media crisis chaotic?* In marketing literature, chaos theory has been limited to conceptual application due to the difficulty of finding datasets suitable for nonlinear methods. Using timestamp data extracted from more than 180,000 tweets, we confirm the #DeleteUber crisis is indeed a *chaotic* state. Of immediate concern for practitioners is that traditional crisis communication responses using a cause-and-effect approach have proven to be inadequate in *chaotic* events. Our efforts to identify unique actors and their tweeting frequency in the #DeleteUber conversation yielded interesting insights that we suggest for developing new crises guidelines for managers.

#DeleteUber: Hashtag Crises and Chaos

Uber is in a state of chaos (Boss, 2017),
Lyft sees big opportunity with chaos at Uber (New York Post, 2017),
Uber apologizes for chaos... (McQuade, 2017).

Social media technology makes it so easy for consumers to express their anger towards a brand, that one viral tweet can ignite a global social media crisis. How these companies respond and the communication strategies they employ are determined by their understanding of these events. One brand in particular, Uber, has faced an enormous amount of consumer backlash between January and June 2017 on *Twitter*. As Uber's story played out for nearly six months, some news outlets began referring to the enduring story as *chaos* (e.g. Boss, 2017). To examine this crisis in more detail, we scraped more than 188,000 tweets using the #DeleteUber hashtag during Uber's six month social media crisis. While the *Harvard Business Review* article, "What 100,000 Tweets about the Volkswagen Scandal Tell Us about Angry Customers." (Swaminathan & Mah, 2016) presents potential damage angry customers can cause a brand, this paper expands upon their study with empirical and conceptual understanding. Our analysis will assist marketing practitioners in determining the best social media crisis response by differentiating between random noise in these crises and *chaos*. Applying chaos theory to a real world event will enable us to evaluate this approach as a possibly useful framework in understanding social media crises. We posit that chaos theory may even show how unrealistic it is to expect marketing practitioners to *manage* a social media crises. Future practitioner guidelines may need to be developed with a focus on mitigating a crisis all together through the identification of and interaction with certain noisy actors exhibiting a higher than average level of participation.

On January 28, 2017, after the Taxi Workers Alliance called for a sixty minute strike in support of those protesting Donald Trump's executive order banning immigrants from seven Muslim-majority countries, Uber's New York City *Twitter* account posted a tweet that it was turning off its surge pricing. Already angered by Trump's executive order and angered by Uber's ongoing refusal to classify drivers as employees, freelance journalist Dan O'Sullivan took Uber's tweet to be yet another tactic by the bold brash company to profit off the *little guy*. He tweeted back, "*congrats to @Uber_NYC on breaking a strike to profit off of refugees being consigned to Hell. eat shit and die*" [sic] (Bro_Pair, 2017). While Uber repeatedly said later (as part of its crisis control efforts) that it did not support the ban and offered financial assistance to drivers impacted, it was too little too late. Unknowingly, O'Sullivan's misinterpretation acted as the *butterfly effect*, or, the seemingly insignificant event responsible for igniting a course of actions with volatile outcomes (Kiel & Elliott, 1996). In this case, O'Sullivan's tweet sparked a six month social media crisis for Uber.

Social media backlash crops up unexpectedly and appears to marketing practitioners as a jumbled mix of emotions, behaviors and comments, often catching the professional off-guard and unprepared. Backlash against companies in 2017 is often part of daily headlines, with anger towards companies like Pepsi, United Airlines and Uber as the most recent examples. What makes the case against Uber interesting for scholars to examine is the event's duration. Overall, Uber made continuous news for more than 100 consecutive days. This is extensive compared to the two days of anger against Pepsi's perceived tone deaf attitude towards social justice (commercial featuring Kendall Jenner) and the 16 days when the viral video of an elderly passenger being forcibly removed from a United Airlines flight surfaced.

Events where brands are suddenly and publicly targeted by consumers via social media channels are conceptualized in academic literature using a variety of terms, including *consumer brand sabotage*

(Kähr, Nyffenegger, & Krohmer), *collaborative brand attacks* (Rauschnabel, Kammerlander, and Ivens, 2016), *nightmares* (Kaplan & Haenlein, 2011), *firestorms* (Pfeffer, Zorbach, and Carley, 2013), *paracrisis* (Coombs & Holladay, 2012), *political consumerism* (Stolle, Hooghe, & Micheletti, 2005), and *digital consumer activism* (Legocki & Walker, 2017). Extant literature confirms that consumers angered by a company's actions are more likely to engage in word-of-mouth behaviors (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). This type of consumer anger has also been examined within the context of consumer revenge (Grégoire, Laufer, & Tripp, 2010), workplace revenge (Tripp & Bies, 2010), and corporate irresponsible behavior (Grappi, Romani, & Bagozzi, 2013). However, marketing literature has not examined this behavior through the viewpoint of the manager – as *chaos*. Therefore, we find it useful to employ chaos theory to examine and understand what happened in the #DeleteUber social media crisis.

Chaos Theory and Social Media Crises

Social media conversations are a non-linear, complex and spontaneous structure that meets chaos theory requirements (Doherty & Delener, 2001). Further, “chaos theory offers an alternative way of explaining the kind of complex, random-looking patterns of behavior often found in marketing...” (Hibbert & Wilkinson, 1994, p. 219). In marketing literature, chaos theory has been introduced but limited to conceptual application by Earl (2012); Smith (2002), Doherty & Delener (2001); Whitby & Tobias (2001), Winsor (1995), and, Hibbert & Wilkinson (1994). One reason for this limitation in the past has been the difficulty in obtaining a large enough dataset over a long enough period of time that could meet the rigorous requirements for nonlinear methods (Hibbert and Wilkinson, 1994). Our dataset from the #DeleteUber crisis contains more than 188,000 time stamped tweets over 132 days. Thus, our data is deemed suitable for answering - *is a social media crisis chaotic?*

This is an important question to answer for both managers and researchers. If these events are *chaotic* then a company's traditional crisis communication approach using a direct cause-and-effect approach would be futile (Paraskevas, 2006). Evidence of *chaos* will also negate industry-wide norm response behavior as the *cure all remedy* for such events. For example, in promoting *Firebell*, their crisis simulation software for Fortune 500 firms, Weber Shandwick states, "The crises [social media conversations] create are, in a word, chaotic. The job is not just to control the chaos, but *master it*" (Agnew, 2014, para. 2). If chaos events are effectively impossible to predict, then how can managers be expected to control it, much less master it?

Using a mixed-method approach, this paper builds on conceptualized approaches to chaos proposed in extant marketing literature and applies it to a contemporary data set of tweets to determine if social media crises are indeed *chaotic*. First, we offer a new framework of how a social media crisis can be viewed through the lens of chaos theory, *does it exhibit characteristics of chaos?* Second, we employ methods proposed by Hibbert and Wilkinson (1994) for detecting chaos in marketing data. Then, we examine actual tweets to study actors and their behaviors during this crisis. Lastly, we present new recommendations for how managers can best deal with social media *chaos*.

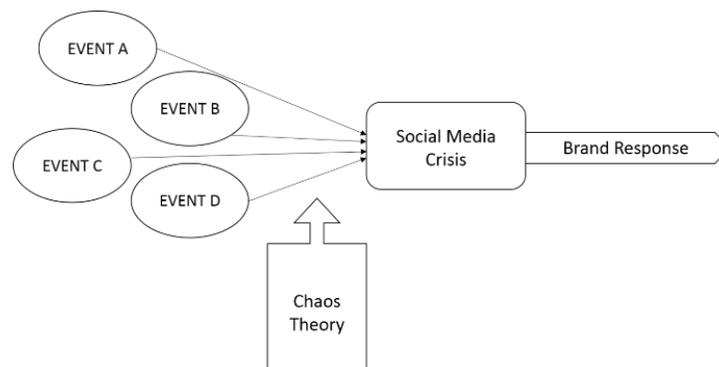
Hashtag Crises and Chaos

Chaos theory has emerged as a useful framework in the social sciences as a way to gain understanding of occurrences that are nonlinear, instable and uncertain (Kiel & Elliott, 1996). Multiple interpretations of chaos theory exist but common theoretical elements applied in the social sciences are (1) sensitive dependence on initial conditions; (2) positive feedback; (3) bifurcations; and (4) strange attractors (Kiel and Elliott, 1996). In this case, the social media crises we examine is multifaceted, with

each tweet differing by user, content, language, time and day of postings. However, the common denominator of all these tweets was the use of the #DeleteUber hashtag.

In their research on how hashtag communities operate as *ad hoc publics*, Bruns & Burgess (2015) found that including a hashtag in one’s tweet is a *performative action* as the hashtag begins to exist the instant it is posted to the platform. Additionally, the complex nature of conversations within hashtag communities on *Twitter* is ideally suited for an examination using chaos theory. When a single hashtag is adopted globally during a crisis, it permits researchers to more easily recognize the presence of key chaos characteristic by quickly determining the beginning of a crisis (sensitive dependence on initial conditions), studying how the community reacts to new and unexpected deviations (positive feedback), identifying dramatic changes of a behavior (bifurcation), and following how the crisis returns to relative stability following a crisis (strange attractor) (see Figure 1).

Figure 1 conceptualizes a social media crisis using elements of chaos theory.



An additional component that distinguished the Uber crisis of 2017 from the crises faced by Pepsi or United Airlines, is the unrelenting flurry of self-inflicted controversies battering the brand. Based upon a *Google* news headline from January 28 through June 8, 2017, the same timeframe as our *Twitter* data, we identified ten key controversies faced by the Uber brand (see Table 1). An event was deemed to be significant if the topic was reported by *USA Today*, *The New York Times* and *The Wall*

Street Journal, the nation’s largest print newspapers based upon circulation (Cision, 2016). We read a minimum of 500 tweets for each of the ten crises in order to summarize the assumed motivation for consumer participation.

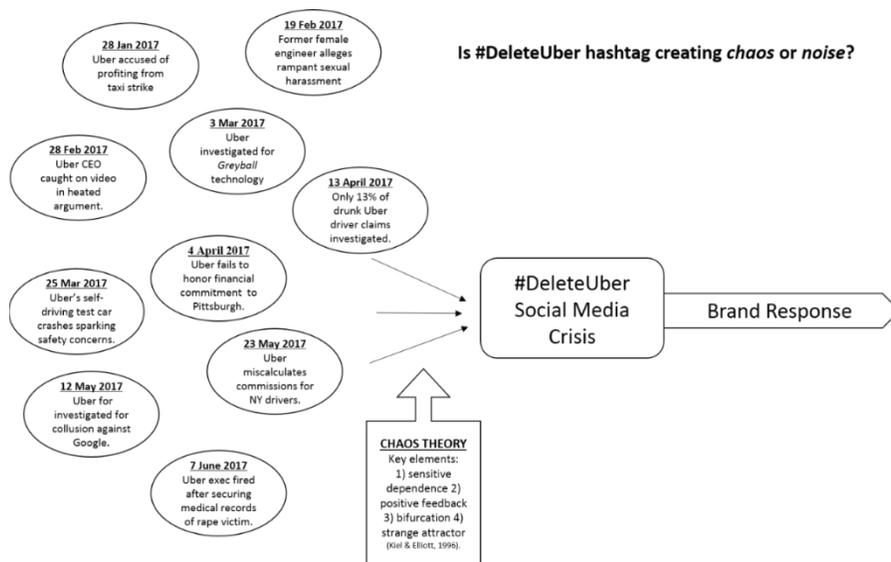
Table 1 lists key Uber controversies.

Dates	Issue	Reason for Consumer Anger	Uber Response
January 28, 2017	Accusations that Uber attempted to profit from a taxi strike at JFK airport after President Trump’s issued an executive order banning refugees and immigrants from certain countries from entering United States (Isaac, 2017).	Greed – Uber removed surge pricing to/from JFK airport as a way to profit from taxi strike.	Uber apologizes for <i>confusion</i> . Commits to \$3 million defense fund for drivers affected by immigration ban. Kalanick says he will talk to Trump re: ban (Lynley, 2017).
February 19, 2017	A former female engineer at Uber posted on her blog about the allegedly rampant sexual harassment at the company (Fung, 2017).	Injustice – Uber ignored sexual harassment charges by female employees.	Kalanick releases comment calling sexual harassment as <i>abhorrent</i> . Announces investigation led by former U.S. Attorney General Eric Holder (Fung, 2017).
February 28, 2017	Uber CEO caught on video having heated argument with Uber driver over compensation for drivers. He reported said, “Some people don't like to take responsibility for their own shit. They blame everything in their life on somebody else” (Fung, 2017, para 8).	Greed – Uber CEO, Travis Kalanick, valued at \$6.3B (Forbes, 2017) lost his temper and acted arrogantly towards his driver.	Kalanick posts apology; admits that he needs to <i>grow up</i> and could benefit from <i>leadership help</i> (Fung, 2017).
March 3, 2017	Justice department launches criminal investigation into Uber’s use of a propriety technology called ‘Greyball’ designed to avoid government officials, law enforcement, and cabdrivers in locations where the service was banned or restricted (Fung, 2017).	Injustice –Uber failed to follow societal norms or government laws.	Uber’s Chief Security Officer posts on company’s blog admitting to using such technology to target local authorities; promised it will be prohibited going forward (Sullivan, 2017)
March 25, 2017	A self-driving car being tested by Uber in Arizona was involved in a traffic accident which sparked concerns about the safety of such technology and the fact that Uber moved its testing program from California to Arizona (Overly, 2017) after Uber was ordered to cease operations in California after the brand began testing its self-driving fleet without the required government permits (Somerville & Sage, 2016).	Injustice –Uber failed to follow societal norms or government laws.	Uber confirms accident to <i>Bloomberg News</i> ; states it is suspending tests in Arizona until investigation is completed (Bergen & Newcomer, 2017)
April 4, 2017	Pittsburgh mayor accuses Uber of not fulfilling its promise to provide matching funds for a federal grants, hire locals to work at the self-driving car test track outside Pittsburg, and offer free rides in self-driving cars to residents (Dugan & Bensinger, 2017).	Greed – Uber failed to honor its financial commitment to Pittsburgh. In fact, it was charging residents for rides in self-driving cars after just a few months.	Uber disputes mayor’s position; claims agreement has created jobs. States <i>the company and the city maintain a great relationship</i> (Gold, 2017).
April 13, 2017	The consumer protection arm of the California Public Utility Commission found that Uber only investigated only 13 percent of passenger reports about drunken driving. The brand could be subjected to more than \$1 million in fines (Fung, 2017).	Injustice –Uber failed to follow societal norms or government laws.	Uber points out that report relates to complaints dating back several years, says, <i>We’ve significantly improved our processes since then</i> (Reuters, 2017).
May 12, 2017	Judge asked federal prosecutors to investigate Uber Technologies and one of its executives for collusion to steal key technology from Google. Possible criminal charges for Uber and CEO Travis Kalanick (Dwoskin, 2017).	Injustice- Uber failed to follow societal norms or government laws.	In its letter terminating executive, Uber said employee’s failure to work with investigators <i>impeded</i> internal investigation, as well as Uber’s legal defense (Fung, 2017)
May 23, 2017	Uber admits to mistake in the way it calculated its commissions, at a cost of tens of millions of dollars to its New York drivers (Scheiber, 2017).	Greed – Uber refuses to make drivers employees then fails to pay them what they earned.	Uber issued statement, “We are committed to paying every driver every penny they are owed — plus interest — as quickly as possible” (Scheiber, 2017).
June 7, 2017	Uber exec obtains medical records of a female passenger who was raped during a ride in India (Swisher & Bhuiyan, 2017).	Injustice- Uber failed to follow societal norms or government laws.	Uber confirms it fired exec, Eric Alexander. Declines to comment further. (Swisher & Bhuiyan, 2017).

Systems, Crisis, and Chaos Analysis

All systems, by nature, contain some degree of instability and change. Even if a system remains in equilibrium for a long period of time, this stability is fragile. That is, there exists the ever-present danger of sudden disturbances. In chaos theory, Earl (2012) explains, “small differences in initial conditions [will] make significant differences to how events unfold in the long term” (p. 1070). Because these controversies and numerous other factors come together by chance in a nonlinear system, trying to forecast how the #DeleteUber crisis will play out is impossible (see Figure 2).

Figure 2 conceptualizes the #DeleteUber crisis using elements of chaos theory.



Methodology and results

As stated earlier, chaos theory has been used in the social sciences to explore crisis communications (Horsley, 2013; Murphy, 1996), natural disasters (Sellnow, Seeger, & Ulmer, 2002), and tourism (Speakman & Sharpley, 2012; McKercher, 1999). However, marketing research has not employed it to understand social media crises. As this paper may be the first to apply chaos theory to a real world marketing event, we examine the #DeleteUber data from both macro and micro perspectives.

First we use nonlinear methods to analyze #DeleteUber as a hashtag event, then, we identify the actors influencing the #DeleteUber conversation.

#Hashtag Event Analysis

First, we need to determine whether or not the #DeleteUber crisis exhibits key elements of *chaos* – whether it demonstrates 1) sensitive dependence, 2) positive feedback, 3) bifurcations, and 4) strange attractors (Kiel & Elliott, 1996). In the following paragraphs we identify and define each of the above characteristic within the context of the #DeleteUber crises. Then, we develop a time series using the day and time data extracted from 188,810 tweets referencing the hashtag #DeleteUber and posted between January 28, 2017, and through June 8, 2017. Time series are critical in chaos research because, as stated by Kantz & Schreiber (2004), “the most direct link between chaos theory and the real world is the analysis of time series from real systems...” (p. xi). Lastly, we analyze the time series to detect chaos using first return maps, the correlation dimension, the Lyapunov exponent, and unpredictability as outlined by Hibbert and Wilkinson (1994) for determining chaos in marketing data. In addition, because “the relationships among the variables in a chaotic system are rather vague and at best, difficult to discern” (Kiel & Elliott, 1996, p. 2) we further examine the #DeleteUber data using recurrence quantification analysis (RQA), a more recent and comprehensive approach for identifying chaotic behavior in a wide range of applications (Webber & Zbilut, 2005; Zbilut & Webber, 1992).

Key Characteristics of Chaos Theory

Crisis communication literature has already applied chaos theory to unpredictable public events and natural disasters, e.g. 2002 Washington, DC, area sniper shootings (Horsley, 2013); and, the 1998 flood at Katherine Gorge in Australia’s Northern Territory (Faulkner & Vikulov, 2001). In a crisis, key

elements of chaos theory - sensitive dependence, positive feedback, bifurcation, and strange attractor - encounter each other in a disordered dance where they react and move in unexpected directions.

Finding patterns in chaotic states can be difficult if they are hidden by a large amount of random noise (Smith, 2004). Chaos theory, however, may prove to be a particularly good framework in cutting through noise to find useful patterns.

Characteristic #1: Sensitive Dependence on Initial Conditions

An event is considered to be in a *chaotic* state when long-term prediction of how it will behave is no longer possible, in part, because the event no longer resembles how it began (Kiel & Elliott, 1996). This morphing and changing is due to environment's sensitive dependence on initial conditions, also known as the *butterfly effect*, or the seemingly inconsequential act that ultimately leads to a crisis (Speakman & Sharpley, 2012). Seeger (2002) found that minor communication oversights, failure to receive warning messages, and lack of information have all sparked major crises for companies.

A misinterpreted tweet was the *butterfly effect* initiating the Uber crisis. While the hashtag #DeleteUber had previously been used, it only ignited by chance into a crisis when, as mentioned prior, a freelance journalist misinterpreted Uber's tweet about surge pricing. O'Sullivan continued his tweeting rant against Uber and Trump, which attracted similar disgruntled users, and thus, launching the global #DeleteUber crisis. Although Uber's communications team and CEO employed traditional crisis communication tactics by releasing statements repeatedly insisting Uber had no intention of breaking a strike, the brand was not seemingly able to control the crisis but rather had to watch it unfold as headline news. O'Sullivan's tweet demonstrates a *sensitive dependence on initial conditions* because it triggered a crisis calling into question Uber's existing leadership and management structure and, possibly, even the brand's long term existence.

Characteristic #2: Positive Feedback

Positive feedback in chaos theory is different than positive feedback typically discussed in marketing literature. Rather, in a chaotic system, feedback indicates how the community reacts to new and unexpected deviations. Chaos evolves by means of positive feedback, where changes are amplified, existing structures break up, and unexpected outcomes are introduced in the form of new patterns and behavior (Kiel & Elliott). In this event, Uber's own communication responses to the crisis created *positive feedback*. For example, after a dashcam video showing his argument with a driver went viral, Uber's CEO Travis Kalanick released what many scholars would consider the perfect apology. In his blog post titled, *A profound apology*, the leader accepts responsibility for his behavior and logically frames a proposed remedy (Kalanick, 2017). Claeys and Cauberghe (2014) found that participants highly involved in a crisis tend to respond favorably to rational, rather than emotional messages. Kalanick's rational approach *should* have been well accepted by the public resulting in a visible reduction in the number of consumers tweeting in the #DeleteUber conversation. Instead, Kalanick's apology statement represents *positive feedback*. The apology only fueled consumers' backlash against the brand on *Twitter*. The online #DeleteUber community failed to behave in an anticipated manner, thus, contributing towards a *chaotic* state.

Characteristic #3: Bifurcation Points

A *bifurcation* is a sudden change in the behavior of time series data (Whitby, Parker, & Tobias, 2001). While nonlinear systems may appear stable at times, sudden changes in the relationship between variables generate dramatic changes. Successive controversies involving Uber, as illustrated earlier in Figure 2, served as a *bifurcations* for this hashtag event. Each time outrage against the brand appeared to be returning to an equilibrium state, another controversy or *bifurcation* would reignite the crisis sending

public conversations off into impulsive directions, thus, making long term predictions impossible. We hold that these controversies or *bifurcations* pushed the events towards a *chaotic* state.

Characteristic #4: Strange Attractors

A *strange attractor* guides a social system back towards relative stability following bifurcations (Sellnow, et al 2002). For Uber, a population of persistent *digital consumer activists* (Legocki & Walker, 2017) act as the *strange attractor*. These consumers continue to tweet hundreds of times per day using the hashtag #DeleteUber regardless of whether new stories or information about the company is released. We reviewed 132 days of tweets between January 2017 and June 2017 and never once has the *Twitter* conversation returned to a zero count of #DeleteUber references, which the brand had previously appreciated. While the hashtag was tweeted sporadically throughout 2016, it never gained momentum. The global visibility of Uber's misdeeds connected disgruntled publics creating a new normal state for the brand on social media. In her analysis of Intel's 1994 Pentium computer chip crisis, Murphy (1996) noted that once isolated and angry individuals encountered on another other in an online Pentium newsgroup, they collectively strengthened in both their "force and complexity" (p. 103) against the brand. Similar to these early online consumer activists, we posit that a small but persistent band of consumers on *Twitter* serve as the *strange attractor* in the #DeleteUber crisis.

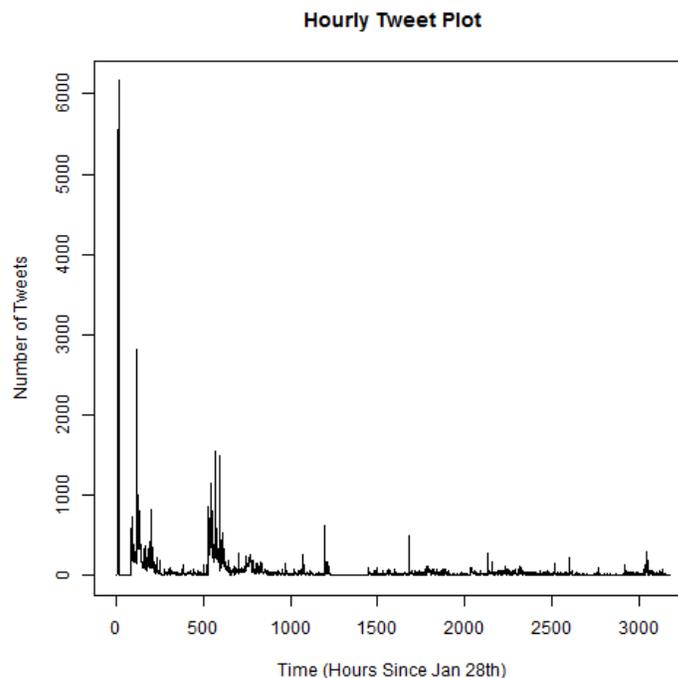
Results of #Hashtag Event Analysis

Now that key elements of chaos theory have been identified in the #DeleteUber event, we next focus on analyzing our dataset. Tweets and retweets using the #DeleteUber hashtag were scraped using the *Twitter Archiving Google Sheets (TAGS)* system (Hawksey, 2014). TAGS interfaces with *Twitter's*

API to search and retrieve tweets. We began the data collection process on January 29, 2017 after the #DeleteUber hashtag came to our attention as a trending *Twitter* topic. A total of 188,810 tweets were retrieved and, after reviewing for completeness of the timestamp data, all tweets were considered usable.

We began our analysis by binning tweets by hour to generate an hourly frequency of tweets (see Figure 3). The range of timestamp data from our tweet set was partitioned into segments or *bins* of equal size. Binning data is viewed as converting data to be more accurate and faster to analyze than using it as a large continuous data set. Because detecting chaotic significance may be subtle, tweets will be optimally structured for thorough scrutiny (Liu, Hussain, Tan, & Dash, 2002).

Figure 3 shows hourly frequency of #DeleteUber tweets.

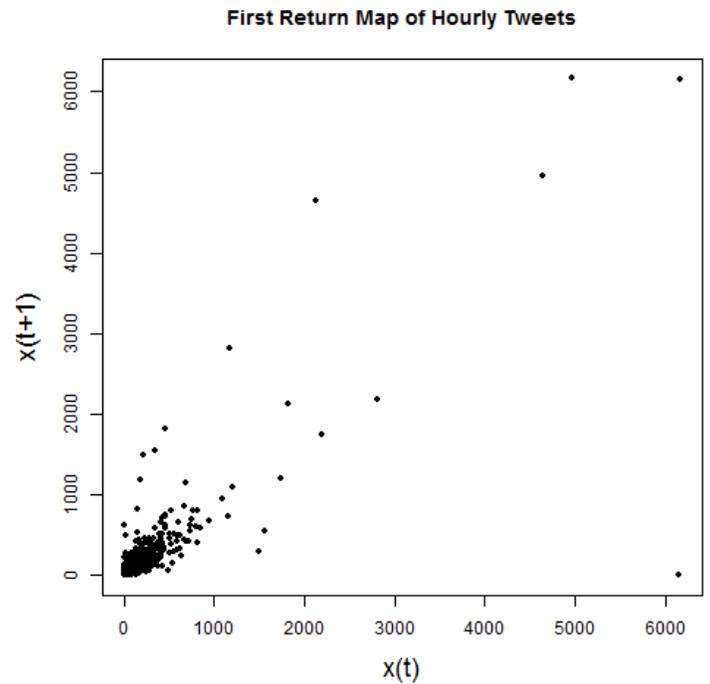
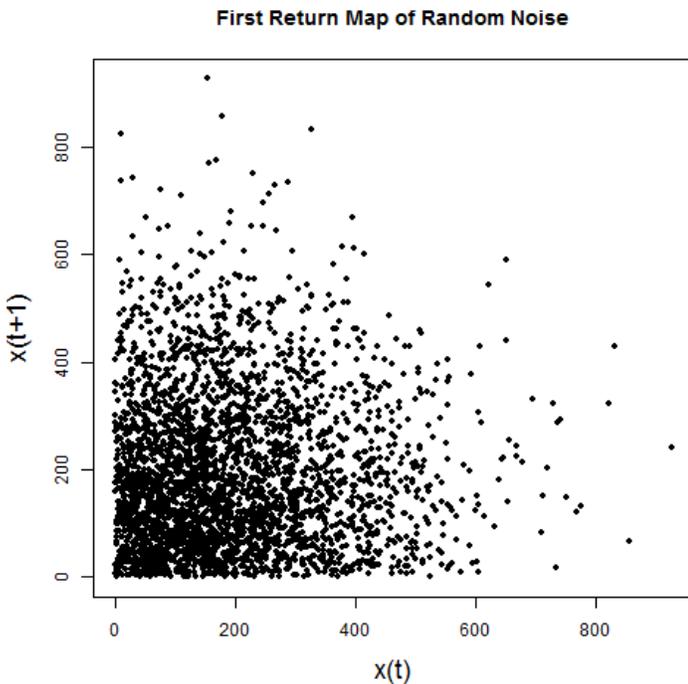


First Return Maps

Next, we analyzed data using first return maps (Hibbert & Wilkinson, 1994) as a way to uncover any hidden patterns of chaos. First return maps shows two time series, Figure 4a depicts the random noise in the #DeleteUber tweets. Figure 4b shows the hidden chaos in #DeleteUber tweets. When plotted for the values of t against $t + 1$, the chaotic first return map revealed a subtle pattern, whereas the random behavior did not. Although difficult to make out, when #DeleteUber tweets were compared with random noise (with similar distributional properties), a slight amount of order appeared in the first return map (see Figure 4b).

Figure 4a shows first return map of random noise

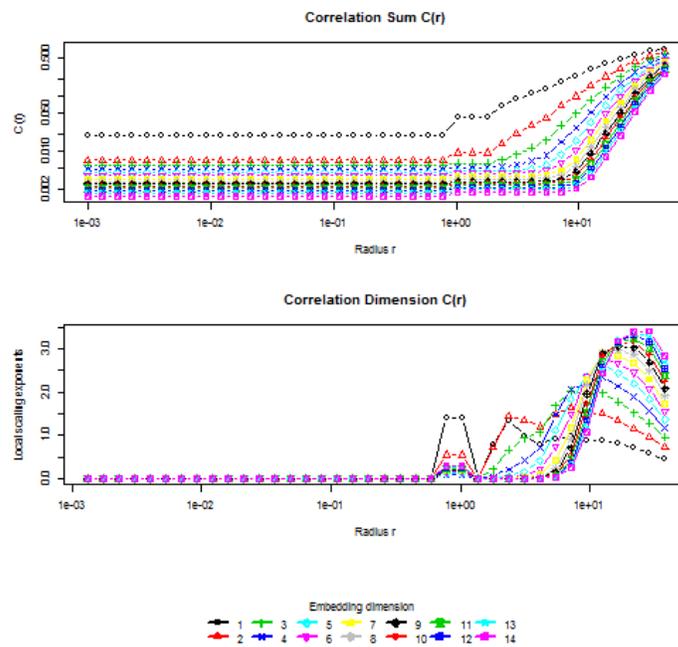
Figure 4b shows first return map of chaos.



Correlation Dimension

Next we used correlation dimension to estimate the dimension of the strange invariant set (chaotic attractor) which characterizes the data (Hibbert & Wilkinson, 1994). The slope of these lines is the estimated correlation dimension (see Figure 5). **For #DeleteUber data, the correlation dimension estimate is 2.43.** Because it is a non-integer, we can infer that the attractor is a strange attractor and the #DeleteUber time series has a fractal structure which may be chaotic (Brown, 1996b).

Figure 5 shows correlation dimension.



Maximum Lyapunov Exponent

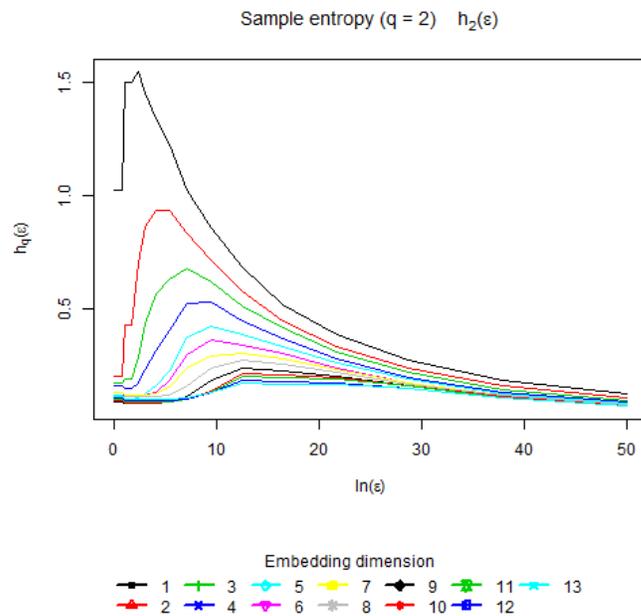
Following these analyses, we determined the Lyapunov exponent, considered to be the strongest measurement to quantify chaos in a time series (Brown, 1996a). The presence of a positive Lyapunov exponent indicates the extent to which small changes, or *butterfly effect*, in

initial conditions produce divergence in a system over time (Kiel & Elliott, 1996). If the Lyapunov exponent has any positive value, it indicates that even the minutest disruption will rapidly grow. The larger the Lyapunov exponent, the more chaos is present (Kellert, 1994). **For #DeleteUber data, the maximum Lyapunov exponent is 0.08.** This indicates a slight amount of divergence. In absence of maximum Lyapunov exponents from similar social media crises for evaluation, we are unable to comment as to the significance of a 0.08 exponent. Before readers discount such a measurement, it should be noted that Siek and Solomatine (2010) created an accurate and reliable short-term storm surge prediction tool based upon data with a maximum Lyapunov exponent of 0.08.

Unpredictability

One difference between chaotic data and random noise is unpredictability. While Hibbert and Wilkinson (1994) proposed using prediction error to determine if the short and long-term predictability of the data set is possible, we opted to employ sample entropy (SampEn) after the first return map revealed just a slight amount of chaotic pattern. SampEn yields similar results as prediction error (see Figure 6) but this more recent method has been proven to be reliable in the analysis of noisy real world data sets, such is the case of #DeleteUber (Richman, Lake & Moorman, 2004) . **For #DeleteUber data, the estimated sample entropy (SampEn) is 0.12.** In general, a positive entropy indicates a strange attractor, or evidence of a chaotic state (Takens, 1981).

Figure 6 shows sample entropy (unpredictability).



Recurrence quantification analysis (RQA)

Quantification of recurrence plots is a more recent, and comprehensive approach to identifying chaotic behavior. RQA is a nonlinear approach to identifying patterns in time-series data by determining if repeated or recurrent data is predictable (deterministic) or if it's the result of random fluctuation. This approach acts "...like a microscope, snooping out higher dimensional subtleties in the dynamics that are not obvious..." (Webber Jr. & Zbilut, 2005, p. 82). Chaotic systems demonstrate noticeable patterns in an RQA while random noise shows no apparent form. (see Figure 6).

Data are then quantified following the RQA process first introduced by Zbilut, & Webber (1992) then later clarified in Webber & Zbilut (2005). First, we determine the percentage of

recurrent points falling within a specified radius for our tweets. **#DeleteUber data was found to have a recurrence variable of 0.08%.** Then, data is examined to define the percentage of recurrent points on diagonal lines which measures predictability in a given time series.

#DeleteUber data has 81% determinism or predictability, indicating that the tweets were most likely not random (Zbilut & Webber, 1992).

Next, data are computed for laminarity or the percent of recurrent points on vertical lines which measures intermittency in a time series. **#DeleteUber data has 83% laminarity** or a highly irregular repetition of phases indicative of a chaotic state. Last, we determine trapping time, or the mean time that the system will tolerate or remain trapped in a specific state (Marwan & Webber, 2015). **#DeleteUber data has a maximum predictability time of 19.18 hours.**

Discussion of #Hashtag Event Analysis

In answer to our research question(s), we confirm that the case of #DeleteUber is a *chaotic* event, thus **a social media crisis can be a chaotic event.** Our hashtag data appears to exhibit chaotic behavior as discernable patterns in the first return map. Assuming the data are chaotic then, the correlation dimension of 2.43 indicates a two to three dimensional system is at play. A maximum Lyapunov exponent of 0.08 along with a positive sample entropy indicates a strange attractor, thus, demonstrating the presence of chaotic behavior. Recurrence quantification analysis (RQA) further identified chaotic behavior in the #DeleteUber crisis, and, determined that the event had a maximum predictability time of an estimated 19 hours, meaning any effort by Uber to predict events beyond 19 hours in the #DeleteUber hashtag campaign would be useless. What this translates into for the marketing manager is that it may be unrealistic to be expected to manage a social media crises once it reaches a chaotic state where

bifurcations determine next steps, and strange attractors guide the crisis back to a level of stability, not a practitioner. Once a social media event spirals out of control, Murphy (1996) suggests that a manager, "...allow events to sort themselves out while trying to fit into the emerging aftermath" (p. 106). This may prove to be sound advice for many brands, but, we want to examine if any clues existed in the conversations that would help managers deter rather than clean up future crises. For answers, we look at the unique actors who participated in the #DeleteUber conversation.

Analysis of Actors in a Hashtag Event

Now that we know a social media crisis can be *chaotic*, more information about consumers participating in a hashtag crisis like #DeleteUber should be explored in order to develop a meaningful response plan. Adapting McKercher's 1999 chaos in tourism model, we re-examine the #DeleteUber data, focusing on persistent actors with highest frequency of engagement. A variety of actors are present in all social media crisis conversations, and by categorizing their tweeted conversations, it may yield hidden patterns.

We employ a mixed-method approach that includes qualitative content analysis of tweets to determine patterns of how consumers use *Twitter* to express their anger towards Uber in the #DeleteUber campaign. We determined actor categories by manually reviewing the tweets and profile descriptions of participants who generated at least one percent of mentions, tweets or retweets.

Starting with our sample of 188,810 tweets used for time series analysis, we conducted an advanced *Twitter* search on the platform to determine if this particular hashtag had been used prior to the crisis start date of January 28, 2017. Our search revealed that the hashtag,

#DeleteUber, had been tweeted or retweeted 216 times since the term was first used on May 18, 2016, nearly eight months earlier.

We manually scraped all metadata, including the timestamp information, from each of the 216 tweets into our existing spreadsheet, increasing our total count to 189,026 tweets. With the additional data, we could now review the entirety of the #DeleteUber conversation for possible clues useful in developing crisis prevention guidelines. Although Dan O’Sullivan’s tweet using the hashtag #DeleteUber has been credited with sparking the 2017 social media crisis against the brand, the hashtag, in fact, originated with a London cab driver (*Twitter* handle: @Sammytxj) to express his anger about the company’s impact on his livelihood.

Next, all non-English, duplicate, and unrelated (e.g. sales spam) tweets were removed leaving a usable sample of 166,979 tweets. From this, we identified 21,611 unique actors, based upon the number of unique *Twitter* identification codes (see Table 2). Every *Twitter* user has a unique numerical identification code. To protect users’ privacy, we opted to analyze data based upon the actor’s *Twitter* ID rather than by username. After calculating the number of tweets per actor, we then sorted our list from high to low based upon the total number of tweets they posted. Due to time and resource limitations, we chose to focus only on actors whose total number of tweets was one percent or more of the total conversation. This created a reasonable sample of 114 actors for review.

Discussion of Actor Analysis Findings

We were surprised to discover that these 114 users tweeted or retweeted a total of 94,317 times, reflecting roughly 56 percent of our sample. Further conversation analysis revealed more surprises. Based upon users’ own public *Twitter* biographies, we coded these 114 actors into six

distinct categories, shown in Table 2. We categorized the largest number of individual actors, a total of sixty-one, as *Taxi Industry*, those self-identifying as working for or are in support of taxi, cab and limousine companies and/or its employees. It was also possible to determine from the actors' biographies and/or tweets that they reside in one of the following five countries: United States, United Kingdom, Australia, Canada and Spain. In regards to the *Taxi Industry*, ninety-two percent of their tweets were posted by users based outside the United States (see Table 2). When we omit behavioral data from these 114 actors from our sample, we find that the average participant (shown as *Participating Public* on Table 2) tweeted or retweeted an average of 3.38 times. In contrast, the **sixty-one actors representing the taxi industry in our sample, tweeted or retweeted an average of 866 times.**

Table 2 identifies unique actors and their behaviors.

<u>Actor</u>	<u>No of Unique Actors</u>	<u>Total Tweets</u>	<u>Mean Freq</u>	<u>Twitter Followers</u>	<u>Tweets - USA</u>	<u>Tweets - UK</u>	<u>Tweets- Aust</u>	<u>Tweets- Cnd/Spn</u>
Uber (Brand)	3	13712	4570.67	332,767	13407	0	0	305
Government Officials	4	4234	1058.50	709,836	0	1151	3083	0
<i>Taxi Industry</i>	61	52815	865.82	36,265	4210	36107	8289	4209
Competitors	4	3132	783.00	64,624	3132	0	0	0
Digital Consumer Activists	20	10974	548.70	181,094	5608	0	4720	646
Target Brands	3	1529	509.67	2,113,333	1529	0	0	0
Media	19	7921	495.06	9,259,547	7921	0	0	0
Participating Public	21,497	72,662	3.38	8,901,056				
Totals	21,611	166,979		21,598,522	35,807	37,258	16,092	5,160

As future crisis response guidelines are researched, proposed and presented for managers, it is important for scholars to recognize that a single crisis is comprised of multiple voices and viewpoints. In their typology of digital consumer activism, Legocki and Walker (2017) referred to this group of small, irate and persistent actors – like those in the taxi industry- using social seeking changes from a brand as *angry activists*. These consumers initiate online petitions, reach

out to celebrities for support, and alert news media of a brand's perceived injustice. *Angry activists* typically exhibit the highest posting frequency of any participant in a social media crisis. Acknowledging or working towards a resolution with these actors could help mitigate a crisis or at the very least, dampen its virality. This persistent group made themselves known back in May 2016, months before the crisis sparked. Future research could determine motivating factors for angry activities for further development of crisis prevention guidelines for managers.

Managerial Implications and Limitations

The susceptibility of a *chaotic* system, such as a social media crisis, to even small shocks explains why Uber was caught off guard when a seemingly insignificant event sparked a global social media crisis. Further, Uber most likely would not have been able to even recognize, much less control the onset of *chaos*, by employing traditional marketing efforts.

By all industry accounts, the type of global social media crisis experienced by Uber will only increase and intensify against brands. Reporter David Ng explains in his *Los Angeles Times* articles on consumer activism, "...what distinguishes the campaigns of recent months is the speed at which they propagate across *Twitter* and Facebook, fueled by partisan passions about Trump" (para. 13). In our paper, for example, the taxi industry had been angrily tweeting using the #DeleteUber hashtag for months, but it was only when their anger towards Uber encountered the angry political tweeting protesting the president's executive travel ban, that circumstances were ripe for O'Sullivan's tweet to spark a *chaotic* crisis for the brand. While unknown at this time, researchers should keep an eye on crisis duration, as the #DeleteUber chaos may possibly become the future norm for brands.

We encourage future research to address the gaps and limitations of our paper. It is impossible to offer a more detailed understanding of our findings without similar analysis for comparison. This paper focused on the detailed examination of one event using English language tweets directed towards a primarily United States-based company that was founded less than ten years ago. It may be interesting for future studies to conduct analysis of crises events where the majority of the *Twitter* conversation is not in the English language; against brands not headquartered in the United States; involving older, iconic companies and brands; and, reflecting additional political viewpoints, such as pro-Trump activism targeting brands. Chaos theory may further be proven to be a useful model for understanding fast-paced, unpredictable events.

References

- Agnew, A. (2014, May 2). Spotlight on *Firebell*: our social media crisis simulator [Blog]. Retrieved <http://webershandwickseattle.com/2014/05/spotlight-on-firebell-our-social-media-crisis-simulator/>
- Boss, J. (2017, June 8). Uber's problem isn't culture, it's this. *Forbes*. Retrieved <https://www.forbes.com/sites/jeffboss/2017/06/08/Ubears-problem-isnt-culture-its-this/#2f95be1f2dc8>
- Bro_Pair. (2017, January, 28). congrats to @Uber_NYC on breaking a strike to profit off of refugees being consigned to Hell. eat shit and die [Tweet]. Retrieved from https://twitter.com/bro_pair/status/825518408682860544?lang=en
- Brown, T. A. (1996a). Measuring chaos using the Lyapunov exponent. *Chaos Theory in the Social Science*, 53-66.
- Brown, T. A. (1996b). Nonlinear politics. *Chaos theory in the social sciences*, 119-137.
- Bruns, A., & Burgess, J. (2015). Twitter hashtags from ad hoc to calculated publics. *Hashtag publics: The power and politics of discursive networks*, 13-28.
- Cision US, Inc. (2016, May 11). Top List Blog: Top 10 US daily newspapers [Blog]. Retrieved <http://www.cision.com/us/2014/06/top-10-us-daily-newspapers/>
- Claeys, A. S., & Cauberghe, V. (2014). What makes crisis response strategies work? The impact of crisis involvement and message framing. *Journal of Business Research*, 67(2), 182-189.
- Coombs, W. T., & Holladay, J. S. (2012). The paracrisis: The challenges created by publicly managing crisis prevention. *Public Relations Review*, 38(3), 408-415.
- Doherty, N., & Delener, N. (2001). Chaos theory: Marketing & management implications. *Journal of Marketing Theory and Practice*, 9(4), 66-75.
- Dugan, I.J., & Bensinger, G. (2017, April 4). Uber self-driving program hits another pothole. *The Wall Street Journal*. Retrieved <https://www.wsj.com/articles/uber-self-driving-program-hits-another-pothole-1491211802>
- Dwoskin, E. (2017, May 17). Judge asks federal prosecutors to investigate Uber in trade secret case. *The Washington Post*. Retrieved https://www.washingtonpost.com/news/the-switch/wp/2017/05/12/judge-asks-federal-prosecutors-to-investigate-uber-in-trade-secret-case/?utm_term=.09e5c5519e54
- Earl, P. E. (2012). Experiential analysis of automotive consumption. *Journal of Business Research*, 65(7), 1067-1072.

- Faulkner, B., & Vikulov, S. (2001). Katherine, washed out one day, back on track the next: a post-mortem of a tourism disaster. *Tourism Management*, 22(4), 331-344.
- Fung, B. (2017, May 5). From #DeleteUber to 'Hell': a short history of Uber's recent struggles. *The Washington Post*. Retrieved https://www.washingtonpost.com/news/the-switch/wp/2017/04/18/from-deleteUber-to-hell-a-short-history-of-Ubers-recent-struggles/?utm_term=.821ba148dcff
- Grappi, S., Romani, S., & Bagozzi, R. P. (2013). Consumer response to corporate irresponsible behavior: Moral emotions and virtues. *Journal of Business Research*, 66(10), 1814-1821.
- Grégoire, Y., Laufer, D., & Tripp, T. M. (2010). A comprehensive model of customer direct and indirect revenge: understanding the effects of perceived greed and customer power. *Journal of the Academy of Marketing Science*, 38(6), 738-758.
- Hawksey, M. (2014). Need a better *Twitter* Archiving Google Sheet? TAGS v6.0 is here! [Blog post]. Retrieved from <https://mashe.hawksey.info/2014/10/need-a-better-twitter-archiving-google-sheet-tags-v6-0-is-here/>.
- 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.
- Hibbert, B., & Wilkinson, I. F. (1994). Chaos theory and the dynamics of marketing systems. *Journal of the Academy of Marketing Science*, 22(3), 218-233.
- Horsley, S. J. (2014). The method in their madness: chaos, communication, and the DC snipers. *Journal of Communication Management*, 18(3), 295-318.
- Isaac, M. (2017, January 31). What You Need to Know About #DeleteUber. *The New York Times*. Retrieved <https://www.nytimes.com/2017/01/31/business/delete-uber.html>
- Kähr, A., Nyffenegger, B., Krohmer, H., & Hoyer, W. D. (2016). When hostile consumers wreak havoc on your brand: The phenomenon of consumer brand sabotage. *Journal of Marketing*, 80(3), 25-41.
- Kalanick, T. (2017, February 28). A profound apology [Blog]. Retrieved <https://newsroom.Uber.com/a-profound-apology/>
- Kantz, H., & Schreiber, T. (2004). *Nonlinear time series analysis* (Vol. 7). Cambridge University Press.
- Kaplan, A. M., & Haenlein, M. (2011). Two hearts in three-quarter time: How to waltz the social media/viral marketing dance. *Business Horizons*, 54(3), 253-263.
- Kellert, S. H. (1994). *In the wake of chaos: Unpredictable order in dynamical systems*. University of Chicago press.
- Kiel, L. D., & Elliott, E. W. (1996). *Chaos theory in the social sciences: Foundations and applications*. University of Michigan Press.

- Legocki, K., & Walker, K. (2017, February 19). Angry Consumers as Digital Consumer Activists: Starting Fires or Fanning Flames?. Paper presented at *AMA Winter Educator's Conference*, Orlando, FL, and (Special Session Track)
- Liu, H., Hussain, F., Tan, C. L., & Dash, M. (2002). Discretization: An enabling technique. *Data Mining and Knowledge Discovery*, 6(4), 393-423.
- Marwan, N., & Webber Jr, C. L. (2015). Mathematical and computational foundations of recurrence quantifications. In *Recurrence Quantification Analysis* (pp. 3-43). Springer International Publishing.
- McKercher, B. (1999). A chaos approach to tourism. *Tourism Management*, 20(4), 425-434.
- McQuade, A. (2017, April 20). Uber apologizes for chaos at SunTrust Park. *WXIA, 11 Alive NBC*, Atlanta, GA. Retrieved <http://www.11alive.com/sports/Uber-apologizes-for-chaos-at-suntrust-park/432777922>
- Murphy, P. (1996). Chaos theory as a model for managing issues and crises. *Public relations review*, 22(2), 95-113.
- New York Post. (2017, March 2). Lyft sees big opportunity with chaos at Uber. *New York Post*. Retrieved <http://nypost.com/2017/03/02/lyft-sees-big-opportunity-with-chaos-at-Uber/>
- Ng, D. (2017, June 13). Advertisers are in the hot seat as activists both for and against Trump call for boycotts. *Los Angeles Times*. Retrieved <http://www.latimes.com/business/hollywood/la-fi-ct-advertiser-boycotts-20170610-story.html>
- Paraskevas, A. (2006). Crisis management or crisis response system? A complexity science approach to organizational crises. *Management Decision*, 44(7), 892-907.
- Pfeffer, J., Zorbach, T., & Carley, K. M. (2014). Understanding online firestorms: Negative word-of-mouth dynamics in social media networks. *Journal of Marketing Communications*, 20(1-2), 117-128.
- Rauschnabel, P. A., Kammerlander, N., & Ivens, B. S. (2016). Collaborative brand attacks in social media: exploring the antecedents, characteristics, and consequences of a new form of brand crises. *Journal of Marketing Theory and Practice*, 24(4), 381-410.
- Richman, J. S., Lake, D. E., & Moorman, J. R. (2004). Sample entropy. *Methods in enzymology*, 384, 172-184.
- Scheiber, N. (2017, May 23). Uber to repay millions to drivers, who could be owed far more. *The New York Times*. Retrieved <https://www.nytimes.com/2017/05/23/business/economy/uber-drivers-tax.html>
- Seeger, M. W. (2002). Chaos and crisis: Propositions for a general theory of crisis communication. *Public Relations Review*, 28(4), 329-337.

- Sellnow, T. L., Seeger, M. W., & Ulmer, R. R. (2002). Chaos theory, informational needs, and natural disasters. *Journal of Applied Communication Research*, 30(4), 269-292.
- Siek, M., & Solomatine, D. P. (2010). Nonlinear chaotic model for predicting storm surges. *Nonlinear Processes in Geophysics*, 17(5), 405.
- Smith, A. (2002). Three scenarios for applying chaos theory in consumer research. *Journal of Marketing Management*, 18(5-6), 517-531.
- Speakman, M., & Sharpley, R. (2012). A chaos theory perspective on destination crisis management: Evidence from Mexico. *Journal of Destination Marketing & Management*, 1(1), 67-77.
- Stolle, D., Hooghe, M., & Micheletti, M. (2005). Politics in the supermarket: Political consumerism as a form of political participation. *International political science review*, 26(3), 245-269.
- Swaminathan, V. & Mah, S. (2016, September 2). What 100,000 tweets about the Volkswagen scandal tell us about angry customers. *Harvard Business Review*. Retrieved <https://hbr.org/2016/09/what-100000-tweets-about-the-volkswagen-scandal-tell-us-about-angry-customers>
- Swisher, K., & Bhuiyan, J. (2017, June 7). A top Uber executive, who obtained the medical records of a customer who was a rape victim, has been fired. *recode*. Retrieved <https://www.recode.net/2017/6/7/15754316/uber-executive-india-assault-rape-medical-records>
- Tripp, T. M., & Bies, R. J. (2010). "Righteous" anger and revenge in the workplace: The fantasies, the feuds, the forgiveness. In *International Handbook of Anger* (pp. 413-431). Springer New York.
- Webber Jr, C. L., & Zbilut, J. P. (2005). Recurrence quantification analysis of nonlinear dynamical systems. *Tutorials in contemporary nonlinear methods for the behavioral sciences*, 26-94.
- Whitby, S., Parker, D., & Tobias, A. (2001). Non-linear dynamics and duopolistic competition: a R&D model and simulation. *Journal of Business Research*, 51(3), 179-191.
- Winsor, R. D. (1995). Marketing under conditions of chaos: percolation metaphors and models. *Journal of Business Research*, 34(3), 181-189.
- Zbilut, J. P., & Webber, C. L. (1992). Embeddings and delays as derived from quantification of recurrence plots. *Physics letters A*, 171(3-4), 199-203.