UNDERSTANDING BRAND REPUTATION AND ONLINE FIRESTORMS THROUGH SOCIAL MEDIA

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Abstract

This study focuses on providing a guide to understanding how online firestorms can affect brand reputation, especially in the context of social media. I will present a review that spans on various academic fields such as psychology, business studies, and network sciences. I will cover literature on how brand reputation has been studied and measured in the context of social media, what online firestorms are and how they occur, and how do existing studies on attitude change hint at the effects of firestorms on changing brand reputation from a viewpoint of attitude change. At the end of the review I will also identify a number of existing gaps in the fields of study that can provide new insights on understanding brand reputation and online firestorms. Finally, I will propose a study that aims to fill one of the gaps by proposing an improved computational method for measuring brand reputation from social media.

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Chapter 1

Introduction

Social media and social networking platforms play a crucial role in how people accept, process and spread information online. With its large volume of daily users and interactions coupled with traceable digital footprints, online social networks have become an interesting field for researchers aiming to understand the collective opinions of mass audiences. A particular domain of interest is the collective attitudes of individuals that are formed on brands, defined as *brand reputation*. Maintaining a positive brand reputation in social media is crucial for companies in that a good reputation can attract potential customers and promote investment opportunities (Bhattacharya & Sen, 2003). Therefore, an increased amount of interest has been put into understanding brand reputation from the social media usage of mass audiences.

The viral nature of social media allows both positive and negative information about the brand to quickly spread, the latter a recently emerging phenomenon labeled as "online firestorms" (Pfeffer et al., 2014). Companies and brands can easily become the targets of online firestorms, receiving negative messages from thousands of angry users for days. As a result of a firestorm the brand's public reputation can quickly dwindle, which can take a long time to recover (Hansen et al., 2018). From a manager's perspective, being able to identify brand reputation levels, understanding the dynamics of online firestorms and how they can lead to changes in brand reputation are all important topics in order to maintain a brand presence in social media.

Based on these interests, I will present the literature review in three stages. In the first stage (Chapter 2), I will set the definition of brand reputation, the target variable of interest, and review existing methods of measuring brand reputation. Especially, I will also examine the more recent studies that have attempted to measure brand reputation from social media, and address current limitations. In the second stage (Chapter 3), I will focus on understanding how word-of-mouth spreading happens in social media, especially in the form of online firestorms. I will draw studies from network sciences to provide a richer understanding of how certain properties within social networks can promote the diffusion of information. In the third stage (Chapter 4), I will explain the motives and processes of how online firestorms change brand reputation by bringing concepts from attitude changes. Finally, I will provide a summary of the findings as well as future research directions that can benefit the understanding of online firestorms and brand reputation.

In addition to the review, I will delve deeper into one of the intellectual gaps addressed in the review. In order to correctly identify the changes of brand reputation levels in large social networks an interpretable and scalable measurement model is necessary, yet existing models failed to do so. Drawing from recent advances in natural language processing, I will propose a framework that will enable theory-driven and yet scalable measurements of brand reputation from social media. I will also design a study aimed to test its validity based on actual survey data.

Chapter 2

Understanding Brand Reputation

A *brand* can be a logo or indicator of a company, an image of functional and emotional characteristics associated to a company, or the company itself (De Chernatony & Dall'Olmo Riley, 1998). The reputation of a company brand, more familiarly known as *brand reputation*, is a concept used to describe how a company or brand is perceived and evaluated by an individual or specific group (Walsh & Beatty, 2007). Maintaining a good brand reputation is beneficial in several aspects for a company, and a large field of research in the fields of business and marketing has centered around understanding the elements of brand reputation as well its effects on a company's performance.

The term brand reputation is frequently used in business studies, resulting in several definitions. Understanding the relationships between these concepts and distinguishing each of them can help ground our understanding on what brand reputation actually means. Therefore, I will conduct a literature review on the various definitions of brand reputation to result in a clearer understanding of what brand reputation actually is and what characteristics to focus on. Additionally, I will show that brand reputation is a concept that requires taking into consideration several factors associated with a brand: the quality and values of products or services associated with a brand, the company's practice in social corporate responsibilities, and customer relationship to list a few. Previous studies that have tried to measure brand reputation have identified these different factors, but under different definitions and scopes. Part of this chapter will also be dedicated to re-organizing the common categories that should be considered when measuring brand reputation.

As people increasingly obtain information of brands and interact with brand accounts in social media platforms, there has also been effort to measure elements of brand reputation from social media interactions. In the last part of the chapter, I will cover the more recent studies that have tried to measure brand reputation with a combination of social media data and computational tools, and will provide explanations on what these studies aimed to measure, how the measurements were conducted, and which aspects could be improved.

2.1 What is Brand Reputation?

As a first step, a clear definition of brand reputation needs to be provided. Brand reputation is a concept that has been studied over decades and is associated with several similar but distinct definitions. This brings a need to disentangle the concepts and provide a clear understanding of what brand reputation is. Throughout this section, I will draw the definitions and findings from several influential studies on brands and brand reputation to come up with a more comprehensive definition that contains the core concepts.

2.1.1 Towards a Unified Concept of Brand Reputation

Brand reputation has been considered in various fields under different research goals, which has led to several different definitions. For example, Fombrun et al. (2000) presented a list of how brand reputation is studied differently in seven different areas of business studies: economics, strategy, accounting, marketing, communications, organization theory, and sociology. In accounting, reputation would be considered as an intangible asset which are difficult to measure but produce value to companies, while in organization theory, reputation would be more about stakeholders' understanding of corporate activities. Such diversity has led to continuous efforts for organizing and synthesizing the various concepts of brand and corporate reputation. One attempt was made by Barnett et al. (2006) where a meta-analysis was conducted on 49 definitions of corporate reputation from literature during 1965-2003. The authors discovered that definitions described reputation using one of the three concepts - reputation as awareness, reputation as an assessment, and reputation as brand assets - and proposed a refined definition of corporate reputation: "observer's collective judgments of a corporation based on assessments of the financial, social, and environmental impacts attributed to the corporation over time."

Table 2.1 contains a collection of studies covered in this review that present the definition of brand reputation. From these definitions, we can draw the following characteristics:

1. They are perceptions of the company or brand that take into consideration several forms of factors, such as social, financial, and environmental impacts
2. They contain evaluative characteristics which affect future decision making

Citation	Definition
Herbig & Milewicz (1993)	An aggregate composite of all previous transactions over the life of an entity, and requires consistency of an entity's actions over a prolonged time
De Chernatony (1999)	Perceptions about a brand over time... assesses perceptions across many stakeholder groups... (which) does not just focus on the most recent impression and is a predictor for stakeholders of future outcomes
Gotsi & Wilson (2001)	A stakeholder's overall evaluation of a company over time... (which) is based on the stakeholder's direct experiences with the company, any other form of communication and symbolism that provides information about the firm's actions and/or a comparison with the actions of other leading rivals
Barnett et al. (2006)	Observers' collective judgments of a corporation based on assessments of the financial, social, and environmental impacts attributed to the corporation over time
Coombs (2007)	An aggregate evaluation stakeholders make about how well an organization is meeting stakeholder expectations based on its past behaviors
Walsh & Beatty (2007)	The customer's overall evaluation of a firm based on his or her reactions to the firm's goods, services, communication activities, interactions with the firm and/or its representatives of constituencies and/or known corporate activities
Keh & Xie (2009)	An overall evaluation of the extent to which a firm is substantially "good" or "bad"
Veloutsou & Moutinho (2009)	The aggregate perception of outsiders on the salient characteristics of companies or brands... something a company earns over time and refers to how various audiences evaluate the brand
Helm & Tolsdorf (2013)	A perceptual construct that resides in the heads of the firm's stakeholders... (resulting) from the positive perceptions of past proper corporate conduct and the established favourable attitudes of stakeholders
Fan et al. (2013)	Opinions rather than facts about a company... (which) can differ by stakeholder groups
He et al. (2016)	General brand evaluations, based on beliefs or automatic affective reactions
Balaji et al. (2016)	An overall evaluation of the service provider based on both direct and indirect experiences
Zheng et al. (2018)	The public's overall evaluation of a firm, or a perceptual representation of a firm's past actions and future prospects
Foroudi (2019)	An immediate picture of a brand based on the aggregated multiple images held by both its internal and external stakeholders over the years
Rust et al. (2021)	The overall impression of what stakeholders think, feel, and talk about a brand

Table 2.1: Definitions of organizational (brand) reputation from selected literature, sorted in chronological order

3. They are formed over time and take into consideration past actions as well as future prospects

4. They are aggregated over groups of observers or stakeholders including customers

These characteristics will be brought throughout the review. For example, brand reputation as an aggregated evaluation of a brand's social, financial and environmental performances will be considered measuring brand reputation. The evaluative nature of brand reputation leading to performance outcomes will be brought up in studies that aim to predict financial outcomes such as stock prices based on measured brand perceptions.

2.1.2 Why is Brand Reputation Important?

Companies strive to maintain a positive brand reputation as it leads to both success and profit (Herbig & Milewicz, 1993). Brands with high reputation have a greater chance to attract and retain customers, as people will be more willing to identify themselves with the brand (Keh & Xie, 2009). This leads to creating more loyal customers who are likely to continue the relationship with the brand (Herbig & Milewicz, 1993), invest in the brand even at the expense of better deals with other brands (Aspara & Tikkanen, 2011; Deephouse, 2000), and further spread positive word-of-mouth of the brand (Bhattacharya & Sen, 2003). Because individuals collect brand information over time to form aggregated views of the brand and assess it, building a stable positive reputation takes long time and effort (Veloutsou & Moutinho, 2009). Therefore, companies with high reputation can stay in an advantageous position over its competitors for a long time by creating barriers (Deephouse, 2000).

Having a positive reputation can also help companies and brands more easily overcome unfavorable situations. Brand reputation can also be a means of protecting the brand and company from negative public attention, thus serving as a means for crisis recovery (Keh & Xie, 2009). This will be discussed with more detail in the following chapter where I focus on negative changes of brand reputation where companies undergo online firestorms and brand crises.

2.2 Dimensions of Brand Reputation

Brand reputation is considered as a comprehensive evaluation of a company or brand that spans through multiple aspects (Barnett et al., 2006). By understanding dimensions that cover the different aspects of how a brand is perceived by others, it becomes able to measure the factors that compose brand reputation and further compare different brands based on the scores of these measurements. An accurate and comprehensive measurement of brand and corporate reputation is crucial as it has the potential to be used as a basis for making future financial decisions, as the risk associated with investing in a company can be represented through the company's reputation scores (Cravens et al., 2003). Also, it gives us a sense of which key aspects companies should focus on in order to maintain a positive reputation. Therefore, in this section I will list a number of past studies that proposed frameworks for measuring brand reputation using survey questionnaires. I will discover recurring themes that appear in these frameworks and reorganize them into a fixed number of categories to provide a more comprehensive understanding of which dimensions are directly related to understanding brand reputation.

Along with the survey-based studies, I will also introduce several studies from a newly emerging field of data-driven research that aims to measure brand reputation using social media data created by user-generated content. I will focus on identifying which datasets have been measured and how the measurements have been represented. Furthermore, using the categories that I have obtained from the prior frameworks, I will identify which aspects of brand reputation can be measured through different social media datasets. Finally, I will conclude the section by addressing both significances and limitations of data-driven approaches in measuring brand reputation as well as suggesting potential directions of improvement.

2.2.1 Existing Frameworks for Measuring Brand Reputation

Frameworks that quantify and measure the reputation levels of brands can benefit both customers and companies. From a customer's perspective, being able to measure the different strengths and weaknesses of brands can provide guidance for future purchases or investments. From a company's perspective, having common measures of performance can be used for comparing one's brand against it competitors. Managers can use the comparisons to examine where their brand is positioned in the market among its competitors, decide future strategies, and benchmark leading brands (Aaker, 1996b). This variety of needs led to the development of several frameworks for measuring brand reputation. Six different frameworks are presented in Table 2.2. All of these frameworks exist as survey questionnaires intended to be answered by customers, employees and other stakeholder groups. In an effort to organize the categories provided by the different frameworks and provide a comprehensive understanding of which dimensions have been widely considered as important for measuring brand reputation, I have grouped the categories of each study into seven common themes, which is presented on the leftmost column of the table.

Products & Services Customer perceptions on the products and services of a brand is a crucial component for understanding brand reputation. All of the different frameworks made the associations between a brand's reputation and how it its related products or services are perceived by consumers. Especially, questions asking customers' perceptions

Reorganized category	Aaker (1996b)	Fombrun et al. (2000)	Cravens et al. (2003)	Feldman et al. (2014)	Fombrun et al. (2015)	Fortune (2019)
# of categories	5 (10)	6	6 (12)	8	7	9
# of questions	31	20	42	8	23	N/A
Products & Services	Perceived quality Perceived value Satisfaction Leadership / popularity Brand awareness Brand personality Differentiation	Products and services	Products and services	Having good products and services	Products and services	Quality of products or services
Corporate performance	Market share	Financial performance	Financial strength		Performance	Financial soundness Long-term investment value
Workplace environment		Workplace environment	Employees	Good workplace environment	Workplace	Ability to attract, develop and keep talented people
Corporate social responsibility		Social and environmental responsibility	Culture	Discretional social responsibility Practice standards in ethics	Governance	Community and environmental responsibility
Managerial aspects	Leadership / Popularity Organizational associations	Leadership Vision	Innovation Strategy External relationships (non-customer)	Leadership Innovation	Leadership Innovation	Innovativeness Quality of management Wise use of corporate assets Effectiveness in doing business globally
Customer relationship and loyalty	Price premium Loyalty		Value creation	Good relationship with consumers		
Emotional evaluations		Emotional appeal		Generating positive feelings in people		

Table 2.2: The categories of measurement for brand reputation from existing studies reorganized into seven distinct categories. Each category is denoted by starting with a capital letter.

of the brand product's price and quality were included in every framework. Other questions included whether a brand stood behind its products and services (Fombrun et al., 2000, 2015; Feldman et al., 2014), how familiar customers were with the brand Cravens et al. (2003), whether the brand made warranty claims to customers (Cravens et al., 2003), and how satisfied customers were with the products (Aaker, 1996b).

Corporate Performance The perceived performance level of the company is also a widely used indicator for identifying brand reputation. The brand's position in the market (Aaker, 1996a; Fombrun et al., 2000; Cravens et al., 2003), record of profitability (Fombrun et al., 2000, 2015) and stability (Cravens et al., 2003), and prospect on future growth (Fombrun et al., 2000, 2015) were questions that were included in the surveys. It is worth noting that performance levels of companies also exist through several financial performance indicators such as stock prices and annual reports, which can be incorporated with survey results to create a more comprehensive understanding of a brand's overall performance.

Workplace Environment Most of the studies that proposed the frameworks also addressed the need to measure people's perspectives on the workplace environment of a company for understanding its brand reputation, since companies that manage to maintain high satisfaction levels for their employees are able to not only keep but also attract talented people (Keller & Lehmann, 2006). Questions in this category center around two themes: (1) whether employees are treated fairly (Cravens et al., 2003; Feldman et al., 2014; Fombrun et al., 2015), and (2) whether the company seems capable of drawing talented employees (Fombrun et al., 2000). One exception was the framework proposed by Aaker (1996b), which is because the focus of this study was on brand equity, a concept of how customers think of a brand's overall strength, as opposed to brand reputation, which takes into account not only customers but also other types of stakeholders.

Corporate Social Responsibility The level of a company's commitment to social and environmental issues is an important theme in evaluating its reputation. Failure to keeping up with social norms can question the morality of the company and its brand, causing customers and stakeholders to form a negative attitude towards the brand (Balaji et al., 2016; Jin & Cameron, 2007). As a result, companies engage in practices of demonstrating social and environmental responsibilities in various ways such as providing financial support or opportunities, which help build a company's reputation (Carroll, 1999). Most of the frameworks contained questions related to the company's social responsibilities, mostly the company's environmental and ethical practices (Fombrun et al., 2000; Cravens et al., 2003; Feldman et al., 2014; Fombrun et al., 2015; *Fortune World's Most Admired Companies 2019*, n.d.). Additional questions were provided from the framework of Cravens et al. (2003) such as whether the company had a reporting procedure for ethics violations, formed an ethics committee, and made charity endeavors.

Managerial aspects Managerial traits such as leadership, innovation, and company vision are what is being measured in this category. The commitment that a company shows towards innovation are strong indicators of product quality and customer satisfaction (Cravens et al., 2003), and thus the perceived level of a company's innovativeness is a frequently asked question in the mentioned studies (Aaker, 1996b; Cravens et al., 2003; Feldman et al., 2014; Fombrun et al., 2015; *Fortune World's Most Admired Companies 2019*, n.d.). Also, the leadership and vision presented by CEOs can build positive images for companies through media coverage, building credibility at the corporate level (Aaker, 1996b; Fombrun et al., 2000; Feldman et al., 2014; Fombrun et al., 2015).

Customer Relationship and Loyalty Brands strive to maintain a positive relationship with their customers (Veloutsou & Moutinho, 2009). Loyal customers can benefit brands in several directions, such as actively spreading positive word-of-mouth related to the brand and selecting the brand over competitors even at the expense of higher prices (Chung & Darke, 2006). A positive customer relationship can be only built by consistently providing positive experiences (Herbig & Milewicz, 1993), and thus directly relates to a good brand reputation. Customer relationship is measured through questions that ask whether a company actively communicates with customers (Feldman et al., 2014) or does a good job in customer retention (Cravens et al., 2003).

Emotional Evaluations The last category measures an individual's overall emotional evaluation towards the company. Feldman et al. (2014) considered the emotional aspect as a separate category, measuring the extent of how the company or brand "generates respect, admiration, esteem and confidence". Similarly, Fombrun et al. (2000) included questions in the survey asking whether participants "have a good feeling about the company" or "admire and respect the company". Based on further analyses of their survey results, Fombrun et al. (2000) suggested that reputation can be considered as a construct that consists of Emotional Appeal and Rational Appeal. This suggest the importance of considering emotional aspects as a distinct category of brand reputation.

2.2.2 Brand Reputation Measured in Social Media

While carefully crafted surveys have been widely used for measuring the reputation of a brand across several dimensions, they can be slow and costly when trying to apply to a large population. Here, social media data created by users has emerged as an alternative that is spontaneous, easily accessible, and both faster and cheaper to acquire

Reference	Dataset		
	Online review pages	Online forum	Social networking services
Decker & Trusov (2010)	V		
Lee & Bradlow (2011)	V		
Netzer et al. (2012)		V	
Mostafa (2013)			V
Tirunillai & Tellis (2014)	V		
Okazaki et al. (2015)			V
Gensler et al. (2015)	V		
Culotta & Cutler (2016)			V
Manaman et al. (2016)			V
X. Liu et al. (2017)			V
Moon & Kamakura (2017)	V		
Klostermann et al. (2018)			V
Rantanen et al. (2019)		V	V
L. Liu et al. (2020)			V
Das Swain et al. (2020)			V
Okazaki et al. (2020)			V
Rust et al. (2021)			V

Table 2.3: The types of dataset used in each study. Most studies are conducted on a single domain of data

compared to traditional surveys (Tirunillai & Tellis, 2014). An increasing amount of studies have explored the possibilities of measuring brand reputation from social media data using natural language processing (NLP) and data mining techniques to extract users perceptions on brands. I have provided a listing of these studies in Table 2.3 where they are organized by two criteria: (1) which dataset is used and (2) how the measured aspects of brand reputation are presented.

Datasets: Current Approaches and Limitations

The first type of social media data used for extracting brand perceptions comes from user-generated reviews. Online retail services such as Amazon provide a review page for each product where customers can share their user experiences with others. These reviews often contain rich descriptions of the pros and cons of a product, which can be used to identify the features that users find appealing or troublesome. Review pages also contain easily comparable evaluation metrics as users are encouraged to enter an overall score for the product that represents their satisfaction levels. Furthermore, it is easy to map a product with the user opinions related to it as a separate review space is allocated to each product. For these reasons, studies such as Decker & Trusov (2010); Lee & Bradlow (2011); Tirunillai & Tellis (2014); Gensler et al. (2015), have used product review pages to extract attitudes towards brands and their products.

Another type of dataset contains user interactions and conversations in online communities. These platforms are likely to be centered around a topic, which could be a

Reference	Products & services	Corporate performance	Workplace environment	Corporate social responsibility	Managerial aspects	Customer relationship	Emotional evaluations
Decker & Trusov (2010)	V						
Lee & Bradlow (2011)	V						
Netzer et al. (2012)	V	V					
Mostafa (2013)	V						V
Tirunillai & Tellis (2014)	V						
Okazaki et al. (2015)						V	
Gensler et al. (2015)	V						
Culotta & Cutler (2016)	V			V			
Manaman et al. (2016)							V
X. Liu et al. (2017)	V						V
Moon & Kamakura (2017)	V						
Klostermann et al. (2018)	V						V
Rantanen et al. (2019)	V			V	V		
L. Liu et al. (2020)	V						V
Das Swain et al. (2020)			V				
Okazaki et al. (2020)				V			
Rust et al. (2021)	V			V	V	V	V

Table 2.4: The categories of brand reputation which are covered in each study. We can observe that the findings of most studies only correspond to one or two dimensions of brand reputation.

brand or a specific product. Topic-specific online communities attract users of that brand product and can foster active conversations on users' experiences with the brand. The range of topics can be very diverse: from day-to-day experiences while using products to their perceptions of the company and its directions. A rich dataset of user opinions can be discovered from long threads created by user participation, which in turn can be used to extract how people think of a brand and its products. Reflecting these properties, Netzer et al. (2012) collected user-generated content from an online forum about cars to identify the attributes people mention when discussing different automobile brands.

Finally, the last source of data that has received a growing amount of attention is that of social networking services such as Twitter, which are convenient platforms for forging connections with different users and getting updated on topics of interest. Unlike online communities or reviews that are closed spaces and only discuss topic-relevant content, social networking services allow users to engage in a wide variety of conversations. This creates an environment where a large number of users can discuss their opinions about a brand or product. Also, companies and brands also actively engage on such platforms to interact with customers and advertise their products. The customer-brand engagement in social networks also can provide important information of how consumers perceive of the brand. Several studies have been conducted using Twitter data (Mostafa, 2013; Manaman et al., 2016; Culotta & Cutler, 2016; X. Liu et al., 2017), while a number of studies that used Instagram data incorporated images and tags to identify associations to a brand (Klostermann et al., 2018; L. Liu et al., 2020).

Datasets: Suggestions for Future Studies

As shown in Table 2.3, most studies use only one type of dataset for measuring user perceptions on brands, whether it be online reviews or social networking platforms. This inevitably leads to a limited number of dimensions of brand reputation that gets measured. Table 2.4 presents the findings presented by each study organized into the categories of brand reputation that was defined in Section 2.2.1. Several of the studies focus on measuring either attributes related to products or services by the brand (Products & services) or user sentiments towards the brand (Emotional evaluations). Furthermore, even the studies that directly aim to measure corporate reputation miss out a number of dimensions (Rantanen et al., 2019; Rust et al., 2021). The lack of coverage is because there is a limited number of topic that can be discussed within a platform. In online reviews one would less expect to find comments about the brand's corporate responsibility. Even in the case of social networking services where the topics of conversations are supposed to be unlimited, some topics might be hard to openly discuss due to privacy issues such as the pros and cons of previous workplaces. Finally, it is also worth noting from Table 2.4 that because a dimension of brand reputation was covered by a study, it does not necessitate that the study managed to entirely cover the aspects of that dimension as one would expect from a survey.

Here it can be suggested that in order to measure every criteria of brand reputation in a comprehensive manner, a wider variety of datasets must be considered. For instance, online services targeted for employees such as Glassdoor provide a rich dataset of workplace evaluations by current and ex-employees. Das Swain et al. (2020) demonstrated that this data can be used to identify a company's organizational culture, a similar concept to the workplace environment of a brand. Several studies already have shown that online reviews can capture product-related evaluations. Also, customer relationship levels can be captured by analyzing the activities of brand accounts in social media. Therefore, a comprehensive understanding of brand reputation using social media data can be best accomplished by considering data from online reviews (Decker & Trusov, 2010; Lee & Bradlow, 2011; Tirunillai & Tellis, 2014), social networking services (Mostafa, 2013; Okazaki et al., 2015; Culotta & Cutler, 2016), online forums (Netzer et al., 2012; Rantanen et al., 2019), and employee-specific online platforms (Das Swain et al., 2020) all at once.

While the addition of diverse datasets is important, it is also necessary to define the boundaries of the content within each dataset to best match the measurement criterion that one wants to measure using social media data. Especially in social networking services such as Twitter, companies can use their brand accounts for different purposes, and these differences have to be taken into consideration before performing analyses at an aggregate level. For instance, while several studies incorporate sentiment analysis on tweets directed to brand accounts to measure users' overall emotions towards a brand (Mostafa, 2013; Culotta & Cutler, 2016), straightforwardly considering the aggregate messages can put brand accounts that directly handle customer complaints in an unfavorable position, as customer complaints are more likely to contain negative sentiment (e.g. Delta Airlines). Therefore, a well-defined subset of user-generated content should be favored in place of an overall aggregate of user activity for measuring different dimensions of brand reputation.

Methods: Current Approaches and Limitations

Several methods have been proposed for extracting the association between a brand and related attributes using text data, each with its own strengths and weaknesses. Some studies applied machine learning models such as conditional random fields for extracting words and phrases from the text that co-occur with brand names and also correspond to brand-related attributes (e.g., "expensive", "high quality"), then measured the association strength between the attribute and the brand through counts (Decker & Trusov, 2010; Culotta & Cutler, 2016; Netzer et al., 2012). Unsupervised machine learning approaches such as topic modeling and clustering have also been used to automatically generate latent topics of related words or phrases, where each topic would map to different brand-related aspects (Tirunillai & Tellis, 2014; X. Liu et al., 2017; Lee & Bradlow, 2011). These methods can capture different dimensions in an unsupervised manner but require human interpretation to understand the latent groupings of words and phrases that are produced as an output. Also, the generated topics are generated through the algorithms and lack theoretical validity in that they may not align with the dimensions of brand reputation that are considered important.

Another branch of studies apply text classification methods where brand-related scores are extracted from text by running classifiers. Sentiment analysis classifiers have been frequently used to enable comparisons of sentiment levels between brands (Mostafa, 2013; Okazaki et al., 2015; Manaman et al., 2016), but sentiment alone does not provide a multidimensional understanding of brand reputation. More recently, Rantanen et al. (2019) extracted six different attributes (innovativeness, pleasantness, quality, reliability, responsibility, and successfulness) from bank reviews by training and running classifiers that were trained on manually labeled data. Although this approach produced measurements of brand attributes that align with existing literature on brand reputation, it required creating and labeling a large text, making it difficult to scale or to apply on different domain datasets.

Finally, a small number of studies constructed dictionaries based on existing taxonomies of brand-related attributes, and obtained attribute strength based on the counts of posts containing words from each of the different dictionaries (Moon & Kamakura, 2017;

Rust et al., 2021). While this approach can also capture attributes related to brand reputation that are grounded by theory, the taxonomy construction requires a large amount of effort which also limits its scalability across different domains of datasets and brand categories.

Methods: Suggestions for Future Studies

A review of the previous approaches on measuring brand reputation revealed two issues: either the resulting attributes do not clearly match widely known measures of brand reputation, or a large amount of effort was required to manually curate labels or dictionaries that correspond to brand reputation dimensions. Fortunately, recent advances in deep learning and NLP have opened up new possibilities and methodologies for measuring text similarity, which can be applied for measuring brand reputation as well. I briefly introduce the concept of word embedding vectors, a widely used representation for words in current NLP applications, and how they can be used to measure dimensions of brand reputation.

Word vector embeddings, a concept first introduced by Mikolov et al. (2013), represents each word into a fixed vector of continuous real numbers. Given a large vocabulary of words, we can obtain vector embeddings for each and every word in our vocabulary set. The strength of word embeddings draws from the training method that determines the values for each embedding. The embedding values are updated using a deep learning algorithm named word2vec that assigns similar values to semantically and syntactically similar words. As a result, we can use word embeddings to measure conceptual similarities of word and sentences by transforming them into vector representations and measuring the similarities of the two vectors.

Das Swain et al. (2020) provide an example of using word embeddings to measure brand-related attributes. In a study that aimed to measuring organizational culture using user-generated reviews, the authors first defined a list of 41 keywords that correspond to the factors that determine the quality of organizational culture (e.g., "relationships", "work-life balance"). They then transformed both the keywords and the text reviews into vectors using word embedding values. By measuring the similarities between the two types of vectors, the authors were able to identify different levels of organizational culture-related factors for each user review.

Future studies that aim to measure brand reputation can directly adopt this approach. Similar to the case of Das Swain et al. (2020), it is possible extract keywords from the survey questionnaires that represent different dimensions of brand reputation. These keywords can be converted into word embeddings and compared against user-generated social media data, which will produce measurements of each dimension related to brand reputation. This approach can be further developed by incorporating other advanced methods that use word embeddings to identify relevant semantic axes from text (Kwak et al., 2020). To conclude, a combination of survey measurements, data curating and deep learning-based text representations can improve the large-scale extraction of brand reputation from user-generated social media data.

Chapter 3

Understanding Online Firestorms

The spreading of word-of-mouth (WOM) is an important factor that affects the success of companies and brands. Especially in the age of social media, electronic word-of-mouth (eWOM) has emerged as a key component for marketing, which has led to a large amount of research on identifying the characteristics of successful eWOM. However, some cases of eWOM can cause unfavorable situations to a company brand. A particular type of eWOM-induced social phenomenon that has received increasing academic interest is an *online firestorm*. Online firestorms have recently emerged in social networking service platforms such as Twitter and Facebook following increased levels of user activity. Online firestorms have received a large amount of attention due to its unprecedented level of high virality and its impact on companies. To better understand online firestorms, I will cover existing studies that identify its causes as well as the several factors that promote its virality.

3.1 Word-of-Mouth in Social Media

3.1.1 An Understanding of Word-of-Mouth

In marketing studies, word-of-mouth (WOM) is understood as the interpersonal communication among consumers concerning a marketing organization or product (Arndt, 1967b). WOM has been considered particularly important for the diffusion of new products or services. Early studies focused on identifying factors that could maximize the spread of new information, especially of new products or services. The tie strength of a dyad (Brown & Reingen, 1987), the perceived risk of the information by the listener (Arndt, 1967a; Engel et al., 1969), and the sentiment of the message (Haywood, 1989) are among the factors that are known to determine the effect of WOM.

Outside of marketing, the importance of WOM was also represented in the two-step flow of communication model, a theory for explaining how information and ideas are spread within social networks. This model, first introduced in Lazarsfeld et al. (1944) and later developed by Katz & Lazarsfeld (1955), argued that (1) individuals were influenced by neighbors (indirect information) more than newspapers (direct information), (2) those who changed their views in a later stage of the campaign were more likely to report changes caused by their peers, and (3) there existed a group of individuals more capable of influencing people around them, known as *opinion leaders*. Therefore, information flow occurs in two steps where during the first step mass media disseminates information to opinion leaders, who again transmit information to mass populations in the second step. Here, word-of-mouth is the driver for information flow in the second step where interpersonal communication between opinion leaders and the majority of people occur.

3.1.2 Electronic Word-of-Mouth

WOM received a surge of attention following the introduction of the Web. Online platforms greatly reduced geographical barriers and the effort to engage in conversations, thus seeing new opportunities for WOM, or electronic WOM (eWOM), which is defined as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet." (Hennig-Thurau et al., 2004). A main focus of this direction has been on understanding factors that promote marketing through eWOM. Advertising through word-of-mouth and virality has always been a core research interest in marketing fields, and social media provides several characteristics which make it a powerful mechanism for such purposes. As a result, there have been numerous approaches to understand which factors contribute to successful eWOM marketing outcomes. Several studies indicated that the virality of a brand-related message in social media is impacted by its level of arousal or sentiment (Berger & Milkman, 2012; Packard & Berger, 2017; Moe & Schweidel, 2012), its informativeness (Erkan & Evans, 2016; Chang et al., 2015), and the network status of the messenger (Araujo et al., 2017; Uzunoğlu & Kip, 2014).

The structure of social networks and eWOM has also changed people's understanding on how information flow happens. Similar to offline social networks, communication flow in two stages have been observed in social media platforms such as Twitter and Facebook (S. Choi, 2015). Opinion leaders correspond to celebrities, news providers or active users with large follower bases (Bergström & Belfrage, 2018; Karlsen, 2015; Uzunoğlu & Kip, 2014). Interestingly, these platforms also exhibit one-step flows, where the information source created by mass media or companies can directly reach consumers due to algorithmic advances (Bennett & Manheim, 2006; Hilbert et al., 2017). New theories such as the curated flow (Thorson & Wells, 2016) have been developed to better describe the complex processes of information exchange and diffusion within online social networks.

3.2 Online Firestorms

An *online firestorm* is a recently introduced concept in business studies, defined as the "sudden discharge of large quantities of messages containing negative WOM and complaint behavior against a person, company, or group in social media networks." (Pfeffer et al., 2014, p.118). Their viral nature and aggressive content combined with its unexpectedness have made online firestorms a formidable threat to managers of brands.

3.2.1 Causes of Online Firestorms

Online firestorms can be considered as an immediate response to the misconduct of a company, organization, or individual. Customers have cognitive and affective attitudes towards companies that can be disrupted when experiencing unethical corporate behavior, leading to actions such as boycotts and a show of public outrage (Lindenmeier et al., 2012). In this sense, participation in an online firestorm can be seen as a show of consumer outrage through posting and sharing negative content targeted towards the brand. Similarly, Johnen et al. (2018) consider online firestorms as the online version of moral panics, a public behavior of hostility towards groups of people that are considered as a threat to societal values and interests. This was supported by their findings on the moral arousal of the issue positively affecting the likeliness to participate. Furthermore, in their study of identifying motivations for participating in online firestorms, the authors discovered that a desire for social recognition and to stand out strongly increases participation likelihood. This finding supports the view that participants of online firestorms consider their actions as a response to moral violations.

Conversely, the highly level of toxic verbal and nonverbal cues intended to damage the target, frequently seen in online firestorms, has raised considerations on whether it should be seen as similar to other problematic online behavior such as flaming (Alonzo & Aiken, 2004) and cyberbullying (Mehari et al., 2014). This behavior is more evident in online firestorms that emerged from company actions that were not unethical nor problematic. A publicly well-known example of an online firestorms is the case of McDonald's where the company received a large burst of negative comments after promoting an event for customers to share their experiences using the hashtag #McDStories (Pfeffer et al., 2014). The New York Police Department suffered from a similar firestorm after promoting the use of the hashtag #myNYPD for Twitter users to share their experiences and photos with the police, where the hashtag was instead used and shared by users who posted their negative experiences that involved the police, often accompanied with violent images and toxic language (**?**). Based on this view of online firestorms as online aggression, Rost et al. (2016) applied the social norm theory to understanding the formation and spread of online firestorms and conducted an experiment to test whether non-anonymity will reduce the aggressiveness of users and thus reduce the size of the firestorm. Results showed that removing anonymity did not have a significant effect, suggesting that firestorms may be more of a public monitoring than irrational behavior. However, the authors raised further questions on whether online firestorms should be justified.

3.2.2 Online Firestorms and Customer Complaints

Another type of negative eWOM targeted towards brands are customer complaints. These complaints, usually written in public messages and directed towards a brand's social media account, can be problematic to a brand as they are often made visible to the public and therefore have to be resolved in a swift manner to prevent an escalation of the complaint level. In fact, providing a timely and appropriate intervention can improve a company's reputation. (Van Noort & Willemsen, 2012) showed that customers preferred when a brand actively responded to a complaint rather than being silent, and when companies performed reactive webcare (responding to negative WOM only when asked by customers) as opposed to proactive webcare (responding to negative WOM unsolicitedly). Ma et al. (2015) performed a simulation where they examined the effect of providing a response to a complaint. Results indicated that doing so improved the sentiment of brand-related messages, signalling an increase in brand reputation levels. Similarly, Abney et al. (2017) showed that customers regarded highly of the company and returned positive reviews when the company was able to provide an adaptive response depending on the situation. These examples show that an appropriate response can turn customers' perspectives of a brand towards a favorable direction. However, companies may not always choose to reply in a timely manner, and the response strategies may vary by company and by situation. Einwiller & Steilen (2015) showed that upon receiving complaints through publicly visible spaces such as Facebook posts, companies tended to use strategies such as asking for further information or diverting the complainant away from the public space to one-on-one communication channels such as direct messages or phone calls. Depending on the situation, companies may also choose to defend themselves by entirely pushing back and denying the blame entirely (Johnen & Schnittka, 2019). These strategies may not always work. The company's success with responding to a complaint is to a large extent dependent on the complaint's history with the company, where in the case of multiple prior failures, the company's webcare might not be so effective (Weitzl et al., 2018). Failure to satisfying customers can cause larger levels of negative sentiment. Though in most cases complaints do not have a large effect on a brand's overall reputation, repeated exposure to the problem can lead to cases where the customer's trust with the brand depletes. If a brand is seen as incapable of solving multiple instances of the same customer complaints, its reputation can go down.

If the cause of the firestorm is a customer complaint, an early detection of the complaint followed by a quick and appropriate response can reduce the probability of the post erupting into an online firestorm (Herhausen et al., 2019). Similarly, Hauser et al. (2017) show through an agent-based simulation setting that firestorms can be calmed down through the adoption of moderators. Nevertheless, negligence to customer complaints can increase frustration levels of customers, and aggregated level of angry customers can lead to more severe levels of negative eWOM such as online firestorms. Therefore, timely and appropriate measures towards customer complaints can be an effective strategy to prevent outbursts of online firestorms.

3.2.3 Online Firestorms and Brand Crises

Another concept that shares several similarities with online firestorms is a *brand crisis.* A brand crisis, defined as "instances of well-publicized claims that a key brand proposition is unsubstantiated or false" (Dawar & Lei, 2009) or "a sudden an unexpected event that threatens to disrupt an organization's operations and poses both a financial and a reputational threat" (Coombs, 2007), has a much longer history of studies than online firestorms, yet is strongly related.

Brand crises can harm companies in a number of ways. A crisis can change how customers and stakeholders decide to interact with the company (Coombs, 2007). Customers who have previously been loyal to the company may be disappointed by the company's violence of customer expectations and choose to sever their ties (Lindenmeier et al., 2012). The damaged reputation also can prevent future customers from engaging with the brand, which further leads to decreased levels of market share and stock prices (Coombs & Holladay, 2014). Also, reputational capital - the company's perceptual and social assets which are accumulated over time - is damaged and lost to an extent. This reputation can take a long time to recover, placing the company at a disadvantageous position over its competitors for a considerable amount of time.

Similar to online firestorms, there are multiple possible causes of a brand crisis. While some crises may arise due to serious product defects or managerial decisions that may harm public safety, others might be more related to advertisements or other corporate activities that violated social norms and offended a group of people (Coombs & Holladay, 2014). Coombs (2007) sorted crises into three clusters: (1) crises such as natural disasters, rumors or product tampering where the organization is also a victim (victim cluster), (2) crises such as technical-error accidents or product harm where the organization had no intentions for the crisis, and (3) crises where the organization was aware of the decisions to be made such as human-led accidents or product harm, or organization-level misdeeds caused by deceiving or management misconduct (preventable cluster). Of these clusters, brand crises belonging to the third cluster can is considered to cause the greatest harm to brand reputation, as it raises a greater level of public anger due to being a form of moral misconduct.

Should online firestorms be considered as identical to brand crises? Researchers have proposed several views towards this question. Hansen et al. (2018) suggested that online firestorms should be seen as "a new, digital form of the broader phenomenon of brand crises" and consider online firestorms as a brand crisis in the digital context. Zheng et al. (2018) described online firestorms as a form of secondary crisis communication (SCC), which are communications during crises where the public share negative comments about the firm and post crisis-relevant content. Meanwhile, Pace et al. (2017) drew differences between brand crises and brand firestorms in that (1) unlike brand crises, firestorms can erupt independently of company misdeed, and (2) brand crises can happen in any form of media, while online firestorms originate in social media. This discrepancy in how online firestorms are defined calls for a need to strictly set up a definition when trying to study online firestorm behaviors.

3.3 Network Properties of Information Diffusion and Online Firestorms

One salient characteristic of online firestorms is its high level of virality. Pfeffer et al. (2014) suggest that this virality may account to network properties that the social network structures of social media platforms contain, and mentions seven properties:

- Speed and volume
- Absence of discursive interactions
- Network clusters
- Unrestrained information flow
- Lack of diversity in surrounding opinions (filter bubbles)
- Echo chambers
- Network-triggered decision processes

These are well-known properties that have been frequently studied in network sciences to understand the mechanisms of information diffusion in social networks. Since online firestorms can be seen as a form of negative information diffusion in social networks, an identification of the factors affecting information diffusion can be used to understan how online firestorms spread as well. An understanding of such factors can be used for providing better explanations and modeling of the spread of online firestorms, which can lead to new research directions.

3.3.1 Sentiment

As argued in Latane's social impact theory (Latané, 1981) and many subsequent studies, the stronger the message is, the more likely that it is to influence the reader and also impact their attitude. This applies to information diffusion in social networks, where the strength of a message can be determined by several factors. An intuitive signal is the emotional sentiment level contained in a message. Therefore, a large number of studies that identify factors of influence in social media have done so through analyzing sentiments of the messages. This analysis is made simple due to natural language processing tools which exist in forms of topic-specific lexicons (Tausczik & Pennebaker, 2010) or plug-and-play models (Hutto & Gilbert, 2014), which of many are publicly available and easy to use.

Findings reveal that sentiment indeed plays a large role in the diffusion of information, but in varying directions. A series of studies from Stieglitz and Dang-Xuan examined the effects of sentiments on how individuals are influenced by posts in online social networks. According to their work, tweets containing emotions, whether it be positive or negative, were more likely to get retweeted and discussed about (Dang-Xuan & Stieglitz, 2012; Dang-Xuan et al., 2013; Stieglitz & Dang-Xuan, 2012, 2013). Similar findings that demonstrated the strength of emotional arousal appeared in other studies (Pfitzner et al., 2012; Ji et al., 2019). However, whether positive or negative tweets are more effective differ upon the settings of the study. For movie ratings, positive reviews were more likely to get retweeted and reach large audiences (Asur & Huberman, 2010). Also, Berger & Milkman (2012) conducted both text-based regression analyses and lab experiments, where they discovered that posts containing positive emotions spreaded more than those with negative emotions, and that the higher the level of arousal, the more viral a post became. Meanwhile, Ferrara & Yang (2015) suggested that while positive tweets were retweeted more, negative tweets gained more initial retweets.

Application to Online Firestorms Studies on the effect of sentiment in information diffusion focused on different topics over different time periods and thus it may be difficult to draw a unified agreement from these diverse findings. Nevertheless, these studies do lead to an agreement that the existence of emotion in a posted message leads to a larger chance of affecting one's attitude towards it, resulting in possible resharing activities.

This is also the case of online firestorms, where the level of negative arousal is known to increase user participation (Johnen et al., 2018), leading to greater impact of the firestorm.

3.3.2 Tie Strength

Information diffusion can occur more frequently among strong ties such as friends or family of frequent contacts. This is because messages obtained from these ties are more likely to be perceived as credible and relevant (Kozinets et al., 2010), and thus have a stronger persuasion effect in WOM spreading (Arndt, 1967a; Brown & Reingen, 1987). Baker et al. (2016) showed that WOM from strong ties lead to a higher probability of changing one's purchase intention, though interestingly the strength of tie did not have an effect on deciding whether to retransmit the information in online channels. Lazer et al. (2010) showed the conformatory effect, where individuals influence their neighbors so that they end up with similar views. Their findings also included that social influence occurs more from social than task-based ties, again stating the strength of strong ties in influencing others.

Application to Online Firestorms Interestingly, there is evidence that the diffusion that occurs in online firestorms does not in fact happen with strong ties. A study by Lamba et al. (2015) revealed that the ties responsible for spreading firestorms were neither previously existing ties nor lasting after the end of the firestorm. These ties were temporary and close to random, suggesting that diffusion patterns of firestorms behave differently from other types of eWOM diffusion. It may be interesting to see if the temporary connections made during online firestorms come from weakly connected neighbors who are two steps away, or are distant neighbors whose appeared only as a result of the social media algorithm's recommendation (e.g. trending tweets).

3.3.3 Influential users

Along with tie strength, the influence of users also impact the spreadability of information. Here, the influence of a user is determined by his presence in the social media space, which is related to the number of connections he may have in forms of online friends or followers. These can be celebrities, politicians, or journalists with hundreds of thousands of followers. Araujo et al. (2017) show that influential users can lead to making more users retweet brand-related tweets. By "influential" the authors mean users that are information brokers and possess strong ties. Stich et al. (2014) emphasize on the importance of influential users, showing that their negative comments can quickly influence large networks and cause online firestorms, even if the majority of members had a neutral attitude initially. Especially in the political sphere, public opinions are known to be shaped largely by influential individuals rather than the media (Habel, 2012). Furthermore, Moussaïd et al. (2013) show the existence of the "expert effect", which is individuals adjusting their opinions based on what other users with expertise have said.

Application to Online Firestorms Influential users form hub structures in a social network, which could be found in online firestorms as well. Jackson & Foucault Welles (2015) conducted a network analysis on the user network of Twitter users who were responsible for the #myNYPD online firestorm to reveal the existence of crowdsourced elites. This structure shows that users may be retweeting content from a small number of central users without further interaction. Although this study only examined a single case of firestorm, coupled with findings from Lamba et al. (2015) that reveal temporal network structures of online firestorms, propose interesting further research directions on identifying how the hub structures in online firestorms are formed.

3.3.4 Community Structures within Networks

Network structures such as communities play a role in the level of influence that occurs in a network. Community structures in the context of social networks correspond to densely clustered subnetworks within a larger network where the nodes (users) are often bounded by characteristics such as same demographics, political affiliation or interests. The prevalence of an opinion shared by one's neighbors within the network can increase the possibility of a user conforming to that opinion (Tang et al., 2013; Kelman, 1961). This effect becomes stronger if the individual does not have a sufficient amount of external information sources outside of their neighbor network (Goel et al., 2012). Studies such as S. Wu et al. (2011) showed that there is a significant level of homophily in communication where users of similar status tend to listen to each other, leading to homogeneous opinions within a group.

The community-like structure of networks have led to a large number of studies in polarized "echo chambers" and its effects on information diffusion, especially in the context of political polarization (Colleoni et al., 2014). Echo chambers accelerate the speed of influence among users within the network (D. Choi et al., 2020), prevent one's exposure to content that oppose the mainstream view provided within the chamber (Bakshy et al., 2015), and effectively strengthens one's existing views, even when exposed to opposing contents (Bail et al., 2018). Visser & Mirabile (2004) revealed that social networks affect not only valence but also duration of an attitude, where like-minded networks are slower to attitude change.

Application to Online Firestorms Although the existence of community structures in online firestorms has been proposed by (Pfeffer et al., 2014), as of far there are no findings of the effect they cause in the spreading of online firestorms. Studies on finding the existence of community structures in either the beginning or the spreading phase of online firestorms can provide additional knowledge on characterizing the group of users who are more likely to participate in firestorms.

3.3.5 Limited Attention and Memory

Finally, I will list two more factors that affect social influence processes. The first is limited attention capacity. People are exposed to multiple sources of information, and due to their limited attention span cannot consider or process all available information at once. This forces them to make selections of which information to focus on at a given point, which may diminish the persuasive effect of some information. Another factor is our limited memory capacity. Even though a piece of information is stored in our memory, the passage of time as well as exposure to other sources of information may wash away any effect that the information had in influencing one's attitude.

While these two factors were originally studied extensively in psychology studies conducted at an individual level through lab experiments, the availability of large-scale social media data has allowed for researchers to measure and identify traits of collective attention and memory in social networks, leading to interesting findings. Studies such as Lorenz-Spreen et al. (2019); Castillo et al. (2014) revealed that over the years our society's collective span has become shorter, a trend that is consistent across several domains such as Twitter and Reddit. Also, a number of studies simulated collective attention to show that different attention mechanisms lead to some topics receiving a large public attention while others may go unnoticed (Moussaid et al., 2009; F. Wu & Huberman, 2007; Weng et al., 2012). Other studies measure the duration of memory for an event based on the volume of related social media communication to show consistent patterns of decay (Candia et al., 2019).

Application to Online Firestorms Human capacities of both limited attention and limited memory can be used for understanding the short lifespans of online firestorms. In social media we are consistently faced with several competing pieces of information while our capacity to process them are limited. This limitation can explain why online firestorms also have a short attention span and die out quickly. Furthermore, studies on limited memory capacity in social media can be applied for examining how long people remember the online firestorms after the passage of time. Although results from Hansen et al. (2018) showed that people remembered the causes of online firestorms even after a time lapse of two years, their results focused on firestorms triggered by product or service failures and do not generalize to the various types of firestorms that were caused by other reasons (e.g., #myNYPD). If these firestorms do not have a lasting effect due to memory constraints, it also can be assumed that their effect on brand reputation may not be as severe.

Chapter 4

Brand Attitude Changes and Brand Reputation

To return to the question of how online firestorms affect brand reputation, I will adopt the perspective that views brand reputation as an aggregate of collective attitudes across individuals. Since the processes and causes of attitude change have been actively studied in psychology and social psychology, an attitude-based understanding of brand reputation enables us to apply well-established models to explain how and why changes in one's attitude occurs. There are several possible causes of brand attitude change, from acquiring new information about the brand to being influenced by individuals or social groups, which I will describe in this chapter. Finally, building on the findings from the literature of brand reputation, brand attitudes and online firestorms, I will summarize my understandings of an online firestorm's impact on brand reputation, and address gaps that have not been addressed in the covered literature.

4.1 Changes of Attitudes and Brand Attitudes

4.1.1 From Brand Attitudes to Brand Reputation

An *attitude*, which can be defined as "the sum total of a man's inclinations and feelings, prejudice or bias, preconceived notions, ideas, fears, threats and convictions about any specified topic" (Thurstone, 1928) is an evaluation made in response to a target, or an *attitude object*. Another definition that well describes the evaluative property of attitudes is that of Ajzen (2001): "a summary evaluation of a psychological object captured in such attribute dimensions as good-bad, harmful- beneficial, pleasant-unpleasant, and likable-dislikable". Both definitions, as well as several others, suggest not only that such

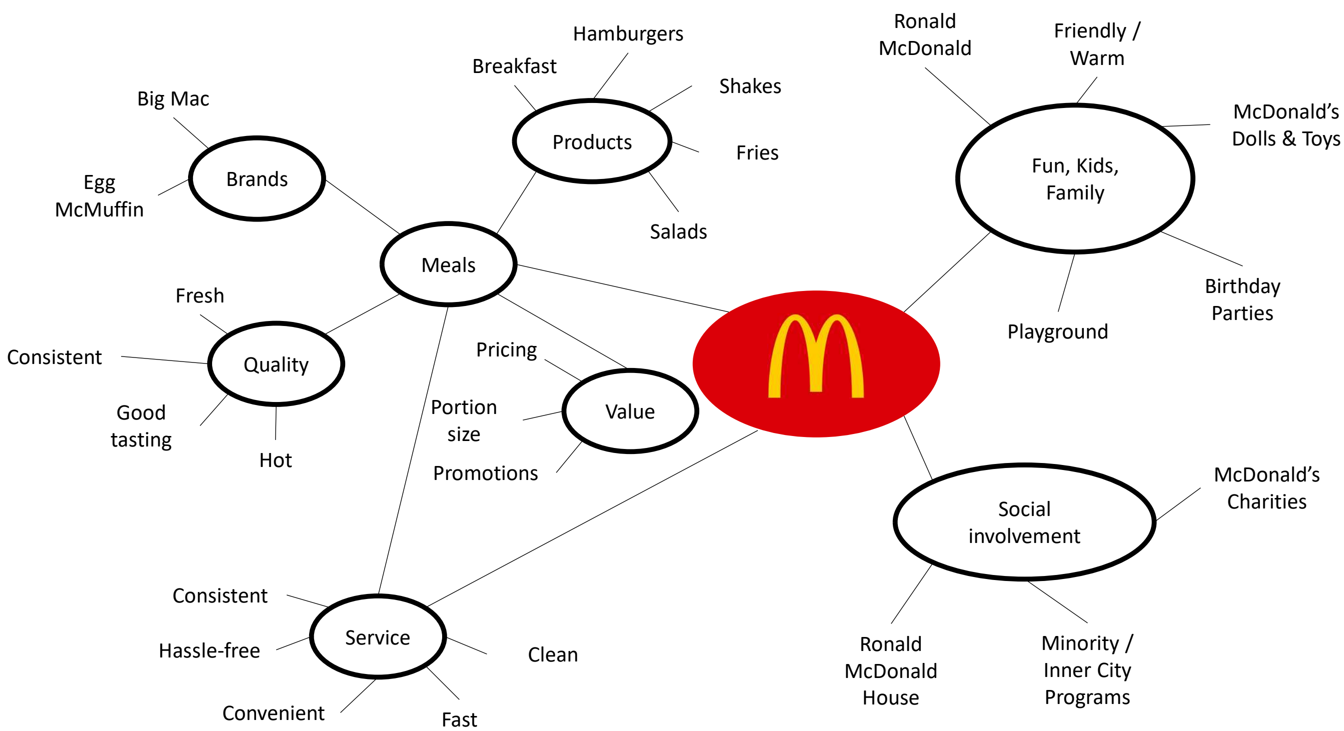

Figure 4.1: A brand association map for McDonalds. Rebuilt from figure in John et al. (2006), original image provided by Aaker (1996a). A brand and its products consist of several connections, or brand associations. This overall map forms a brand image of McDonald's.

an evaluative aspect exists but also that attitude formation involves combining the evaluations of several dimensions. These dimensions, which may range from natural instincts such as fear to socially acquired concepts such as prejudice, all may play a role in forming an overall attitude of an object.

Similarly, brand attitudes are an overall evaluation of a brand defined from a combination of the attributes and benefits associated with the brand (Keller, 1993). According to Keller, the various attributes and benefits that an individual associates with a brand are called *brand associations* and are stored in one's memory in forms of associative memory structures. where a brand association is any information linked to that brand (Keller, 1993). Information or knowledge such as a brand product's price or quality is stored as nodes and connected to the brand object through links, much like a network (John et al., 2006). Figure 4.1 shows an example of a brand association map for McDonald's. Therefore, a brand attitude can be seen as an evaluative summarization of the various brand associations, and by aggregating the brand attitudes of different individuals we can obtain an overall reputation of the brand. In order to understand what causes changes in brand reputation, we can instead look at the factors that affect an individual's brand attitude.

4.1.2 Attitude Changes Caused through Different Cognitive Processing

The formation and change of attitudes largely depend on properties of the provided information. The late 20th century marks an age where theories that tried to explain attitude formation change as a dual process emerged. Two representative models of this age are the Heuristic-Systematic Model (Chaiken, 1980) and the Elaboration Likelihood Model (Petty et al., 1983). Although using slightly different terms, both suggest that when processing a message and incorporating it into one's beliefs, one can choose to either consider the information carefully or make a quick decision based on heuristic cues. Both models have greatly contributed to the development of subsequent theories in explaining attitude formation and change. Subsequent models such as the MODE (Motivation and Opportunity as DEterminants) model by Fazio (1990) borrow this concept that information processing happens through either deliberative or spontaneous routes depending on the individual's motivation and opportunities.

When taking the central/systematic route of information processing, the individual puts large effort into fully comprehending the provided information. During this process the individual assesses the message's validity and looks for messages that can attribute to the resulting attitude they are about to make from the given information. This process is slow as it requires fully understanding the provided information. On the other hand, a peripheral/heuristic approach is carried out using additional signals other than the message itself. Here, instead of focusing solely on the message, the processing individual also identifies "cues" that can affect the attitude-building process, such as the individual's first impression towards the message, the individual's current mood, the reputation and status of the information source, and the reactions of peers toward the information. These heuristics are easier to discover compared to comprehending the entire message, and thus attitudes formed through heuristic processing can happen at a much quicker rate. The two processes are not independent of each other, and attitude formation can attribute both processes happening at the same time (Chaiken, 1980). According to Petty et al. (1983), which process to follow is determined by factors such as the individual's motivation to process the message and also his capability to process the message. Factors such as the individual's business at the time of processing also affect the process.

Relations to Brand Attitude Changes

The elaboration likelihood model and the heuristic-systematic model have been applied mainly for understanding advertising strategies and their effects on influencing potential customers. Especially in the era of social media, both central and peripheral cues are used extensively for processing information posted online and making subsequent decisions. The messages posted in social media platforms contain several different types of metadata along with the message itself. For example, a typical tweet from Twitter includes information about the sender's popularity (number of followers) and other's response towards the message (number of likes or retweets the tweet received) along with the original message. Given these properties, when reading user-generated posts in online social networks for deciding future purchases, individuals perform both in-depth considerations of the post's quality and usefulness (Erkan & Evans, 2016) as well as heuristic-based evaluations by observing traits such as images (Can et al., 2013).

The models that describe attitude change as a dual process can be applied to explaining how people adjust their attitudes in response to online firestorms. One key factor can be how relevant people believe the source of the firestorm is to themselves. Previous studies have pointed out that individuals participate more actively in firestorms (Johnen et al., 2018; Pace et al., 2017) when considering it relevant to their interests. Likewise, people tend to switch more to the systematic process of information processing when they believe the issue is relevant to their own interests (Chaiken, 1980). This is supported by a study from Hansen et al. (2018) which showed that individuals remembered more details of past online firestorms when they considered it as more relevant.

4.1.3 The Existence of Multiple Attitudes

At times it is possible to have two conflicting attitudes regarding a single attitude object. An example given by Wilson et al. (2000) comes from the novel *Remembrance of Things*

Past where the male protagonist is at one point convinced that he does not love the female protagonist, but at the very next moment changes his thoughts towards her. This has been difficult to explain from the perspective that views attitudes as constructs stored in one's memory and are updated over time. To overcome this problem, the dual attitude model proposed by Wilson et al. (2000) suggested the existence of not one but multiple attitudes stored in one's memory, and that different attitudes are accessed at different points. Wilson makes a distinction between implicit and explicit attitudes. An implicit attitude as one that is activated automatically, is uncontrollable, and comes from origins that the person making the evaluation is unaware of (Greenwald & Banaji, 1995; Wilson et al., 2000). This attitude is something that one would expect to happen in the unconscious, instinctive level. In contrast, an explicit attitude is stored in the memory and requires more effort to be retrieved. This is the attitude that one feels more comfortable reporting to others, as one can provide reasons behind this attitude. When forming an attitude regarding an object, the implicit attitude which is constructed automatically will prevail, but can be overrode by the explicit memory if it can be successfully retrieved. This can explain why it is possible to contain opposite valences toward the same object.

The coexistence of multiple attitudes has been widely considered in subsequent models such as the MCM (Meta-Cognitive) model (Petty et al., 2007) and the APE model (Gawronski & Bodenhausen, 2006). The MCM model acknowledges that past attitudes are not removed when new information enters and attitudes change; the past attitudes are merely tagged as false. They still remain in one's memory, but now become associated with the false tag whenever there is an attempt to recall that attitude. Meanwhile, the APE model suggests that attitudes are formed through a combination of (1) associative evaluations, which are automatic activations in response to information and thus relevant to implicit attitudes, and (2) propositional reasoning, making inferences to reach a particular judgment, the basis for explicit attitudes. Both models demonstrate how attitude changes can be explained as a combination of implicit, innate attitudes formed in one's unconsciousness and explicit, external attitudes caused by the information.

Relations to Brand Attitude Changes

Multiple attitudes can be used to explain how people perceive a brand from multiple angles. Brands are associated with several attributes (Aaker, 1996b) (refer to Figure 4.1), and depending on the attribute of focus it is possible to have different attitudes even towards the same brand. For example, one may value a company's products highly but have a more negative view towards its limited role in corporate social responsibility practices, as is represented by the various dimensions used when measuring brand reputation (Fombrun et al., 2000; Cravens et al., 2003). When making a decision based on brand reputation such as whether to make a future purchase or investment, different weightings of the attributes may lead to different decisions even regarding the same brand.

The existence of multiple attitudes may also have an effect on people's attitude changes following negative events such as online firestorms. People who have been exposed to the firestorm and informed of the brand's misconducts may consider that piece of information when making judgments that require explicit attitudes such as purchasing after comparing with other products, but not consider the same information when making on-the-fly purchases that are based on intrinsic attitudes. This perspective can help understand the effect of online firestorms on brand reputation as it would mean that a decreased favor towards the brand due to online firestorms may not necessarily mean a decreased attitude when considering other aspects as well. Or it could be that disappointment towards the brand has reached the unconscious level and impacts the overall brand attitude. This aspect has not been studied as of today and provides an interesting research question.

4.1.4 Attitude Changes Caused by Social Influence

Social influence plays a large role in affecting one's attitude and thus leading to attitude change. Kelman (1958, 1961) proposed three different processes for individuals to change one's opinion: compliance, identification, and internalization.

Compliance

The first motivation, *compliance*, stems from the fact that individuals are social beings. People want to maintain a favorable relationship with others surrounding them, sometimes even at the expense of changing their attitudes towards certain topics. As seen in the classic experiments of Asch & Guetzkow (1951); Asch (1955, 1956), the social pressure from a group causes individuals to change their attitudes and opinions to the group's accepted views, even if it is against their own belief. This concept of conformity appeared in several subsequent theories under different terms. Deutsch & Gerard (1955) used the concept *normative social influence* while Kelman (1961) called it the *compliance* process. This process also risks the possibility of making a group unable to make diverse opinions. In fear of becoming isolated from the majority members of a group or organization, the minority may decide to not express their opinions. Known as the "spiral of silence" effect, a term first brought up by Noelle-Neumann (1974), this conformity would result in only the majority voicing their opinions and the group's overall opinion appearing more and more unified.

Identification

There is a second version of conformity in which the individual is more willing to change one's attitude compared to compliance, which is *identification*. Here, the individual decides to change one's opinion in order to gain the favor of a particular individual or group and maintain a positive relationship. Although Kelman defines this as a separate category, attitude change through identification has been studied less than that of compliance and internalization, which are distinguishable based on whether the individual experiences an internal need for change.

Internalization

Internalization is caused by stronger motives than to earn the favor of a group. Attitude change through influence occurs when an individual realizes that the introduced information is relevant to their internal value system. In this case, attitude change happens not only on the surface as is with the compliance process, but also changing their internal beliefs. The attitude change induced through this process is defined as *informational social influence* by Deutsch & Gerard (1955) and *internalization* by Kelman (1961).

Internalization is made through a higher level of cognitive processing and rationalization than compliance, as it requires the individual to believe that the information aligns with his own beliefs. While it is easy to assume that conformity to a group's predominant opinion is only associated with compliance, the same effect can also appear even in the internalization process. For instance, knowing that the majority of peers follow a particular attitude may strengthen an individual's agreement towards that attitude. Group conformity again plays a strong role in forming and changing one's attitude regarding a topic.

Relations to Brand Attitude Changes

How can we relate these processes to changes in brand attitudes? Previous studies have connected the internalization process to brand attachment, which is the identification of oneself with a company's corporate identity (Bhattacharya & Sen, 2003; Aspara & Tikkanen, 2011; Keh & Xie, 2009). An individual's identification with a company has a positive impact which has been mentioned such as being more likely to invest in the company (Aspara & Tikkanen, 2011) and spread positive comments about the company brand (Bhattacharya & Sen, 2003).

A question of further interest would be to know which of the three processes are relevant for the spreading of online firestorms. The participation of an online firestorm involves three stages: (1) exposure to one or multiple message(s) of others expressing negative content towards the brand, (2) being influenced by the messages, and (3) further posting messages that contain similar negative views. Which influence processes dominantly appear in the process of influencing users to the extent that they participate? If there is a prevalence of the compliance process caused by social pressure to assimilate others, then the negative information exposed during a firestorm would not greatly change one's brand attitude towards the brand in the long run. This is partially supported by results revealing that social recognition happened to be a strong motivation for participation in online firestorms Johnen et al. (2018). However, participants also view online firestorms as a social norm enforcement process and a practice of sousveilance, meaning they might have a stronger motivation caused due to disappointment towards the brand. This would indicate that the effects of online firestorms would have a longer or even permanent brand attitude change. An understanding of the influence processes that cause attitude towards participation can help one understand the lasting effects of attitude change caused by online firestorms.

4.2 Summary of Findings

In this section, I will summarize the progress of research that has been made towards understanding our initial question of interest: to what extent do online firestorms affect brand reputation? I will also reiterate the suggested directions for future research to understand dimensions of brand reputation and online firestorms which have been left unaddressed in previous work.

4.2.1 A Comprehensive, Data-Driven Approach for Measuring Brand Reputation

In Chapter 2, I reviewed literature on our target variable of interest, brand reputation. Based on the various definitions of brand reputation as well as studies that provided frameworks for measuring the concept, I synthesized the findings to create a list of categories that comprehensively cover the various dimensions of brand reputation. Furthermore, I examined recent studies that aimed to measure brand-related aspects from user-generated text data in social media platforms, and identified the various objectives and dimensions of the measured constructs from these studies as well as the strengths and weaknesses of these approaches.

A synthesis of the literature revealed that although social media data contains the potential to replace traditional survey-based methods to measure quick, large-scale interpretations of brand reputation, as of far there are many obstacles towards fulfilling that goal. One limitation emerged due to the nature of social media platforms. While platforms such as online communities and social networking services encourage conversations between users, platform purposes and concerns of privacy may prevent them from discussing all related dimensions of brand reputation in a single space, which reduces the coverage of a single social media platform as a dataset for understanding the entirety of brand reputation. A proposed solution would be to first identify the expected type and form of conversation in each platform to which dimension of brand reputation it would most likely contain, then conduct a comprehensive analysis by collecting a large dataset from multiple domains. Another limitation came from the capacity of existing machine learning at the time the studies were conducted. When choosing between unsupervised and supervised machine learning frameworks for identifying brand-related concepts, unsupervised models that used algorithms to identify attributes lacked interpretability, while supervised approaches required extensive handwork on creating labels or crafting dictionaries. More recent studies such as that of (Das Swain et al., 2020) suggest the possibility of combined methods that use theory-driven attributes as well as deep learning-based text representations to identify dimensions of brand reputation at a large scale without too much manual effort. The introduction of more advanced approaches combined with further curation of datasets can create frameworks for accurately and efficiently measuring the various dimensions of brand reputation from social media at a large scale.

4.2.2 Understanding Online Firestorms and Further Examination on Network Properties

In Chapter 3, I provided a brief understanding of word-of-mouth in the context of its importance in explaining information spreading in social networks. I then reviewed studies on one negative case of WOM spreading known as online firestorms, which is the other main concept of interest in this study. Based on current literature, I identified the different views on the cause of online firestorms and their relations to similar concepts such as customer complaints and brand crises to provide a clearer distinction between the concepts. Finally, I conducted a review on various network properties that are known for affecting information diffusion processes and examined the possibility of using these properties to explain the dynamics of online firestorm diffusions.

My findings revealed that although online firestorms have gained increased academic interest over the years, the concept itself was introduced fairly recently (Pfeffer et al., 2014), resulting in a large open space of research for understanding its dynamics through network properties. Earlier results have already suggested interesting findings: the existence of hub structures (Jackson & Foucault Welles, 2015) and its structure as a temporary network that greatly differs from pre- and post-firestorm times (Lamba et al., 2015). These properties of online firestorms suggest that additional work that identify different network properties within online firestorms can contribute to greater understanding of how these firestorms emerge and spread. I propose two specific directions for future studies. First, studies on the existence of community structures in the initial formation or propagation of online firestorms can provide new findings on identifying characteristic of the users that play an important role in making firestorms viral. It is possible that the users who set up the firestorms share some demographic or user properties. Another research direction is the inclusion of limited attention and memory capacities of individuals and networks. In order for online firestorms to spread, they must compete against other sources of information to reach and influence potential participants. Modeling the amount of competing attention as well as limited memory capacities can help understand what causes firestorms to survive or die out at different rates.

4.2.3 Understanding Brand Reputation Changes from Attitude Changes

Finally, in Chapter 4 I introduced the concept of brand attitudes to describe the processes behind attitude changes, which leads on to brand reputation changes. I first provided a description on how brand attitudes are related to brand reputations, then used this relationship as evidence to explain the possible routes of brand reputation being affected by online firestorms. I examined three properties of attitude changes - (1) the different processes of forming and changing attitudes, (2) the existence of multiple attitudes, and (3) the different processes of social influence resulting in attitude change.

The suggestions for future research that I propose in this chapter directly relate to answering the question of understanding the effect that online firestorms have on brand reputation change. The main question of interest here is whether the perceived toxicity and danger of online firestorms actually match that of subsequent decreases in brand reputation, which can be explained through the different processes of attitude change. The first research direction I suggest is understanding whether exposure to the negative content from online firestorms induces heuristic or systematic processing. If there is evidence that people process such information based on heuristics, one can hypothesize that agreeing to and further participating in a firestorm would not necessitate that the information was fully processed, leading to a lesser degree of change in brand attitude. Similarly, one can also examine whether participation was induced by compliance to one's social group or by internalization. Last of all, the existence of multiple attitudes regarding brands can be used to explain how people evaluate the same brand across different categories after the brand has been the victim of an online firestorm. A possible result is that while the brand's overall reputation drops, the drop rates differ across different categories of reputation. These directions can provide a clear understanding on the effect of online firestorms on brand reputation.

Chapter 5

Proposed Study

5.1 Research Question

A literature review on past studies that measured brand-related concepts using social media data revealed a number of limitations. One limitation was the difficulty of balancing between theoretical validity (which unsupervised methods lacked) and scalability (which dictionary or supervised classification methods found hard to satisfy). A solution to this issue can be the adoption of contextualised word embeddings for measuring the relevance of a user-generated text to a brand-related concept. This approach has been recently applied in identifying socially defined concepts such as organizational culture (Das Swain et al., 2020), framing (Kwak et al., 2020) and signals of dehumanization (Mendelsohn et al., 2020) from social media text, which provides an encouraging setup for applying it for identifying different dimensions of brand reputation as well. Therefore, the research question that I propose focuses towards constructing a framework for measuring brand reputation from social media datasets:

> **RQ:** Can a word embedding-based measurement improve the performance of measuring brand reputation from social media datasets?

The proposed model is interpretable, scalable and will be built on state-of-the-art methods that are used for text analysis. There are several potential benefits that this model can bring. First, accurate but costly methods such as questionnaire surveys can be supplemented or even replaced by automated methods that are much cheaper to run at large scales, easily measuring reputation levels from millions of users. Second, from a managerial perspective the model can be used to make timely measurements of a brand's reputation at different populations, which may be crucial when having to make immediate decisions. For example, when a company is facing an unfavorable situation such as a brand crisis, the measurements made by this model can be used to track which user groups experienced the largest change in brand attitudes, guiding towards making adequate strategies for reputation recovery. Third, a demonstration of working on brand reputation, a social construct, can lead to the possibility of introducing other models that measure similar important constructs such as public opinion toward a policy or political party (Jungherr et al., 2017; Lin et al., 2013; Adams-Cohen, 2020).

5.2 Data Collection

5.2.1 Identifying Twitter Accounts of Brands

The first step of data collection involves compiling a list of brands to be included in this study. I will create a list of brands from the Fortune 500 list[1], then perform searches to collect the main Twitter account for each brand. For brands with multiple accounts, I will select the account that (1) does not a suffix attached to its account (e.g., @Microsoft vs. @MicrosoftLife) and (2) has the largest amount of followers. If the two criteria collide, I will read the account descriptions as well as a sample of tweets to determine the "main account" of that brand. Furthermore, for each brand I will check the existence of a hashtag that indicates the brand (e.g., #microsoft). The resulting dataset will be a table containing each brand's name, industry type (provided by Fortune 500), Twitter brand account, and an optional set of hashtags that correspond to a brand.

5.2.2 Collecting Existing Data on Brand Reputation

Similar to Hansen et al. (2018), I will gain access to the YouGov BrandIndex Score[2] as a ground truth value for brand reputation. YouGov provides a daily measure of brand perception measured across thousands of consumers selected from an online panel of more than 11 million users, and thus can be considered as providing a valid measure of brand reputation. Its brand perception measure ranges across six categories:

- **Perceived brand quality:** Which of the brands in the sector do you associate with high or poor quality?

- **Perceived brand value:** Which of the brands do you associate with good or poor value-for-money?

- **Perceived brand satisfaction:** Would you identify yourself as a recently satisfied or an unsatisfied customer of any of these brands?

[1] https://fortune.com/fortune500/
[2] https://business.yougov.com/product/brandindex

- **Perceived brand recommendation:** Which brands would you recommend to a friend or suggest avoiding?

- **Perceived brand impression:** For which brands do you have a 'generally positive' or 'generally negative' feeling?

- **Perceived brand workplace reputation:** Which of the brands would you be proud/embarrassed to work for?

The score for each category is calculated using the fraction of respondents who replied positively or negatively towards the question, and lies within the range of -100 to +100 (Hansen et al., 2018). The daily scores are provided for each individual brand. From this dataset, I will collect the six brand category scores of the brands that have experienced an online firestorm during the time frame of this study.

5.2.3 Collecting Social Media Data for Measuring Dimensions of Brand Reputation

Online reviews pages: brand quality, brand value, brand recommendation

Online review pages contain a large amount of customer reviews regarding brand products, which has made it an ideal dataset for mining customer opinions on product value and quality (Decker & Trusov, 2010; Lee & Bradlow, 2011; Moon & Kamakura, 2017). In line with earlier studies, I will consider these datasets to collect user-generated reviews for the purpose of measuring brand quality and value. One issue is that unlike previous work, this study is conducted on a wide variety of brands that exist across different markets, which inevitably calls for the need of multiple review pages. To address this issue, I will use the industry categorizations of each brand provided by Fortune to group brands into industries, then assign the most popular online review platform for each industry (e.g., restaruants - Yelp, hotels - Expedia.com). For each brand, I will collect all reviews generated during the timeframe of the study.

Glassdoor: workplace reputation

I will adopt the study of Das Swain et al. (2020) and crawl a dataset from Glassdoor, which is an online platform for employees to share information of their hiring process, compensation, and workplace experiences. For the timeframe of the study, I will collect comments under the category of work experiences for each brand in our dataset.

Brand reputation category	Semantic axis	Corresponding dataset
Brand quality	great - poor	online review
Brand value	valuable - valueless	online review
Brand satisfaction	satisfiable - insatiable	Twitter
Brand recommendation	recommend - disregard	online review
Brand impression	positive - negative	Twitter
Brand workplace	proud - embarrassed	Glassdoor

Table 5.1: An example of the semantic axes to apply to the model for measuring brand reputation

Twitter: brand satisfaction, brand impression

For the remaining two dimensions, brand satisfaction and brand impression, I will use Twitter data. This is in line with previous studies that measured customer relationships (Okazaki et al., 2015; Rust et al., 2021) and overall emotional evaluations from customers (Mostafa, 2013; Manaman et al., 2016; X. Liu et al., 2017; Klostermann et al., 2018) based on user-generated content on Twitter. Using the identified Twitter accounts of the brand, I will collect user-generated tweets that mention the brand during the timeframe of our study.

5.3 Methods

The research question is to measure different dimensions of brand reputation from user-generated content using word embeddings. I will first briefly describe how the model works, then provide experiment settings for the validation task.

5.3.1 Introduction of Word Embedding Model

A recent study by Kwak et al. (2020) built upon the idea that the word embeddings of antonyms can be used for measuring an arbitrary document's alignment to a semantic axis which is constructed by the antonym pair. For example, a document's intensity towards the 'happy-sad' axis can reflect how many emotional words are used in the document regardless of the direction, and the bias towards the axis shows how the document's content is close to being either happy, sad, or neutral, both which can be measured using the word embeddings of the document and the antonym pair. The authors presented a framework titled FrameAxis which contains the semantic axes (or *microframes* as denoted by the authors) of 1,621 antonym pairs including 'tasteful-tasteless', 'courteous-discourteous' and 'inferior-superior', and will be the basis of the model for measuring brand reputation which I propose.

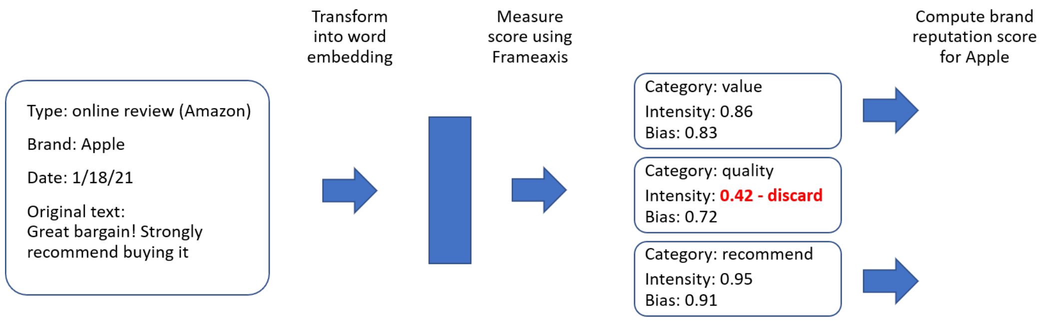

Figure 5.1: An illustration of obtaining brand reputation scores from a user-generated review using word embedding

5.3.2 Creating Semantic Axes for Brand Reputation Categories

As the YouGov scores, that is the ground truth dataset containing scores for brand reputation, consists of six categories, the reputation scores measured by the proposed model should also match the same number of categories to enable equal comparison. Based on the six questions from YouGov's survey, I will select six semantic axes from the framework of Kwak et al. (2020) as can be seen in Table 5.1. The word representing the semantic axis can differ depending on the model's current set of available antonym pairs.

5.3.3 Measuring Brand Reputations Using Semantic Axes

Using the six semantic axes, I will measure the brand reputation scores for each user-generated message. In order to represent each message into word vectors, every single message will be tokenized into word level, mapped to the corresponding word vectors, and averaged into a single vector. Depending on the type of message, different types of semantic axes will be applied as according to 5.1. For each brand reputation category measured on a document, the model outputs two scores: bias and intensity, both between the range of [0,1]. The intensity score will be used as a filter to remove messages that are unrelated to the brand reputation category being measured, where a score of 0.5 will be set as a threshold. For messages whose intensity scores passed the threshold and are considered relevant to the category, I will take the bias score of the message. Taking the average of the bias preserved bias scores across all messages related to a brand will produce the reputation score of a particular brand for that category.

As a result, there shall be six scores per brand for each day, identical to the YouGov survey data.

5.3.4 Testing Validity on Survey Data

The last step consists of testing the validity across the two sets of scores. I plan to test the validity of the proposed model by performing a ranking correlation test of the reputation scores of all available brands for a given day. I will select a number of separate days, then for each date will compare the reputation scores of all available brands by pairing the values created from the model versus the values from YouGov. The ideal metric for comparison is the Spearman's rank correlation coefficient. A coefficient score of 1 will indicate a perfect match, whereas a value of 0 indicates zero correlation, and -1 means total correlation on the opposite direction. The anticipated coefficient scores are between 0 and 1.

In order to provide estimates of how good or bad the correlations should be, I will introduce two additional baselines. The first is an implementation of the brand reputation measurement model proposed by Rust et al. (2021), which uses counts of words to measure brand reputation scores from three categories: the Brand driver, the Relationship driver, and the Value driver. The second baseline is brand reputation scores provided by the Centre for Corporate Reputation at Oxford's Saïd School of Business. Similar to YouGov, this baseline consists of scores measured by surveys, and has been used as the baseline for validating the model of Rust et al. (2021).

Given these two additional baselines, I will conduct another round of measuring Spearman's rank correlation coefficient where the two baselines and the proposed model are measured against YouGov's data. In an ideal situation, the similarity between my proposed model and YouGov should be higher than the coefficient obtained by comparing YouGov and Rust et al. (2021), and comparable with the coefficient obtained by comparing YouGov and Oxford.

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