The Thesis Committee for Jisoo Kang
Certifies that this is the approved version of the following Thesis:

Consumer Perception of Brand in Social Media: 3Es as Drivers of Brand Admiration

APPROVED BY
SUPERVISING COMMITTEE:

Gary Wilcox, Supervisor

JoAnn Sciarrino

Consumer Perception of Brand in Social Media:
3Es as Drivers of Brand Admiration

by

Jisoo Kang

Thesis

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Master of Arts

The University of Texas at Austin

May 2019

Acknowledgements

I would like to express my sincere gratitude to my supervisor Dr. Wilcox who helped me by providing valuable assistance and time throughout my thesis writing process. I would also like to thank Professor JoAnn Sciarrino for her suggestions and help throughout this project, without which I could not have completed.

Last, but not least, I deeply thank my family and friends for their unconditional love, trust and support.

Abstract

Consumer Perception of Brand in Social Media: 3Es as Drivers of Brand Admiration

Jisoo Kang, M.A.

The University of Texas at Austin, 2019

Supervisor: Gary Wilcox

In postmodern market, consumers are increasingly exposed to a flood of brands in their everyday purchasing experiences. In an effort to help companies garner a strong and positive brand relationship with consumers, this paper presents an in-depth case study which implemented topic modeling to analyze unstructured contents on Twitter of three energy drink brands: Red Bull, Monster Energy, and Rockstar Energy. The twitter conversation on each brand was collected, preprocessed, and then analyzed in order to infer public perception for the brands.

The result provides the insight to increase intangible brand assets such as brand loyalty and brand admiration by examining how much value customers perceive from the current offering of the brand in respect with the benefits of 3Es(enable, entice, enrich). Furthermore, the study reveals the value of topic modeling as a powerful technology to bring out business value from a massive amount of accessible social media data.

Table of Contents

Chapter 1 - Introduction

The value of building a robust brand-consumer relationship has been emphasized in many pieces of marketing literature (Ahluwalia, Burnkrant, & Unnava, 2000; Aggarwal, 2001; Park, Eisingerich, & Park, 2013; Mostafa, 2013; Fournier, 1009; Park, MacInnis, Priester, Eisingerich, & Lacobucci, 2010) In postmodern market, consumers are increasingly exposed to a flood of brands in their everyday purchasing experiences. In this context, garnering and maintaining strong brand relationships with consumers is one of the significant challenges in strategic brand management.

Thus, customer-brand relationship research has been one of the popular research streams in marketing literature. Park, MacInnis, and Eisingerich (2016) propose the brand admiration management system which guides how to make consumers admire the brand. The model posits that brand should provide customers the critical benefits (enabling benefit, enticing benefit, enriching benefits), called the 3Es for short, to earn admiration, and those benefits "have an exponential effect on customers' relationship with a brand."(pp.14)

Based on the construct of brand admiration suggested by Park, MacInnis and Eisingerich (2016), This exploratory research aims to examine the customer-brand relationship of Red Bull, Monster and Rockstar, three energy drink brands with highest market share in U.S. by exploring how much value customers perceive from the current offering of these brands in respect with each of the 3 Es.

The study used a text modeling approach to uncover the public conversation on energy drink brands existing on Twitter. The twitter conversation on each brand was collected, preprocessed, and then analyzed in order to infer public perception for the brands. This research seeks to serve as a case study that implements the 3 Es as

determinants to diagnose consumer-brand relationship to provide novel insight to develop a better brand management strategy.

Chapter 2 of this thesis provides a literature review on the premises of customer-brand relationships and the value of brand admiration management system. Then, chapter 3 gives the background of the energy drink industry in the U.S. and text-mining methodology which is employed in this exploratory research, with an in-depth explanation for each research step. Next, chapter 4 presents the findings of this study, and chapter 5 concludes with a reflection of the research and a discussion for the result followed by recommendations for future research.

Chapter 2 - Literature Review

Chapter 2 endeavors to provide an in-depth review of literature that presents the premise and the value of the relationship between consumers and brands. First, it illustrates how consumers engage with the brand by bringing up the construct of brand personality and brand love. Second, it introduces the construct of brand admiration management system proposed by Park, MacInnis, and Eisingerich (2016). Last, the chapter introduces the value of the 3Es, the main drivers to foster a stable and solid consumer-brand relationship.

2.1. Consumer-Brand Relationship

Park, MacInnis, and Eisingerich (2016) define a brand as an entity or name that generates value relevant to the customers and the brand owner. In other words, a brand is not merely a name given to an offering from a specific source. Instead, the brand is a collection of all values identified by the consumers concerning products or services provided.

Early in 1958, Pierre said that non-material factor that makes the store special is the personality of the store. As he mentioned, customers tend to permeate brands with the traits of human personalities based on the value the brands offer. Aaker (1997) called the human characteristic traits given to brand as a brand personality.

As Keller (1993) noted, as consumers personify a brand as a complete human being, they do not only focus on the brands' utilitarian function but also symbolic and self-expression function. Furthermore, they also humanize the brands and engage themselves in a relationship with brands (Fournier, 1998). Park, Eisingerich, & Park (2013) proposed that anthropomorphic perspective of the customer-brand relationship became a theoretical

foundation for the scheme of customer-brand interaction. Since then, marketing literature examined that the way consumers perceive their relationship with a brand is similar as to how they perceive their relationship with other people in a social setting (Fournier & Alvarez, 2012; Keller, 2012; Kervyn, Fiske, & Malone, 2012; MacInnis, 2012).

Recent contributions in marketing literature have paid attention to the successful relationship that consumers may develop with a brand and its positive consequences. One of the constructs that yield strong consumer-brand relationship is brand love (Shimp & Madden 1988, Ahuvia, 2005; Albert, Merunka, & Florence, 2008; Batra, Ahuvia, & Bagozzi, 2012). Schimp and Madden (1988) adopted the triangular theory on theory of love (Sternberg, 1986) and transformed the components of interpersonal love to a marketing context, proposing that brand love composes of components of consumer's intimacy, passion, commitment toward the brand. While Ahuvia (2005) showed that consumers tend to establish a powerful emotional relationship with brands. Batra, Ahuvia, and Bagozzi, 2012 uncovered the attributes of the strong association of brand and consumers, which is characterized as "self-brand integration, passion-driven behaviors, positive emotional connection, long-term relationship, positive overall attitude valence, attitude certainty and confidence (strength) and anticipated separation distress" (p.1)

2.2. BRAND ADMIRATION

Brand admiration is defined as "the degree to which customers have a salient, personal connection with the brand, emanating from their trust in, love of, and respect for the brand" (Park, MacInnis, and Eisingerich, 2016, p38)

The self-brand connection accompanies brand admiration (Park, MacInnis, Priester, Eisingerich, & Iacobucci 2010; Thomson, MacInniss, & Park, 2005). It is closely

related to the logic of brand attachment which provided the theoretical foundation of the construct of brand admiration. Aron and Aron's (1986) self-expansion model explains that the strength of the relationship between one and other depends on how they share something in common. Park et al. (2013) compared the consumer-brand relationship to the self-expansion model and proposed that the more overlapped between the brand and self, the more positive the relationship becomes.

Arnould and Thomson (2005) stated that consumers tend to use brands to confirm their sense of identity and also to realize self-expansion. In line with this statement, Park et al. (2013) suggested the construct of brand attachment and aversion. When a brand enables a consumer to realize self-expansion, the consumer may feel they are firmly attached to the brand, which is called brand attachment. In contrast, if a brand hinders them from comprehending self-expansion, they feel averse to the brand, and it is depicted as brand aversion. In other words, self-brand connection engenders consumers to achieve self-expansion throughout the brand experience, building up the level of brand admiration as well as the brand attachment.

The compelling brand itself serves as an identifier that enables a company to stand from competitors in the marketplace. However, Park et al. (2016) argues that building strong brand admiration brings more than solid identity of the brand and generates following substantive practical values: "Revenue Generator", "Cost-Efficiency Enhancer", "Growth Facilitator", "Human-Capital Builder", "Employee-Morale Booster", "Second-Chance Provider", "Market-Protector", "Alliance Facilitator" (p.4)

An admired brand attracts new customers and yield existing customer's brand loyalty, which in turn generate the revenue and facilitate the growth of the company. Brand loyalty is a "biased behavior response expressed overtime by some decision-making unit concerning one or more alternative brands out of a set of such brand" (Jacoby and Chestnut

1978, p.80). It does not only allow a brand to dominate the marketplace, but also compensate for the mistakes the company makes by allowing customers to become the ambassadors of the brand. Furthermore, consumers who admire the brand are likely to generate favorable and strong word of mouth (WOM), which further contribute to company's marketing efficiency (Wallace, Buil, & Chernatony, 2014) In such a way, brand admiration also enables companies to realize cost-efficiency by allowing them to lower advertising and promotion cost from the budget.

Brand admiration not only develops a delicate consumer-brand relationship but also strengthens its relationship with its employees or external partners. It enables companies to recruit a talented employee who will finally become the company's prosperity in the market place. Also, existing employees are motivated to devote to the protection and thrive of the brand. An admired brand can also bring in compelling external partners and these alliances further increase the revenue by helping the company with areas that lack expertise in its resources.

2.3. BRAND EQUITY

The values that brand admiration fetch can increase brand equity. Due to the broad nature of brand equity, there are many different interpretations across the disciplines. While brand equity can be assessed with a consumer-oriented mindset (Aaker 1991, Aaker, 1997; You, Xueming, & Donthu, 2001; Keller, 1993) , it can also be approached with financial perspective (Motanemi & Shahroki, 1998; Ferijani, Madiha, Jedidi, & Jagpal 2009; Simon & Sullivan 1993). From a financial point of view, brand equity is a future cash flow that results from the benefits the brand name brings to the sales of a product or services (Motanemi & Shahroki, 1998). Although financial oriented measures of brand equity

quantify the potential of brand value and performance indicators to the company, the parameters can be volatile and subjective to gauge the future value of the brand (Simon & Sullivan 1993). Conversely, Keller (1993) interprets brand equity from the consumers' point of view and propose that it refers to how consumers respond to brand marketing activities based on the awareness and perception for the brand. However, Heitmann Lehmann and Neslin pointed out that the consumer-wise metric of brand equity provides little information on the company's quantifiable profitability and market performance.

Park et al. (2016) defined the brand equity as the construct that "reflects the financial value of the brand to the brand holder (the company) based on the company's effort to build brand admiration among customers"(p.218). In addition, it should be able to reflect the difference between "customers' endowment to a brand (e.g., the price they are willing to pay and the number of units they are willing to buy and the investment the brand holder has had to bear to secure this endowment from customers (e.g., the costs incurred to market to these customers)" (p.218)

Along with the definition, they suggested a way to measure brand equity, which applies to consumer-oriented and financial-oriented standpoint. According to the study, marketing surplus and marketing efficiency are the two essential components of brand equity, and they are produced by three variables: unit price, unit market costs, and quantity sold.

Marketing surplus is the difference between the cost that customer paid to purchase a unit item and a unit marketing cost. Thus, the marketing surplus becomes larger if the unit marketing cost of the brand is lower than the unit price that consumer paid for the brand, and a large quantity is sold for the brand. Because the unit price of the brand represents the consumer's perspective, and the unit marketing cost represents the company's, marketing surplus reflects both consumer and company's side.

Marketing efficiency reflects the ratio of total marketing cost (the quantity sold for brand × the unit marketing cost of the brand) over total revenue (the quantity sold for brand × the unit price that consumer paid for the brand) Like marketing surplus, marketing efficiency reflects the input of consumer and company. Consistent with the model explained, when the total marketing cost of the brand is smaller than the total revenue of it, the marketing efficiency increases.

The brand equity is ultimately demonstrated as a multiplied value of marketing surplus and marketing efficiency. Based on the logic behind marketing surplus and marketing efficiency, critical drivers of these two components are marketing cost and the revenue. Park et al. (2016) argue that marketing cost and revenue are in turn affected by brand admiration. They mentioned that admired brand is more likely to facilitate the alliances with powerful external partners, citing the case of Apple Pay's partnership with Mastercard, which allows the company to raise revenue or expand the market without costly investments in areas of their low expertise. Furthermore, brand admiration helps the company to attract and recruit talented people who ultimately contribute to the success of the brand in the marketplace. Whereas, brand admiration further leads consumers to have brand loyalty and brand advocacy. Based on these factors, the brand can achieve marketing cost efficiency. To sum up, brand admiration has an exponential impact on brand management in that it increases brand revenue and marketing cost efficiency, and in turn, strengthens overall brand equity.

2.4. 3 ES (ENABLE, ENTICE, ENRICH)

Park et al. (2016) propose the brand admiration management system which guides how to make consumers admire the brand. The model posits that brands should provide customers the critical benefits (enabling benefit, enticing benefit, enriching benefits), called the 3Es for short, to earn admiration, and those benefits "have an exponential effect on customers' relationship with a brand."(pp.14)

These determinants parallel with the three assets of the brand, which Park, Jaworski, and MacInnis (1986) introduced: functional, hedonic and symbolic liability. Further, these 3 Es have also a similarity with four values of the brand proposed by Richins (1994). These four values include the brand's capacity to serve functional, entertainment, self-expression, and interpersonal connection function. While the main focus of Richins' (1994) and Park et al. 's (1986) is the inherent asset of the brand itself, Park et al. (2013) noted how these assets could further make the brand meaningful for customers.

According to Park et al. (2016), how much value consumers perceive from the offering of the brand in respect with these 3 Es significantly predicts the Attachment-aversion (AA) of customer-brand relationship (Park et al. 2013). One of the critical components of AA relationship is the self-brand distance which is defined as "perceived distance between the brand and a self" (Park et al. 2013, p.23). Depending on whether consumers perceive the values of the brand in respect of the 3Es, they are likely to be attached or averse to the brand, which in turn drives their brand admiration level and consumer-brand relationship. However, it should be noted that those 3Es, enabling, enticing and enriching benefits of the brand each serves different functions in leveraging consumer-brand attachment and provides different type of positive feelings to consumers. (Park et al. 2013).

2.4.1. Enable

Enabling benefits is related to practical and functional aspects of the brand. When consumer perceives the brand enables them to serve what they intend to do, they are empowered to feel "secure, in control, confident, and relieved" (Park et al., 2016, p.43). According to Park et al. (2016), this is not only in a situation where brand helps consumers to solve the problems they face, but also where it allows them to conserve their resources such as time, money and physical or psychological energy. In other words, when consumers feel that brand acts on the customer's behalf, they feel the value of the brand with respect to the enabling benefit.

The critical components of enabling aspects of the brand are to be reliable and versatile. When consumers can rely on the brand throughout the journey while they address the problem, they start to trust the brand. Then, they become eager to build a self-brand relationship because the brand trust "enhances feelings of security, lower anxiety, and enhances confidence in the brand as a relationship partner" (Park et al. 2016, p.43) Park et al. (2013) cite the versatile application and endurance of Swiss Army Knives, which allowed consumers to have frictionless brand experience and build trust for the brand. Furthermore, according to his admiration management system, brand trust is one of the drivers of brand attachment and increase brand admiration level.

Similarly, Giles and Maltby (2004) presented that consumers tend to shorten the psychological distance from the brand when the brand allows them to become in control of the environment surrounding them. Therefore, a close connection with the brand may escort consumers to have a high level of brand attachment. In contrast, if the brand keeps them from being autonomous and efficient, they are likely to feel averse to the brand, which may lower the brand attachment level (Park et al., 2013). Therefore, adding enabling

benefits to the brand is critical to build trust in the brand and foster a positive self-brand relationship.

2.4.2. Entice

Park et al. (2013) articulate that enticing value of the brand accompanies with a sensory or cognitive pleasure experience. In order to serve enticing benefits to consumers, the brand should communicate in a way to arouse imagination or to stimulate the senses. The enticing assets of the brand allow consumers to feel "gratified, engaged, entertained, upbeat, and warmhearted" throughout their experience from the brand (Park 2016 p. 43). Krishna (2012) also proposed that providing enticing benefits to the consumer may generate positive perception and yield brand advocacy behaviors through her research.

While enabling benefits generate brand trust, enticing benefits create brand love. Park (2016) described that consumers are inclined to a brand that offers gratification and positive emotional stimulation and feel an attachment to the brand, which resembles the attributes of what brand love creates. (Shimp & Madden 1988, Ahuvia, 2005; Albert et al., 2008; Batra et al., 2012)

2.4.3. Enrich

The enriching benefit of the brand refers to the brand's capacity to symbolically represent consumers' value and beliefs to make a better world. It is also generated when a brand can make consumers feel a sense of belonging or make themselves unique in a group.

The brand works for symbolic function when it communicates in a way to identify who one is in the past, present and further in the future (Belk, 1988; Escalas & Bettman

2005; Markus & Nurius, 1986). According to Park et al. (2016), people are enriched when they can define themselves from the experience of the brand and find that the brand they consume shares the value(s) that they support. Because consumers tend to believe their value(s) are moral and just, they similarly believe that consuming the brand aligns with their beliefs, which bolsters self-esteem.

On the other hand, brand can also enrich customers by providing them a "sense of belonging as a member of group" or the feeling of being unique and distinctive relative to others (Park et al., 2016, p.44) Although these two traits appear to be very conflicting in nature, they are all deeply related to human instincts. Research support that while consumers desire to belong to the specific community by being connected to them (Park et al. 2016), they also want to believe themselves as to be autonomous and independent from the others. (Berger & Heath, 2007; Chan, Berger, & Boven, 2012)

Park and McInnis (2013) propose that consumers foster respect for the brand when the brand enriches them. In fact, among three drivers (brand trust, brand love, brand respect) of brand admiration, brand respect offers the most exponential power in increasing brand admiration. Unlike the other components, brand respect appeals to the internal belief of consumers and its power never goes off unless the consumer gives up their faith or values. By establishing an enriching brand, it can be engaged with a hard-to-treat relationship with consumers. Therefore, the brand should deliver the enriching benefit to consumers to sustain its delicate relationship with consumers. (Park et al., 2013; Park et al., 2016)

Chapter 3 - Case Study

3.1. Overview of methodology

This exploratory research aims to examine the customer-brand relationship of Red Bull, Monster and Rockstar, three energy drink brands with the highest market share in the U.S. by exploring how much value customers perceive from the current offering of these brands in respect with each of the 3 Es through public conversations existing on Twitter.

The study focused on the energy drink industry in the U.S. for the following reasons. First, according to research conducted by IBIS World (2018), the energy drink market in the U.S. is already highly crowded, and competition within the market is becoming more and more intense. Further, since the U.K. government proposed the ban of energy drink sales to children under 16 in 2018, there has been a growing public concern about the string of health problem and high content of caffeine in energy drinks, imposing the risk on global energy drink industry (The Guardian, 2018). In such a context, it is critical for manufacturers in the market to enhance the quality of their consumer-brand relationship to gain and retain the competitive position over the rivals (Choi, 2010). Besides, strong brand admiration among consumers accompanies brand loyalty, which has been endorsed by literature as an asset that helps to overcome the crisis (Stockmyer, 1996). Thus, energy drink brands in the U.S. are selected as a topic of this case study, because building brand strategies to increase brand admiration may play a key role for them not only to control the crisis they face but also to dominate the market over the competitors in the highly crowded marketplace.

The exploratory research took text modeling approach and examined the public's conversations on energy drink brands that existed on Twitter. Twitter is selected as an ideal platform for the study due to its popularity as microblogging service (Duggan et al. 2015)

and capacity of delivering conversation-like messages within the astronomical community (Kim & Ko, 2012; Kwon & Sung 2011)

The workflow for this study adopted human and technological analysis and employed following steps: the twitter conversation on each brand was collected, preprocessed, and then analyzed and categorized in order to examine benefit the brand provide consumers in respect with 3Es. This case study seeks to implement the 3 Es as determinants to diagnose consumer-brand relationship and provide novel insight to develop a better brand management strategy.

This chapter first introduces the background of text mining and topic modeling, which is employed as the main analysis methodology in this study. Then, it presents the background of the energy drink industry to help to understand the result. Afterward, the workflow of this research is presented with an in-depth explanation for each research step. Then, it follows the results and discussion.

3.2. BACKGROUND

3.2.1. Text Mining and Topic Modeling

Social media platforms built "virtual customer environments where online communities of interest form around specific firms, brands, or products" (Culnan & McHuge, 2010, p.243). With the proliferation of social media, consumers have experienced a new way to search and retrieve the information on a certain issue (Bai, 2011; Eirinaki, Pisal, & Singh, 2012). According to Hootsuite's 'The Global State of Digital in 2019 Report' (2019), out of 4.388 billion people who actively use the Internet around the globe, 3.484 billion is the users of social media, which is the number that corresponds to about 80% of the total number of Internet users. With the growth of social media users and the

multiplication of information accompanying it, the conversation fulfilled in social media plays a crucial role in forming public opinions and behavior over many areas. Moreover, knowledge from social media is highly unbiased because it is gathered through millions of opinions expressed about a specific topic (Mostafa, 2013) For these reasons, companies accommodate the growth of social media and increasingly adopt it in order to interact with customers and gain business values (Culnan & McHuge, 2010)

According to Zeng, Chen, Lusch, and Li, "social media analytics is concerned with developing and evaluating informatics tools and frameworks to collect, monitor, analyze, summarize, and visualize social media data, usually driven by specific requirements from a target application" (p.14). The purpose of this interdisciplinary research is to "facilitate conversations and interaction between online communities and extract useful patterns and intelligence to serve entities that include, but are not limited to, active contributors in ongoing dialogues" (p.14). The data gained through social media shares many characteristics with big data (Guellil & Boukhalfa, 2015; Lynn et al., 2015). Big data is the term that "encompasses data obtained from vastly different sources and in very different disciplines" (Stieglitz, Mirbabaie, Ross, Neuberger, 2018, p.156).

The main difficulty of dealing with big data lies in its vast volume. With the emergence of big data, the size of textual data pulled from the Internet goes beyond the information processing capacities of a human researcher (Debortoli, Müller, Junglas, & Brocke, 2016). Also, manually processing the massive volume of data is inefficient because it requires significant knowledge and long hours of labor (Quinn, Monroe, Colaresi, Crespin, & Radev, 2010). To overcome these obstacles, researchers have established "computer-aided approaches for text analysis by applying dictionary-based or machine learning algorithms" (Debortoli et al., 2016, p.3)

Among various type of data existing online, most information in social media consist of textual format, and thus text mining is frequently used to find meaningful information in social media research. (Stavrianou, Andritosos, & Nicloyannis, 2007) Text mining, also known as text analysis, is generally referred as "the process of extracting interesting and non-trivial patterns or knowledge from unstructured text documents" (Tan, 2000, p.1)

However, computer-mediated text analysis process requires some preliminary steps to get rid of the noise and convert " the words and phrases in unstructured information into numerical values" (Vijayarani & Janani, 2016, p.37) According to Mostafa (2013), Large part of text-based online communication disobeys the rules of grammar and spelling, which makes it hard to process the text data without human intervention. According to Boiy and Moens (2016), web texts have been classified as noise due to their problems at the lexical and syntactic level. At the lexical level, "jargon, contractions of existing words/abbreviations, the use of emoticons and the creation of new words" are prevalent in online communication. At the syntactic level, the sentences on the most forms of computer-mediated communications are written in a certain style. Derk, Fischer, and Bos (2018) stated that they are presented in a way which is different from the style we speak in everyday life. Therefore, in almost all cases, the data must undergo a thorough cleaning and preprocess phases to filter out the noise and gradually "turn qualitative textual data into a numerical representation that is amenable to latter statistical analysis" (Debortoli et al., 2016, p.9)

Text categorization is one of the fundamental tasks in text analysis, and it is "the task of assigning chunks of texts (e.g., e-mails, social media comments, news) to one or more categories (e.g., spam or no spam, positive or negative sentiment, business or politics or sports news)" (Debortoli et al., 2018, p.3). Topic modeling, the main data analysis

methodology of this exploratory research, is one of the text categorization tools and allows to automatically uncover pervasive themes and hidden topics in a collection of documents (Blei and Lafferty 2009; Blei 2012). The topics refer to "a recurring pattern of co-occurring words" (Brett, 2012), or, statistically speaking, "a distribution over a fixed vocabulary" (Blei 2012, p. 78).

The topic modeling has allowed discovering significant content from unstructured online documents through some literature. In marketing research, topic model is used to aid consumer profiling (Trusov, Ma, & Jamal, 2016), to make purchase predictions by analyzing consumers' buying patterns (Hruschka 2016; Jacobs, Donkers, & Fok, 2016), and to uncover conversations in online communities (Ngyen & Velcin, 2015; Paul & Girju, 2019;Paul & Dredze 2014; Lazard et al., 2016). The insights extracted by applying topic model helped to increase the efficiency of online advertisings (Le, Nguyen, Coltech, Phan, & Horiguchi, 2008), and to build the recommender systems in online market platforms (Christidis & Mentzas, 2013)

According to Amado, Cortez, Rita, and Moro (2018), Latent Dirichlet Allocation (LDA) is the most popular algorithm in topic modeling and proven to be reliable. The basic idea of this model is that the data is composed of a random mixture of topics that are specified by a distribution of words (Jelodar & Wang, 2018). LDA discovers "latent structure in a collection of documents by representing each document as a mixture of latent topics, where a topic is itself represented as a distribution of words that tend to co-occur" (Ramage, Dumais, & Liebling, 2010, p.132) Based on the discussion above, this exploratory study attempts to analyze social media text using topic modeling with LDA algorithm, to discover and classify the prevalent themes and topics existing in social media conversation on Twitter.

3.2.2. Energy Drinks Market in the U.S.

Energy drinks refer to caffeinated ready-to-drink beverages designed to increase metabolism and enhance alertness. (Pennay & Lubman, 2012) They are differentiated from other soft drinks, and sports drinks by its high content of caffeine and its function to relieve fatigue and boost the energy. (Oddy & O'Sullivan, 2009) The energy drink was first consumed in Europe and Asia in 1960s but had not been popular until it appeared in the US market in 1997. Since then, the energy drink market has been grown globally, and by 2006, more than 500 energy drink brands had emerged, with annual sales exceeding $500 million just in the US (Miller, 2008)

Many studies have warned the overconsumption of caffeine through energy drink and proposed the regulation of energy drink sales due to its potentially adverse effect on consumers' health (Reissig, Strain, & Griffiths, 2008). Nevertheless, whereas the sales of soda drink have been decreased in recent years with health concerns among consumers, the sales of energy drink have been continuously grown dramatically (Hammond & Reid, 2017)

According to Mintel (2018), the size of energy drink market in the US has been increased over last five years and also expected to grow by 4-5% every year until 2022, reaching out $16.9 billion. The research presented that demographic trends play a vital part in the revival of the energy drink market. It turned out that consumers aged from 18 to 34 are the most engaged energy drink consumers and the share of its population among the U.S. population is expected to grow through 2023.

The largest manufacturers including Monster Energy, Red Bull, and Rockstar Energy together account for 85% of market share for 52 weeks ending January 28, 2018. The market share leader is Monster energy. Since its partnership with Coca-Cola, Monster Energy has expanded its distribution network and increased the ability to promote the

brand. Red Bull accounted for the second largest market share in the U.S. The product portfolio of Red Bull is more streamlined than the other two manufacturers, Monster and Rockstar. According to the research, the promotion of all three manufacturers with the highest market share includes activities appealing to the demographics of core consumers by involving gaming, athletic sponsorships, and sports (Mintel, 2018)

Consistent with the controversy over the health concern with energy drinks and also with the revival of its market, researches have covered the marketing performance in Energy Drink Industry. Hammond and Reid (2018) explored the exposure and perceptions of marketing for caffeinated energy drinks among young Canadians, and found "major global brands such as Red Bull and Monster Energy engage in high-profile sports sponsorships, particularly those that appeal disproportionately to young people, such as X Games, biking, skiing and skateboarding events" (p. 536). Emond, Sargent, & Gilbert-Diamond (2016) discovered the patterns of Energy drink advertising over US television networks and concerned that TV commercials of energy drinks mainly targeted teenagers who are vulnerable to caffeine. Other literature has addressed the growing expenditure of social media advertising in the energy drink industry and also found its effectiveness to reach the main consumer demographics. (Hammond & Reid 2018; Rambe, 2017; Harris et al., 2014; Emond et al., 2016). Rambe (2017) studied the effect of social media advertising on students' consumption and preference for energy drink brands. According to the study, consumption and preference for energy drink brands are more affected by the availability and convenience of purchase and peer influence than by social media advertising per se. However, this study lacks its practical application but largely theoretical in that it only relied on the "exploration of extant literature and personal reflections on student engagement in social media-supported decision making about brands" (p.664)

Based on the literature presented above, this exploratory study aims to examine the public conversation on energy drink brands in social media, especially Twitter, and discover hidden patterns of the discussion and how public perceive each brand in respect with 3Es (enable, entice, enrich). The study mainly focuses on three brands with the highest market share in the United States, Red Bull, Monster Energy and Rockstar Energy. The research implemented a topic model approach based on text analysis, which hopes to help to provide insight to discover the in-depth understanding of public perception of the brands and examine how much value customers apprehend from the current offering of the brands with respect to the 3 Es (enable, entice, enrich) through public conversations existing on Twitter.

3.3. METHODOLOGY

The study used text mining approach to examine prevalent themes and topics of unstructured public conversation on Twitter. The workflow for this study adopted human and technological analysis and employed following steps: the twitter conversation on each brand was collected, preprocessed, and then analyzed and categorized in order to examine benefit the brand provide consumers in respect with 3Es.

Three sets of Twitter data on three brands with the highest market shares in the energy drink industry in the U.S. were collected: Red Bull, Monster, Rockstar. Data of the most recent 1000 public post that include specific keywords related to each brand were collected from Twitter API. The collection was conducted for about 50 days, from January 8, 2018, to March 1, 2019, using the Netlytic (Gruzd, 2016), a software application that authorizes third-party access to Twitter API.

3.3.1. Data Collection

The keywords used to collect the data included the name of the brand and the products that each brand launched for energy stimulation purpose. The data for Red Bull were collected using only one keyword, 'Red Bull,' because all items Red Bull launched contain its name such as 'Red Bull Energy,' 'Red Bull Sugar-Free'. The data of the Monster Energy was collected through seven keywords (''Monster Energy', 'Monster Rehab', 'Monster Tea', 'Juice Monster', 'Punch Monster', 'Monster Maxx', 'Monster Hydro'), and Rockstar Energy used six keywords ('Rockstar Energy', 'Rockstar sugar free', 'Rockstar pure zero', 'Rockstar recovery', 'Rockstar zero carb', 'Rockstar Revolt') Data was gathered if Twitter post contains all the keywords, regardless of whitespace or capitals in the keywords. Data was first collected by keyword, using the Netlytic (Gruzd, 2016), a software application that authorizes third-party access to Twitter API, and after collection, it was merged into three data sets according to the brand.

3.3.2. Data Preprocessing

With the help of Python script, the obtained texts were first cleaned in a way to remove the duplications, unrecognized characters and valueless part from tweets such as punctuations, emoticons, URLs. The purpose of cleaning was to avoid biased result, exclude tweets generated by an automatic bot, to get rid of the parts of speech that cannot be interpreted purely at the text analysis level and to avoid issues related to translation or data written in any language other than English.

Before analysis began, data were pre-processed with the help of several Python libraries such as Gensim (Řehůřek & Sojka, 2011), Natural Language Toolkit (NLTK) (Loper & Bird, 2002), and SpaCy (Neumann, King, Beltagy, & Ammar, 2019). The

purpose of pre-processing the data was to "turn qualitative textual data into a numerical representation that is amenable to latter statistical analysis" (Debortoli et al., 2016, p.10). In this study, the preprocessing task was accomplished through the following steps.

First, data was tokenized, and each tweet was split up to the single word. Collocations, the words that composed of multiple words, were taken as one token (e.g., social-network, steak-house) Next, all the characters were lower-cased and went through lemmatization to convert all the words into dictionary form. (e.g. 'went' to 'go'). Then frequently used words but with no other information, so-called stop-words were removed. To prevent words with little contribution to forming a meaning of the message from being overly highlighted in the result, the analysis was limited to the words whose part of speech is noun, verb, adjective, and adverb. Lastly, each word in data(token) was transformed to numerical id and matrix of "id of the word by frequency" was created as corpus.

3.3.3. Data Analysis

After cleaning and preprocessing the data, topics were finally extracted by performing Latent Dirichlet Allocation (Blei, Ng, & Jordan, 2003). It was implemented in a set of Python libraries, Gensim, package version 3.4 for Python (Řehůřek & Sojka, 2011). Models with a different value of the number of topics were executed, ranging from 5 to 20 topics and one with the highest topic coherence value (Newman, 2010) was selected for the interpretation. Topic coherence value is an indicator to capture "the tendency of a topic's high probability words to co-occur in the same document, and exclusivity, which captures whether those high probability words are specific to a single topic." (Robert, Stewart, & Tingley, 2015, p.13). Topic coherence value has been popularly chosen as an indicator of the quality of the topic model, and the results of topic modeling based on the

topic coherence level are very reliable in that they closely match the results of the human experts' labeling. (Arora et al., 2013; Mimno, Wallach, Tallery, Leenders, & McCallum, 2011)

To obtain the valid dataset without any potential source of bias and noise, the inspection was further conducted after visually examining the output the software generated (Allem & Ferrara, 2016). In this process, individual messages from each topic were examined. After execution, the topics and subordinate words which do not clearly illustrate the main keywords were filtered out. The final set of topics for each brand is presented with the description in Table 1, 2 and 3, showing the top 5 words in each topic.

Chapter 4 - Findings

The result is a set of words for each topic listed by the probability of each word being on the topic. Since LDA is based on multinomial distribution, a word may belong to several topics with different probabilities. The final set of topics for each brand is presented with the description in Table 1, 2 and 3, showing the top ten words in each topic.

4.1. ROCKSTAR ENERGY

	Gensim LDA Topic	n	Description of Topic
1	0.160*"energy" + 0.159*"rockstar" + 0.136*"drink" + 0.015*"go" + "0.011*"find" + 0.009*"make" + 0.009*"will" + 0.008*"back" + 0.008*"taste"	159	Taste of Rockstar Energy Drink
2	0.148*"husqvarna" + 0.131*"factory" + 0.114*"rockstar" + 0.114*"energy" + 0.097*"racing" + 0.009*"start" + 0.008*"olsen" + 0.008*"arlington" + 0.008*"sx" + 0.008*"pauls_jonass"	154	Racing schedule of Rockstar Energy Husqvarna Factory Racing Team
3	0.095*"rockstar" + 0.088*"energy" + 0.066*"drink" + 0.023*"work" + 0.023*"buy" + 0.018*"good" + 0.017*"pm" + 0.015*"year" + 0.012*"ready" + 0.012*"show"	102	Effect of Rockstar Energy Drink
4	0.067*"get" + 0.034*"team" + 0.033*"dean_wilson" + 0.030*"energy"+ 0.030*"rockstar" + 0.021*"time" + 0.021*"come" + 0.019*"jason_anderson"+ 0.016*"top" + 0.014*"season"	90	Conversation about the athletes in Husqvarna Factory Racing team
5	0.043*"husqvarna" + 0.038*"energy" + 0.037*"rockstar" + 0.032*"factory" + 0.029*"racing" + 0.028*"rider" + 0.025*"place" + 0.022*"stage" + 0.021*"die" + 0.019*"dakar_rally"	88	Participation of Rockstar Energy Husqvarna Factory Racing team in Dakar Rally

Table 1: Rockstar Energy tweets by topic

6	0.051*"mxgp" + 0.019*"ice_one" + 0.017*"tonight" + 0.015*"weekend" + 0.013*"want" + 0.010*"sign" + 0.010*"shoot" + 0.010*"motocross" + 0.010*"meet" + 0.009*"play"	85	Update on Motorcycle world championship (mxgp)
7	0.089*"team" + 0.061*"rockstar" + 0.057*"energy" + 0.051*"race" + 0.026*"video" + 0.014*"big" + 0.014*"mit" + 0.012*"injure" + 0.011*"road" + 0.010*"yoko"	80	Partnership of Rockstar Energy Husqvarna Factory Racing team and Yoko
8	0.025*"rockstar" + 0.022*"energy" + 0.020*"game" + 0.016*"high" + 0.016*"race" + 0.012*"always" + 0.012*"many" + 0.010*"hat" + 0.010*"send" + 0.009*"be"	59	Promotion for the release of Destiny 2

Table 1: Rockstar Energy tweets by topic

Out of 1793 tweets related to Rockstar Energy, a total of 1083 tweets were included in the final topic group after filtering out the noise and preprocessing process. The tweets are sorted to 7 topics as shown in Table 1.

The most popular topic in analysis covers the evaluation of the taste of rock star energy. Looking at each Twitter message in the topic, the assessment for the taste is mostly turned out to be negative. It includes evaluation for the new product and reviews for the various product lines launched by Rockstar Energy.

The second most popular topic in the analysis represented a diverse public conversation about the Rockstar Energy Husqvarna Factory Racing Team, an off-road motorcycle racing team sponsored by Rockstar Energy. The topic was dominated by rally racing game schedule that Husqvarna participates and also the rally result of those games. It also includes talks about the performances of the athletes belonging to the team.

The third topic is about the effect of drinking Rockstar Energy in enhancing alertness. It emphasizes the functional aspects of beverages and tends to accompany the purpose of drinking rock star energy and describe the context of its consumption.

The fourth topic is composed of messages about specific athletes in Husqvarna Factory. It addresses two phases of issues. One is about Dean Wilson's transfer to Rockstar Energy Husqvarna Factory Racing team. His return to Rockstar Energy Husqvarna Factory Racing team was announced at the beginning of February, at the time of data collection, and the tweets in this topic reveal public reaction to the news. The other is the injury of Jason Anderson, 2018 Supercross Champion, and his incapacity to participate 2019 Supercross for the title defense.

The fifth topic includes the conversation about the performance of Rockstar Energy Husqvarna Factory Racing team in the 2019 Dakar Rally held from January 6th to 17th 2019. The sixth topic covers the comments about Motocross World Championship(mxgp), the premier championship of motocross racing, whereas the seventh deal with the partnership between YOKO, one of the original motocross brands, and Rockstar Energy Husqvarna Factory Racing team.

The last topic includes the conversation about Destiny 2, a video game available through PlayStation 4 and Xbox. Rockstar Energy partnered with Destiny 2 and went through promotion by releasing limited edition can with Destiny 2 features, and also Destiny 2 players were able to gain bonus benefit in the game when purchasing Rockstar Energy drinks.

4.1.1. Summary

The study divided Twitter talks on Rockstar Energy into eight topics, most of which were related to Rockstar Energy Husqvarna Factory Racing Team, an off-road motorcycle racing team sponsored by Rockstar Energy. The conversation included its participation and update of the team's performance in racing rallies, the athletes in the team and the partnership team made with the manufacturers such as Yoko.

Other topics covered dynamic conversations about the Rockstar Energy Drink product itself. For example, they consist of review on the tastes of the beverages or comment on its effect on alertness enhancement. The evaluation of the taste of the product is mostly negative.

4.2. MONSTER ENERGY

	Gensim LDA Topic	n	Description of Topic
1	0.309*"monster" + 0.306*"energy" + 0.086*"drink" + 0.017*"go" + "0.008*"love" + 0.007*"free" + 0.007*"people" + 0.006*"game" + "0.005*"yamaha" + 0.005*"give"	3218	Support for the activities of Monsters Energy Drink
2	0.121*"nascar" + 0.120*"series" + 0.114*"cup" + 0.032*"new" + "0.022*"las_vegas" + 0.019*"driver" + 0.017*"last" + 0.013*"big" + "0.012*"season" + 0.011*"auto_club"	1097	Conversation about Monster Energy NASCAR Cup Series
3	0.063*"ticket" + 0.031*"fold" + 0.030*"speedway" + 0.027*"grab" + 0.024*"atlanta_motor" + 0.024*"daytona" + 0.020*"honor_quiktrip" + "0.015*"winner" + 0.013*"tour" + 0.012*"follow"	747	Updates on Daytona 500 of Monster Energy NASCAR Cup Series
4	0.152*"race" + 0.057*"team" + 0.048*"take" + 0.043*"day" + 0.017*"kawasaki"+ 0.016*"action" + 0.014*"lap" + 0.013*"joe_gibb" +0.013*"finish" + "0.013*"photo"	711	Updates on The Monster Energy® Kawasaki race team
5	0.043*"see" + 0.040*"watch" + 0.034*"sunday" + 0.024*"post" + 0.023*"wear" + 0.022*"favorite" + 0.021*"ama" + 0.020*"championship" + 0.020*"buy" + "0.016*"shirt"	603	Broadcast Schedule for Daytona 500 of Monster Energy NASCAR Cup Series
6	0.066*"win" + 0.044*"live" + 0.041*"racing" + 0.039*"look" + 0.029*"top" + "0.017*"tonight" + 0.017*"thing" + 0.017*"name" + 0.016*"play" + "0.015*"great"	579	Information on upcoming racing series with live stream link
7	0.174*"supercross" + 0.106*"atlanta" + 0.027*"detroit" + "0.022*"triple_crown" + 0.021*"official_videogame" + 0.015*"argentina" + "0.014*"sale" + 0.014*"february" + 0.010*"kick" + 0.010*"preview"	542	Conversation about Monster Energy AMA Supercross Championship
8	0.034*"guy" + 0.023*"do" + 0.022*"coffee" + 0.022*"sleep" + 0.022*"pack" + 0.021*"second" + 0.019*"can" + 0.018*"much" + 0.012*"caffeine" + 0.012*"ahead"	506	Effect of Monster Energy Drink

Table 2: Monster Energy tweets by topic

9	0.050*"know" + 0.044*"start" + 0.039*"car" + 0.033*"back" + "0.026*"yamaha_motogp" + 0.015*"cold" + 0.015*"end" + 0.012*"always" + "0.011*"put" + 0.010*"visit"	542	Talk about Monster Energy Yamaha MotoGP
10	0.050*"video" + 0.031*"say" + 0.030*"full" + 0.025*"official" + "0.023*"week" + 0.020*"stage" + 0.018*"report" + 0.016*"sit" + 0.015*"show"+ 0.013*"schedule"	482	Share of the official trailer of video game. Monster Energy Supercross
11	0.022*"black" + 0.018*"eat" + 0.017*"next" + 0.017*"enjoy" + 0.016*"help" + "0.016*"high" + 0.015*"zero_ultra" + 0.014*"drinking" + 0.014*"turn" + "0.014*"experience"	458	Taste of Monster Energy Ultra Series
12	0.060*"weekend" + 0.023*"check" + 0.021*"bike" + 0.020*"find" + 0.017*"ford" + 0.017*"home" + 0.012*"round" + 0.010*"que" + 0.008*"hab" + "0.008*"wilvo_yamaha"	422	Updates on Monster Energy Wilvo Yamaha MXGP Team
13	0.038*"need" + 0.023*"want" + 0.023*"event" + 0.022*"partnership" + 0.017*"hour" + 0.016*"stay" + 0.015*"motorsport" + 0.013*"xfinity" + 0.012*"mix" + 0.012*"awake"	410	Conversation about NASCAR Xfinity Series

Table 2: Monster Energy tweets by topic

Out of 31173 tweets related to Monster Energy, a total of 12054 tweets were included in the final topic group after filtering out the noise and preprocessing process. The tweets are sorted to 13 topics as shown in Table 2.

The most popular topic consists of a range of conversations representing support for the brand. Within the topic, many comments show an affinity for something related to the brand, ranging from the product itself and the brand logo to a team and its athlete that Monster Energy supports.

The second most popular topic covers the comments about Monster Energy NASCAR Cup Series, a top racing series of the National Association for Stock Car Auto

Racing. Most of the Twitter messages on that topic talk about a particular player as well as the game schedule or reaction to the result of the game.

The third and fifth topic deals with Daytona 500 of Monster Energy NASCAR Cup Series. Daytona 500 is a 500-mile-long motor racing series held at Daytona Beach, Florida on February 17th, 2019. The comments consist of any updates on the game per se, including the schedule, line-up and the result. Further, conversation sharing information on the broadcast schedule was prevalent in this topic too.

The fourth, ninth and twelfth topic deals with Monster Energy's sponsorship for motocross racing teams, such as The Monster Energy® Kawasaki race team, Wilvo Yamaha MXGP Team and Monster Energy Yamaha MotoGP. The tweets in this topic mostly cover their participation to Monster AMA Supercross Championship and also discussion on the performance of specific players in the teams.

The dominant comments of the sixth topic were sharing the information of various racings supported by Monster Energy, focusing on their upcoming schedules and available link to watch live stream video for the games.

The seventh popular topic includes the conversation about Monster Energy AMA Supercross Championship. The comments in this topic cover the line-up for the racing held on February 23nd in Detroit and another held in May 2nd in Atlanta. They mainly focused on about Triple Crown Champion of Super Cross Championship 2019. Triple Crown is a new racing format newly implemented in 2018, in which the results from the three races are tallied to declare a champion of it. The first of these three games were held in Arnhem on January 19, and the second was held in Detroit on February 23, and thus there were active discussions on Twitter about who would be the winner during the data collection period, January and February.

The tenth topic is about Monster Energy Supercross Video Game, a fast-paced bike racing game that allows players to feel the excitement of Monster Energy Supercross Championship. The tweets with official trailer video of the game are dominant in this topic.

The eighth and eleventh topic focused on the product of Monster Energy itself, by covering the conversation on the various flavors that Monster Energy launched, especially Monster Energy Ultra series. They also include the discussion on its high caffeine content that prevents drowsiness.

4.2.1. Summary

The tweets related to Monster Energy is divided into 13 topics, most of which are related to extreme sports that Monster Energy offers sponsorship. They are divided into two phases. One is motorcycle racing, and the other is auto racing. When it comes to motor racing, the topics cover various conversations about a various form of racings held under the Monster Energy AMA Supercross, and the motor racing teams sponsored by Monsters Energy: Monster Energy Yamaha MotoGP, Monster Energy Wilvo Yamaha MXGP Team. Another topic represents another sponsorship of Monster Energy to Monster Energy NASCAR Cup Series, the top racing series of the National Association for Stock Car Auto Racing. One of the topics, also related to extreme sports, included the comments on official trailer Monster Energy Supercross video game, which implemented the dynamic of Supercross series into game format.

There is also a topic on Monster Energy Drinks itself, focusing on the high caffeine content of the beverages and its effect. Further, among the product lines, Monster Energy Ultra series was mentioned the most in the conversation on Twitter.

4.3. RED BULL

	Gensim LDA Topic	n	Description of Topic
1	0.336*"red" + 0.333*"bull" + 0.019*"get" + 0.006*"vodka" + 0.006*"will" + 0.004*"final" + 0.004*"love" + 0.004*"track" + 0.004*"man" + 0.004*"big"	26533	Context of consuming Red Bull
2	0.047*"drink" + 0.042*"go" + 0.036*"day" + 0.026*"coffee" + 0.024*"need" + 0.020*"coffee" + 0.018*"today" + 0.018*"work" + 0.015*"take" + 0.011*"die"	9403	Effect of Red Bull
3	0.065*"ferrari" + 0.037*"merced" + 0.019*"make" + 0.019*"toro_rosso" + '0.019*"honda" + 0.016*"mclaren" + 0.015*"still" + 0.010*"mercede" + 0.010*"van" + 0.010*"taste"	7727	Conversation about Scuderia Toro Rosso
4	0.050*"gasly" + 0.030*"crash" + 0.018*"know" + 0.017*"race" + 0.011*"try" + 0.010*"live" + 0.010*"also" + 0.009*"pista" + 0.009*"ricciardo" + 0.008*"music"	7727	Crash of Pier Gasly in Barcelona Formula one pre-season testing
5	0.021*"car" + 0.019*"testing" + 0.016*"arena" + 0.015*"max_verstappen" + 0.014*"do" + 0.008*"brasil" + 0.007*"news" + 0.007*"hand"+ 0.007*"wait"	6982	Comments about Max Vestappen in Red Bull F1 Racing Team
6	0.034*"time" + 0.027*"team" + 0.019*"look" + 0.016*"hour" + 0.016*"show" + 0.013*"really" + 0.011*"bring" + 0.010*"night" + 0.010*"way" + 0.010*"can"	6982	Conversation about Red Bull Racing Team

Table 3: Red Bull tweets by topic

Out of 197727 tweets related to Red Bull, a total of 93099 tweets were covered in the final topic group after filtering out the noise and preprocessing process. The tweets are sorted to 13 topics as shown in Table 3.

The most dominant topic around Red Bull about the liking for the brand and the context of consuming Red Bull, focusing on the style of mixing Red Bull with Alcohol, especially vodka. Studies have found that the popular trend of alcohol mixing with energy

drinks among college students in the U.S. (Mary, Thomas, Scott, Ashley, & Mark, 2008; Pennay & Lubman, 2012)

The next popular topic covers the comments about the effect of Red Bull in boosting the energy and relieving the fatigue. Most describe the situation of when and why drinking Red Bull. What is unusual is that the effects of Red Bull are often compared to coffee, and comments in this topic reveal that these two stimulants are often consumed together to maximize the effect of caffeine.

The third topic covers many conversations about Scuderia Toro Rosso, one of the two Formula One teams(F1) owned by Red Bull. In this topic, racing teams owned by vehicle manufacturers such as Ferrari and Honda are mostly mentioned as a competitor of Scuderia Toro Rosso. The other Formula One team sponsored by Red Bull is Red Bull Racing which is covered through the last topic.

The fourth topic consists of comments of reaction to the crash accident of Pierre Gasly, a French racing driver in Red Bull Racing, during the pre-season testing in Barcelona on 28th February. The fifth topic was also about Max Verstappen, an athlete of the same team. The comments in this topic presented the supports for him and included the update on his participants and performance in Formula One racings.

4.3.1. Summary

The tweets about Red Bull was divided into seven topics. Most of the topics include the various conversation about Formula One (F1). Notably, the domain of comments was about the F1 racing teams sponsored by Red Bull, Red Bull Racing Team and Scuderia Toro Rosso. The Twitter messages that correspond to each topic consists of updates of teams' racing schedules, the result of games and also mentions supporting specific racing athletes.

The topic related to the functional aspect of Red Bull also prevailed. Another topic that took up a large portion of Twitter messages on Red Bull was about drinking Red Bull with alcohol, especially Vodka. There was also a topic consisting of conversations that mention the stimulating function of Red Bull. Noteworthy is the number of tweets that mention side effects of overconsuming caffeine in Red Bull.

Chapter 5 - Conclusions and Discussion

This chapter endeavors to present the result of the research and provide insight into what the result means concerning consumer-brand relationship and brand admiration. Furthermore, the chapter aims to open up the possibility of applicability of this exploratory research for brand management strategies over a range of industries and offer recommendations for future research.

5.1. Summary of Important Findings

With the proliferation of new brands and products, it is essential to know what consumers think and feel about the brand to increase its competitiveness in the marketplace. This study endeavors to explore how Twitter is used to conduct the conversation on certain brands, to classify the conversation and identify the prevalent theme. Also, the study aims to investigate the public perception of the brand and further gain the insight to allow fostering the better consumer-brand relationship.

While the research conducted a case study regarding the brands in Energy Drink Industry in the U.S., a similar approach could be used for other industries. One key implication from this study is that it adopted the constructs of brand admiration and measured consumer-brand relationship through public conversation existing on social media. This means by examining how consumers value the 3Es of benefits from the offering of the brands, the stakeholders of the company can develop more valuable branding strategies and make their communication effort much more effective.

The aggregated data and the result of its analysis aims to provide the ground for answering the research question, accompanying theoretical reflection. The initial insights found in this study can be used as a foundation for future research examining the

relationship between consumers and brand, and further, suggest a concrete strategy to strengthen brand equity.

5.2 CONCLUSIONS

With the growth of the energy drink industry and the population increase of its main consumer segment, energy drink brands are expanding their social media advertising proportion, and conversation on each brand have also been increased in social media (Miller, 2008; Mintel, 20718; Hammond & Reid, 2018)

According to brand admiration management model suggested by Park et al. (2016), the capability of the brand to provide enabling, enticing and enriching benefit to consumers plays a pivotal role to build a stable and positive consumer-brand relationship. Those 3Es are the drivers that yield to consumers brand trust, love and respect for the brand. Based on the brand admiration management system, the purpose of this case study was to provide insight to examine the consumer-brand relationship of three energy drink brands in respects with the value of 3Es.

The study uncovered the public conversation and examined pervasive themes and trending topics for each brand. The result revealed that the topics of the public conversation about all three brands on Twitter were mostly related to extreme sports such as motorcycle racing, cross country racing and formula one. The prevalence of these topics in public dialogue is not surprising considering they have involved in extreme sports sponsorship as one of their main promotion strategies to engage with their main consumer segment, male aged from 18 to 34. (Mintel, 2018)

According to Keller (1993) exposure of the brand public through sports sponsorship is effective in raising brand equity, which occurs when consumers feel familiar with the

brands and associate the brand with something favorable. The research found that when three brands are mentioned on Twitter, they are mostly with extreme sports games and the teams they support. The strong presence of this topic may demonstrate the effectiveness of their sports sponsorship, which results in an enhanced brand image as well as an increase of accessibility of the name of brands in consumers' memory.

Further, the study found that the tweets corresponding to these topics present the capacity of brands to entice consumers. According to Park et al. (2016), the brand can build a healthy and positive relationship with consumers by yielding brand admiration to them. Enticing value is one of the drivers to boost brand admiration, and it is fulfilled when allowing the consumers to feel entertained, engaged and upbeat with the aid of brand. Thus, the fact that the public perceives these energy drink brands with what they are excited in including the extreme sports, athletes they support and also video games may demonstrate that the increase of brand equity and brand admiration level.

Some topics cover the enabling aspect of the products launched by the brands, which addresses the enabling benefits of the brand. They demonstrate the effectiveness of energy drinks to enhance their alertness and relieve fatigue, mentioning the high content of caffeine. Notably, it was pervasive among conversations on Red Bull, and they mentioned the tagline of Red Bull "Red Bull give you the wings" to emphasize how much they are engaged with the product in a way to boost the energy. As Park et al. mentioned (2016), consumers establish trust in the brand when it empowers them to solve the problems and control over their environments. Further, as consumers realize the brand help addressing their problems, they become dependent on the brand and foster the psychological connection with the brand. In other words, the comments eulogizing the effect of energy drinks may demonstrate that the brand provides enabling benefits to consumers, which consequently help to establish a strong and positive brand-consumer relationship.

However, the comments in this topic do not just demonstrate the enabling value of the brands in a positive tone. All three brands included tweets concerning the adverse effect of overconsuming high caffeine content products. Moreover, when it comes to Rockstar Energy, one of the topics consisted of comments revealing the negative taste of the product.

An interesting point in the results of the study is that there is a word, "love," in one of the most frequently mentioned topics of two brands: Monster Energy and Red Bull. the monster beverage and red fire analysis that is one of the most frequently mentioned topics. According to Park's research, enticing benefits of a brand allow consumers to feel love for the brand. However, the in-depth analysis for the data presents that the fact that the word "love" belongs to the topic cannot be an indicator to characterize the topic in a way to emphasize a particular aspect of 3Es. To be more specific, in terms of Monster Energy, the use of this word in the context of the topic was to reveal the general affinity of the brand itself as well as the support for the brand's enticing benefits. In the case of Red Bull, it was selected as a word to emphasize the pleasant experience when consuming the product of Red Bull, which was mainly accompanied by the experience of drinking it with vodka. In other words, it may be appropriate to interpret the incident presence of the word, “love”, in topics as general affection for the brand rather than the evident indicator to support the specific value of 3 E, and the fact that the word is included in dominant topics affirms the positive relationship with the brands and consumers.

When it comes to Red Bull tagline ("Red Bull Gives You Wings") was mentioned to emphasize the boosting effect of the product, but at the same time, to despise and mock the brand. For example, one of the prevalent comments were comparing death caused by overconsumption of Red Bull with going to heaven with ‘wings’ that Red Bull gives to them. Just as the relationship between a brand and consumer is shaped by how much a brand gives enabling benefits to consumers, the opposite disappoints the consumers and

keeps them from building trust on the brands. Considering that there are many voices warnings about the danger of energy drinks and some countries regulate the sales of them, such conversations uncover the factor that hinders the brands from fostering the positive relationship with consumers.

What is particularly interest thing is that there was no topic related to the enriching value of the brand. It is not a positive indicator of strong brand-consumer relationship, because to the extent which brand offers enriching benefits to consumers have the most significant impact on brand admiration among 3Es (Park et al. 2013). Consumers perceive the brand enriches them when the brand reflects their values and beliefs for a better future. The enriching benefit of brands allows consumers to feel "inspired, proud, connected, validated and influential" (Park et al., 2016, p.11).

This study examined the public conversation on energy drink brands and categorized them into several topics. However, few of them hardley demonstrated how each brand support their personal value and beliefs on what is moral, right and justice.It may present the lack of public perception of the enriching benefit of each brand. Considering the importance of enabling value in building fulfilling brand equity, the result of the study provides insight where they can reinforce to strengthen their customer-brand relationship.

5.3. LIMITATIONS

There are several limitations to study. First, the sample used in this case study was collected over a short period of about two months. If the data were collected over a more extended time, the number of samples would have been increased, which would give more

validity to study. Furthermore, the more extensive data set would have found additional topics and better demonstrated broad and accurate public perception for each brand.

The study entails the limitation of secondary data analysis. Since the samples used in this study was not created to address specific research question or hypothesis, they may not contain all the content necessary to address the research questions of this study. In the same vein, “the data may not be collected for all population subgroups of interest or all geographic regions of interest” (Cheng & Phillips, 2014, p.384)

Furthermore, not all topics found in this case study specifically fit with the 3 Es that is defined above. Given that this is secondary research, samples(tweets) were not necessarily restricted to reveal the user's perception of one of the three values of the brand.

While an analysis that captured a comprehensive range of conversation from tweets offered insights about prevalent themes and topics for each brand, this does not represent all Tweeter users’ perception of each brand. It is because the sample does not include the conversation occurred from the private account users who do not allow their tweets to be shared in public due to the privacy issue. Besides, Topic modeling is often criticized for the risk of oversimplifying the data (Shafiei & Milios, 2006). Since it categorizes the information with much information into just classes of large chunks, there is a possibility that some conversations outside the prescribed topic are not reflected in the results.

It should be also noted that the of this study cannot be generalized because Twitter is a reactionary medium that reflects the current events. Thus, even if the same method is used in future research, the results may vary depending on what happens with certain brands at that time.

5.3.1. Recommendations for Future Research

While the research conducted a case study regarding the brands in Energy Drink Industry in the U.S., a similar approach could be used for other industries. Despite the limitations mentioned above, the result of its analysis provides insight to examine the relationship between consumers and brand with the value of 3Es, and further, suggest a concrete strategy to strengthen brand equity.

Future research is expected to expand this study by first collecting the data set more extended period to allow aggregating more tweets over time. Increasing time frame of collection and the number of samples in data set will allow investigating more accurate and novel insight, which were not applicable given the current data set. Furthermore, due to the nature of Twitter as a reactionary medium, the increasing timeframe would increase possibilities of catching public reaction to a range of events related to brands.

Moreover, it is recommended to implement human analysis as well as computer-based analysis to more accurately interpret topics that are difficult to predict the theme with a mere combination of words. Future research should also incorporate data from other social media platforms as well as Twitter to better understand the public's perception of the brand through conversation existing online. To extend the platform of research, especially Facebook and Instagram, the authority to collect data using API must be authorized to be studied, and advanced technology to examine the contents of images should be implemented for the analysis.

Reference

Aaker, D.A. (1991). Managing Brand Equity: Capitalizing on the value of a brand name. New York: Free Press.

Aaker, J. (1997). Dimensions of Brand Personality. Journal of Marketing Research, 34(3), 347-356. doi:10.2307/3151897

Ahuvia. (2005). Beyond the Extended Self: Loved Objects and Consumers' Identity Narratives. Journal of Consumer Research, 22 (1), 171–84.

Albert, Noël & Merunka, Dwight & Valette-Florence, Pierre. (2008). When consumers love their brands: Exploring the concept and its dimensions. Journal of Business Research, 61, 1062-1075.

Alexandra Amado, Paulo Cortez, Paulo Rita, Sérgio Moro. (2018). Research trends on Big Data in Marketing: A text mining and topic modeling based literature analysis. European Research on Management and Business Economics, 24(1), 1-7

Allem JP, Ferrara E. (2016). The importance of debiasing social media data to better understand e-cigarette-related attitudes and behaviors. J Med Internet Res. Aug 09;18(8):e219. doi: 10.2196/jmir.6185. http://www.jmir.org/2016/8/e219/

Arnould, E. J., & Thompson, C. J. (2005). Consumer culture theory (CCT): Twenty years of research. Journal of Consumer Research, 31(4), 868–882.

Aron, A., & Aron, E. N. (1986). Love and the expansion of self: Understanding attraction and satisfaction. New York, NY, US: Hemisphere Publishing Corp/Harper & Row Publishers.

Arora, S., Ge, R., Halpern, Y., Mimno, D.M., Moitra, A., Sontag, D.A., Wu, Y., & Zhu, M. (2013). A Practical Algorithm for Topic Modeling with Provable Guarantees. ICML.

Bai, X. (2011). Predicting consumer sentiments from online text. Decision Support Systems. 50, 732–742.

Batra, R., Ahuvia, A., & Bagozzi, R. P. (2012). Brand Love. Journal of Marketing, 76(2), 1–16. https://doi.org/10.1509/jm.09.0339

Blei DM (2012) Probabilistic topic models. Surveying a suite of algorithms that offer a solution to man- aging large document archives. Commun ACM 55(4):77–84

Blei DM, Lafferty JD. (2009). Topic models. In: Srivastava A, Sahami M (eds) Chapman and Hall/CRC. data mining and knowledge discovery series. Taylor and Francis Group, LLC, New York, p 71

Blei DM, Ng AY, Jordan MI. (2003. Latent dirichlet allocation. J Mach Learn Res 3(Jan):993–1022

Boiy, E., & Moens, M. (2009). A machine learning approach to sentiment analysis in multilingual web texts. Information Retrieval, 12, 526–558.

Brett, M.R. (2012). Topic modeling: a basic introduction. Journal of Digital Humanities. 2. 12-16.

C. Whan Park, Andreas B. Eisingerich, Jason Whan Park. (2013). Attachment–aversion (AA) model of customer–brand relationships. Journal of Consumer Psychology. 23(2), 229-248

Cheng, H. G., & Phillips, M. R. (2014). Secondary analysis of existing data: opportunities and implementation. Shanghai archives of psychiatry, 26(6), 371–375. doi:10.11919/j.issn.1002-0829.214171

Choi, Y. (2010). Evaluating Relationships among Brand Experience , Brand Personality , Brand Prestige , Brand Relationship Quality , and Brand Loyalty : An Empirical Study of Coffeehouse Brands.

Christidis K, Mentzas G (2013) A topic-based recommender system for electronic marketplace platforms. Expert Syst Appl 40:4370–4379 Clement

Christodoulides, George & de Chernatony, L. (2010). Consumer-Based Brand Equity Conceptualization and Measurement: A Literature Review. International Journal of Market Research. 52.

Culnan, Mary & McHugh, Patrick & I. Zubillaga, Jesus. (2010). How Large U.S. Companies Can Use Twitter and Other Social Media to Gain Business Value.. MIS Quarterly Executive. 9. 243-259.

Dan Sabbagh. (2018, August 29). Government to ban energy drink sales to children in England. The Guardian. Retrieved from https://www.theguardian.com/business/2018/aug/29/ban-sale-energy-drinks-to-children-uk-government-combat-obesity

De Chernatony, Leslie & J. Harris, Fiona & Christodoulides, George. (2004). Developing a brand performance measure for financial services brands. Service Industries Journal. 24. 10.1080/02642060412331301232.

Debortoli, S., Müller, O., Junglas, I.A., & Brocke, J.V. (2016). Text Mining For Information Systems Researchers: An Annotated Topic Modeling Tutorial. CAIS, 39, 7.

Derks, D., Fischer, A., & Bos, A. (2008). The role of emotion in computer-mediated communication: A review. Computers in Human Behavior, 24, 766–785.

Duggan, Maeve, Nicole B. Ellison, Cliff Lampe, Amanda Lenhart, Mary Madden. (2015).Social media update 2014. Pew Reseach Center URL http://www.pewinternet.org/2015/01/09/ social-media-update-2014.

Emond, J. A., Sargent, J. D., & Gilbert-Diamond, D. (2015). Patterns of energy drink advertising over US television networks. Journal of nutrition education and behavior, 47(2), 120–6.e1. doi:10.1016/j.jneb.2014.11.005

Escalas, J. E., &Bettman, J. R. (2005). Self-construal, reference groups, and brand meaning. Journal ofConsumer Research, 32(3), 378–389.

Ferjani, Madiha, Kamel Jedidi, and Sharan Jagpal (2009), "A Conjoint Approach for Consumer- and Firm-Level Brand Valuation," Journal of Marketing Research, 46 (6), 846-862.

Fournier, S. (1998). Consumers and their brands: Developing relationship theory in consumer research. Journal of Consumer Research, 24(4), 343–373.

Fournier, S. (1998). Consumers and Their Brands: Developing Relationship Theory in Consumer Research. Journal of Consumer Research, 24(4), 343-353. doi:10.1086/209515

Fournier, S., & Alvarez, C. (2012). Brands as relationship partners: Warmth, competence, and in-between. Journal of Consumer Psychology, 22(2), 177–185.

Giles, D. C., & Maltby, J. (2004). The role of media figures in adolescent development: Relations between autonomy, attachment, and interest in celebrities. Personality and Individual Differences, 36(4), 813-822. http://dx.doi.org/10.1016/S0191-8869(03)00154-5"

Gruzd, A. (2016). Netlytic: Software for Automated Text and Social Network Analysis. Available at http://Netlytic.org

Guellil, I., & Boukhalfa, K. (2015). Social big data mining: A survey focused on opinion mining and sentiments analysis. 12th international symposium on programming and systems, ISPS 2015, 132–141. http://dx.doi.org/10.1109/ISPS.2015.7244976.

Hammond, D., & Reid, J.L. (2018). Exposure and perceptions of marketing for caffeinated energy drinks among young Canadians. Public health nutrition, 21 3, 535-542 Harris JL, Schwartz MB, LoDolce M, et al. 2014. Sugary Drink FACTS 2014: Some Progress But Much Room For Improvement in Marketing to Youth. New Haven, CT: Rudd Center for Food Policy and Obesity, October.

Hruschka H (2014) Linking multi-category purchases to latent activities of shoppers: analysing market baskets by topic models. Market ZFP 36(4):267–274

J. Jacoby and R. Chestnut. (1978) "Brand Loyalty: Measurement and Management," John Wiley and Sons, New York

Jacobs BJD, Donkers B, Fok D (2016) Model-based purchase predictions for large assortments. Market Sci 35(3):389–404

Jelodar, H., Wang, Y., Yuan, C. et al. Multimed Tools Appl (2018). https://doi.org/10.1007/s11042-018-6894-4

John Stockmyer (1996). Brands in Crisis: Consumer Help For Deserving Victims, in NA - Advances in Consumer Research Volume 23, eds. Kim P. Corfman and John G. Lynch Jr., Provo, UT : Association for Consumer Research, Pages: 429-435.

Keller, K. F. (2012). Understanding the richness of brand relationships: Research dialogue on brands as intentional agents. Journal of Consumer Psychology, 22(2), 186–190.

Keller, K. L. (1993). Conceptualizing, measuring, and Managing Customer-Based Brand Equity. Journal of Marketing, 57(1), 1-22.

Keller, K.L. (2008). Strategic brand management: Building, measuring, and managing brand equity. 3rd ed. Upper Saddle River, NJ: Prentice Hall.

Keller, Kevin L. (1993), ""Conceptualizing, Measuring,and Man- aging Customer-BasedBrandEquity,""Journalof Marketing, 57 (January),1-22.

Kervyn, N., Fiske, S. T., & Malone, C. (2012). Brands as intentional agents framework: How perceived intentions and ability can map brand perception. Journal of Consumer Psychology, 22(2), 166–176.

Kim, Angella J, Eunju Ko. (2012). Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand. Journal of Business Research 65(10) 1480–1486.

Krishna, A. (2012). An integrative review of sensory marketing: Engaging the senses to affect perception, judgment and behavior. Journal of Consumer Psychology, 22(3), 332–351.

Kwon, Eun Sook, Yongjun Sung. (2011). Follow me! Global marketers' Twitter use. Journal of Interactive Advertising 12(1) 4–16.

Lazard, A. J., Saffer, A. J., Wilcox, G. B., Chung, A. D., Mackert, M. S., & Bernhardt, J. M. (2016). E-Cigarette Social Media Messages: A Text Mining Analysis of Marketing and Consumer Conversations on Twitter. JMIR public health and surveillance, 2(2), e171. doi:10.2196/publichealth.6551

Le D-T, Nguyen C-T, Coltech Q-TH, Phan X-H, Horiguchi S (2008) Matching and ranking with hidden topics towards online contextual advertising. 2008 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology

Loper, E., S. Bird. (2002) NLTK: the natural language toolkit. In Proceedings of the ACL-02 Workshop on Effective tools and methodologies for teaching natural language processing and computational linguistics. 2002.

Lynn, T., Healy, P., Kilroy, S., Hunt, G., van der Werff, L., Venkatagiri, S., & Morrison, J. (2015). Towards a general research framework for social media research using big data. In 2015 IEEE International Professional Communication Conference (IPCC) 1–8. https://doi.org/10.1109/IPCC.2015.7235843.

MacInnis, D. J. (2012). Brands as intentional agents: Questions and extensions. Journal of Consumer Psychology, 22(2), 195–198.

Magdalini Eirinaki, Shamita Pisal, Japinder Singh,Feature-based opinion mining and ranking. (2012) Journal of Computer and System Sciences,78(4),1175-1184,

Markus, H., & Nurius, P. (1986). Possible selves. American Psychologist, 41(9), 954–969

Mary T. Fajer and John W. Schouten (1995) ,"Breakdown and Dissolution of Person-Brand Relationships", in NA - Advances in Consumer Research Volume 22, eds. Frank R. Kardes and Mita Sujan, Provo, UT : Association for Consumer Research, Pages: 663-667.

Miller KE. Energy drinks, race and problem behaviours among college students. J Adol Health2008;43:490-7

Mimno, D.M., Wallach, H.M., Talley, E.M., Leenders, M., & McCallum, A. (2011). Optimizing Semantic Coherence in Topic Models. EMNLP.

Mintel. (2018). Energy Drinks - US - May 2018. Retrieved from http://academic.mintel.com.ezproxy.lib.utexas.edu/display/860443/

Mohamed M. Mostafa. (2013) More than words: Social networks' text mining for consumer brand sentiments,Expert Systems with Applications,40(10), 4241-4251

Mostafa, M.M. (2013). More than words: Social networks' text mining for consumer brand sentiments. Expert Syst. Appl., 40, 4241-4251.

Motameni R, Shahrokhi M. (1998) Brand equity valuation: a global perspective[J]. Journal of product & brand management, 7(4): 275-290.

Neumann, M., King, D., Beltagy, I., & Ammar, W. (2019). ScispaCy: Fast and Robust Models for Biomedical Natural Language Processing. CoRR, abs/1902.07669.

Ngyen TH, Shirai K, Velcin J (2015) Sentiment analysis on social media for stock movement prediction. Expert Syst Appl 42(2015):9603–9611Ngyen TH, Shirai K, Velcin J (2015) Sentiment analysis on social media for stock movement prediction. Expert Syst Appl 42(2015):9603–9611

O'Brien, M.C., McCoy, T.P., Rhodes, S.D., Wagoner, A.R., & Wolfson, M. (2008). Caffeinated cocktails: energy drink consumption, high-risk drinking, and alcohol-related consequences among college students. *Academic emergency medicine : official journal of the Society for Academic Emergency Medicine, 15 5*, 453-60 .

Oddy, Wendy & O'Sullivan, Therese. (2009). Energy drinks for children and adolescents. BMJ (Clinical research ed.). 339. b5268. 10.1136/bmj.b5268.

Pankaj Aggarwal. (2004) The Effects of Brand Relationship Norms on Consumer Attitudes and Behavior, Journal of Consumer Research, 31(1), 87–101

Park, C. W., Macinnis, D. J., Priester, J., Eisingerich, A. B., & Iacobucci, D. (2010). Brand Attachment and Brand Attitude Strength: Conceptual and Empirical Differentiation

of Two Critical Brand Equity Drivers. Journal of Marketing, 74(6), 1–17. https://doi.org/10.1509/jmkg.74.6.1

Park, C.W., Jaworski, B.J. and Maclnnis, D.J. (1986) Strategic Brand Concept-Image Management. Journal of Marketing, 50, 135-145. http://dx.doi.org/10.2307/1251291

Park, C.W., Macinnis, D.J., Priester, J., Eisingerich, A.B. and Iacobucci, D. (2010) Brand Attachment and Brand Attitude Strength: Conceptual and Empirical Differentiation of Two Critical Brand Equity Drivers. Journal of Marketing, 74, 1-17. http://dx.doi.org/10.1509/jmkg.74.6.1

Park, Cheol., Macinnis, Deborah & Eisingerich, Andreas. (2016). Brand Admiration: Building a Business People Love.

Paul M, Girju R (2009) Cross-cultural analysis of blogs and forums with mixed-collection topic models. In: Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing, pp 1408–1417, Singapore, 6–7 August 2009. c 2009 ACL and AFNLP

Paul MJ, Dredze M (2011) You are what you tweet: analyzing twitter for public health. Icwsm 20:265– 272

Pennay, A., & Lubman, D. I. (2012). Alcohol and energy drinks: a pilot study exploring patterns of consumption, social contexts, benefits and harms. BMC research notes, 5, 369. doi:10.1186/1756-0500-5-369

Quinn, K. M., Monroe, B. L., Colaresi, M., Crespin, M. H., & Radev, D. R. (2010). How to analyze political attention with minimal assumptions and costs. American Journal of Political Science, 54(1), 209– 228.

R. Ahluwalia. (2000) Examination of psychological processes underlying resistance to persuasion. Journal of Consumer Research. 27, 217–232.

Ramage, Daniel & T. Dumais, Susan & J. Liebling, Daniel. (2010). Characterizing Microblogs with Topic Models. ICWSM.

Rambe, Patient. (2017). Impact Of Social Media Advertising On High Energy Drink Preferences And Consumption. The Journal of Applied Business Research. 33. 10.19030/jabr.v33i4.9977.

Řehůřek R. and Sojka P., (2011) "Gensim-Python Framework for Vector Space Modelling," Masaryk University, Brno, Czech Republic, 2011.

Reissig, C. J., Strain, E. C., & Griffiths, R. R. (2008). Caffeinated energy drinks--a growing problem. Drug and alcohol dependence, 99(1-3), 1–10. doi:10.1016/j.drugalcdep.2008.08.001

Richins, M. L. (1994). Possessions and the expression of material values. Journal ofConsumer Research, 21(3), 522–533.

Roberts, M.E. & Stewart, B.M. & Tingley, D. (2016). Navigating the local modes of big data: The case of topic models. 10.1017/9781316257340.004.

Shafiei MM, Milios EE (2006) Latent Dirichlet co-clustering. In: Proceedings of the Sixth International Conference on Data Mining (ICDM'06). 0-7695-2701-9/06. pp 1–10

Shimp, TelTence. & Thomas Madden (1988). "Consumer- Object Relations: A Conceptual Framework Based Analogously on Stemnberg's Triangular Theory of Love," in Advances in Consumer Research, Vol. 15, ed. M. Houston, Provo, UT: Association for Consumer Research, 163 - 168.

Simon, Carol & Sullivan, Mary. (1993). The Measurement of Determinants of Brand Equity: A Financial Approach. Marketing Science, 12, 28-52. 10.1287/mksc.12.1.28.

Stahl, F., Heitmann, M., Lehmann, D. R., & Neslin, S. A. (2012). The Impact of Brand Equity on Customer Acquisition, Retention, and Profit Margin. Journal of Marketing, 76(4), 44–63. https://doi.org/10.1509/jm.10.0522

Stavrianou, A, P Andritosos and N Nicloyannis. (2007). Overview and semant issues of text mining. ACM SIGMOD Record, 36(3), 23-34)

Stefan Stieglitz, Milad Mirbabaie, Björn Ross, Christoph Neuberger. (2018). Social media analytics – Challenges in topic discovery, data collection, and data preparation, International Journal of Information Management,39, 156-178

Sternberg, Robert J. (1986), "A Triangular Theory of Love," Psychological Review, 93 (2), 119–35.

Tan, A. (2000). Text Mining: The state of the art and the challenges.

Thomson, M., MacInnis, D. J., & Park, C. W. (2005). The ties that bind: Measuring the strength of consumers' emotional attachments to brands. Journal ofConsumer Psychology, 15(1), 77–91.

Trusov M, MA L, Jamal Z (2016) Crumbs of the cookie: user profiling in customer-base analysis and behavioral targeting. Market Sci 35(3):405–426

Vijayarani, S & R Janani, Ms. (2016). Text Mining: open Source Tokenization Tools – An Analysis. Advanced Computational Intelligence: An International Journal (ACII). 3. 10.5121/acii.2016.3104.

Wallace, Elaine & Buil, Isabel & de Chernatony, Leslie. (2014). Consumer engagement with self-expressive brands: Brand love and WOM outcomes. Journal of Product and Brand Management. 23. 10.1108/JPBM-06-2013-0326.

Whan Park, C & Eisingerich, Andreas & Whan Park, Jason. (2013). From brand aversion or indifference to brand attachment: Authors' response to commentaries to Park, Eisingerich, and Park's brand attachment–aversion model. Journal of Consumer Psychology. 23. 269–274. 10.1016/j.jcps.2013.01.006.

You, Xueming and Naveen Donthu (2001), "Developing and Validating a Multidimensional Consumer-Based Brand Equity Scale," Journal of Business Research, 52 (April), 1–14.

Zeng, D., Chen, H., Lusch, R., & Li, S. H. (2010). Social media analytics and intelligence. IEEE Intelligent Systems, 25(6), 13–16. http://dx.doi.org/10.1109/MIS.2010.151.