ISCTE Business School
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THE EFFECT OF COMPANY RESPONSES TO SOCIAL MEDIA NEGATIVE WORD OF MOUTH: A TEXT MINING APPROACH.

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Dissertation submitted as partial requirement for the conferral of Master in Marketing

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October 2019

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Acknowledgements

First, I want to thank my parents for being the best out there. You are the ground that I am supporting on. Even though we live miles apart and we only see each other once a year, you have been my greatest support system.

I would like to say "Thank you and I'm sorry" to my supervisor João Guerreiro for being the most patient and the most critical. Thank you for believing in this project and helping me keep believing in it when I was not and felt hopeless.

Third, I want to thank my friends. Living alone in another country for this long is not easy. You have been not only my friends, but also my family. Any of this wouldn't be possible without your endless love and support.

Finally, I would like to thank myself. Giving self-recognition is an important thing to do. You are doing well, keep going Liliane.

Abstract

Word-of-mouth (WOM) is emerging in importance for brand reputation and understanding of consumer behavior. Motivations to engage in WOM has been largely studied in marketing literature. How companies respond to WOM online was accounted in marketing literature to deliver distinguishing managerial response strategies to brands. This research project focuses on identifying which response strategy is the most crucial to make customers satisfied after a negative WOM. Text mining and sentiment analysis were used in order to draw conclusions from actual online consumer behavior. Negative WOM (NWOM) was extracted from different brand pages on Facebook, as well as the responses from the companies to these NWOM and the reaction from the NWOM's writer to the brand's response. A literature-based framework using Davidow's Facilitation, Apology and Attentiveness, and Benoit's Corrective Action was tested on the data. Further moderation analysis was conducted to test effects of NWOM's polarity and industry on the relationship between the responses and satisfaction. Results reveal that Facilitation is important to response satisfaction. Whenever brands re-directed original NWOM writers to formal complaint means, their satisfaction increased. This was especially true for hospitality and e-commerce industries. Reversely, for hospitality and e-commerce industries, Apology had a negative impact on response satisfaction. Results yielded that Attentiveness decreased response satisfaction when polarity was a moderator. Managers should provide effective means for consumers to voice their disappointment and not rely on apologies alone. Future research should tackle more in depth the intricacies of languages and the distinction of complainers and brand haters on response strategies.

Keywords: NWOM; response satisfaction, online, consumer behavior

JEL Classification System: M31 - Marketing; M37 – Advertising

Resumo

O *word-of-mouth* (WOM) está a crescer em importância no ramo da reputação da marca e a compreensão do comportamento do consumidor. As motivações para engajar em WOM tem sido amplamente estudado na literatura de *marketing*. A forma como as empresas respondem ao WOM *online* foi contabilizado na literatura para fornecer às marcas estratégias de resposta diferenciadas. Este projeto concentra-se em identificar qual a estratégia mais crucial para satisfazer os clientes. O método escolhido foi o *text mining* e *sentiment analysis* devido à necessidade na literatura de obter respostas sobre comportamentos reais de consumidores. Extraímos WOM negativo (NWOM) de diferentes páginas de marcas no *Facebook*, as suas respostas e a reação dos escritores do NWOM a essas respostas. Um modelo da literatura utilizando *Facilitation*, *Apology*, *Attentiveness* de Davidow e *Corrective Action* de Benoit, foi construído. Análises de moderação foram realizadas para testar os efeitos da polaridade e da indústria da NWOM na relação entre os tipos de respostas e a satisfação. Os resultados revelam que *Facilitation* é importante para a satisfação. Quando as marcas redirecionavam os escritores da NWOM para meios formais de reclamação, a sua satisfação aumentava. Revela-se verdade para as indústrias de hospitalidade e *e-commerce*. Adicionalmente, *Apology* teve impacto negativo na satisfação. *Attentiveness* diminui a satisfação quando a polaridade é moderador. Os gestores devem construir melhores meios de reclamações e não contar somente nas suas desculpas. Futuros investigadores devem abordar a complexidade das línguas e a distinção entre escritores de reclamações e aversão à marca nas estratégias de resposta.

Palavras-chave: NWOM, satisfação de resposta, *online*, comportamento do consumidor

Sistema de Classificação JEL: M31 – Marketing; M37 – Advertising

Table of Contents

1. Introduction 1
2. Literature Review and Theoretical Framework 3
2.1 Web 2.0 and Technology Adoption 3
2.2. Word-of-Mouth and Electronic (WOM) 5
2.3 Negative Word-of-Mouth (NWOM) 7
2.3.1 Electronic Negative Word-of-Mouth (e-NWOM) 7
2.3.2 Sources of NWOM: Service Failure, Attribution Theory and Anger 9
2.3.3 Literature-based typification of social media NWOM 11
2.4 Managing NWOM 12
2.4.1 Perceptions of Justice in service recovery 13
2.4.2 Response strategies to NWOM 14
3. Methodology 20
3.1 Research Approach 20
3.2 Secondary Data Extraction 21
3.3 Quantitative Research 22
3.3.1 Text Mining 22
3.3.2 Design and Dictionaries 23
3.3.3 Sample 26
3.3.4 Results 28
4. Conclusion 39
4.1 Discussion and Managerial Implications 39
4.2 Limitations and Future Research Directions 42
5. References 44
6. Appendix 56
Appendix 1 56
Appendix 2 57
Appendix 3 58
Appendix 4 60
Appendix 5 61
Appendix 6 62
Appendix 7 64
Appendix 8 65
Appendix 10 66
Appendix 11 67
Appendix 12 68
Appendix 13 69

List of Figures and Graphs

Figure 1 Proposed IACM model by Erkan and Evans 4
Figure 2 Benoit's Image Restoration Strategies.. 17
Figure 3 Main model derived from literature review 19
Figure 4 Types of data collected.. 21
Figure 5 Percentage words used of NWOM types in each industry............................ 29
Figure 6 Average revenge usage by industry 30
Figure 7 Average threat usage by industry 30
Figure 8 Average warning usage by industry.. 31
Figure 9 Average polarity usage by industry.. 31
Figure 10 Percentage words used of brand responses types in each industry 32

List of Tables

Table 1 Company Response Types Dictionary.. 24
Table 2 Online NWOM Types Dictionary 25
Table 3 Sample characteristics and distribution 26
Table 4 Final sample distribution 26
Table 5 Top 10 most used words on the retrieved data set of NWOM 28
Table 6 Total words used of NWOM types and brand response types......................... 29
Table 7 Correlation Matrix of corporate responses with Response Satisfaction......... 33
Table 8 Summarized results of linear relationships and moderation analysis............. 35
Table 9 Summarized results between Facilitation and R. Satisfaction on Hospitality 36
Table 10 Summarized results between Facilitation and R. Satisfaction on E-Commerce 36
Table 11 Summarized results between Apology and R. Satisfaction on E-Commerce and Hospitality... 37
Table 12 Influence of Polarity in moderating Attentiveness and R. Satisfaction....... 37
Table 13 Hypothesis results summary 38

1. Introduction

The rise of Web 2.0 facilitated the emergence of a new kind of word-of-mouth (WOM), the electronic word-of-mouth (e-WOM). This new kind of WOM is fast-paced, easily available and more informative (Constantinides and Fountain, 2007; Erkan & Evans, 2016). However, before the internet, people relied on company-controlled information like ads and press releases. The most credible source for these consumers was the experience friends and family had with a certain product (Constantinides and Fountain, 2007). Now, about 78% of consumers trust online reviews just as they would trust their friends and family (Murphy, 2018).

For consumers who need help deciding on what to consume, product review is a major decision-making tool. The information retrieved from an online word-of-mouth review has to be of value to the consumer who is reading (Cheung et al., 2009; Liu and Zhang, 2010; You et al, 2015). These consumers are highly influenced by the content and emotions behind the review which, consequently, means continuing or retracting from purchasing (I. Erkan & Evans, 2016; Gu, Park, & Konana, 2012; Luo, Huang, Chen, Xie, & Fan, 2018).

Negative word-of-mouth (NWOM) is perceived as information of higher value to the consumer for decision-making in comparison to positive word-of-mouth (PWOM) (Relling, Schnittka, Sattler, & Johnen, 2016). If these consumers encounter a negative review they are likely to not purchase the said product or service. In a recent survey 94% of respondents stated that an online review has convinced them to avoid a business (ReviewTrackers, 2018). Even though there are more PWOM available than NWOM, to even out the impact of NWOM it is required that positives are of larger volume than negatives (Melián-González, Bulchand-Gidumal, & González López-Valcárcel, 2013). This is important as company reputation is reflected on e-WOM (Casidy & Shin, 2015; H.H. Chang, Tsai, Wong, Wang, & Cho, 2015; Hong & Yang, 2009).

Responding to NWOM online affects reputation and satisfaction positively as it influences consumers' justice perceptions (Saleem et al, 2018; Gelbrich & Roschk, 2011; del Río-Lanza et al, 2009; Gursoy et al, 2007). Furthermore, replying to reviews can lead to higher ratings and volume of positive reviews in the future (Xie, Zhang, Zhang, Singh, & Lee, 2016). However, reports show that around 79% of consumers are ignored by companies after sharing a poor experience (Groove HQ, 2019).

When replying to a NWOM post, brands need to be accountable of how they phrase and show concern to the consumer's negative experience. Different responses yield different perceptions and levels of attribution of fault (of the service failure) (H.H. Chang et al., 2015). Available research body is thin when it comes to satisfaction, or consumer reaction, with response strategies.

Recent studies have somehow studied how firms respond to electronic negative word-of-mouth (H.H. Chang et al., 2015; Dutta & Pullig, 2011; Esmark Jones et al., 2018; Istanbulluoglu, 2017; C. Li et al., 2018; Sparks, So, & Bradley, 2016; Xie et al., 2016). However, this research looks on a different spectrum that is still to be addressed: it questions actual consumers' behavior. Instead of conducting interviews and questionnaires to predict behavior, we look at actual online consumer behavior by extracting real reviews, company responses and reactions. Often when conducting surveys or interviews, subjects are conscious that they are taking part of a study and responses are likely to be biased not minding the probable existence of a gap between perception (of their own behavior) and reality (their real behavior) (Hox and Boeije, 2005).

We extracted reviews and comments from Facebook. Although unstructured data such can come from various sources such as heavy documentation, videos, interviews and more, these types of unstructured data can now be found also in platforms like online communities, forums, review sites, blogs and social networks (I. Lee, 2017). By treating these data through techniques like text mining and sentiment analysis, companies aim to improve customer knowledge by quantifying it (Cambria, Schuller, Xia, & Havasi, 2013; Fan et al., 2006).

The current dissertation uses text mining and sentiment analysis to deduct information from a large data set of reviews and comments. It is important to mirror real behavior using this method, because it has not been considered much in available literature and reflects more accurately how consumers handle companies responses to NOWM. We could deduce two groups of literature: the ones that studied the impact of brand responses of online NWOM (i.e: Esmark Jones et al., 2018; Sparks et al., 2016; Xie et al., 2016) and the ones that studied online NWOM using text mining (Hu, Bose, Koh, & Liu, 2012; Kim, Kang, & Jeong, 2018). Crossing these two lanes of literature is the ultimate aim of this project.

This research dissertation aims to provide valuable guide to managers to start a well-rounded customer experience plan for social media. As well as contribute to existing literature on consumer behavior and relationship marketing disciplines.

2. Literature Review and Theoretical Framework

2.1 Web 2.0 and Technology Adoption

Every day it gets easier and easier to search and to post information online. Before the Internet, consumers used to share information with their closest social ties (Brown and Reingen, 1987). However, with the Internet, and particularly after the rise of Web 2.0, consumers could reach a whole new range of people to share their experiences with.

The term Web 2.0 was proposed by O'Reilly (2005) and later, Constantinides and Fountain (2007) described Web 2.0 as a collection of open-source, interactive and user controlled online applications expanding the experiences, knowledge and market power of the users as participants in business and social processes. These Web 2.0 applications are based on content generated by users. As the authors explain, they symbolize a shift of market power from producers to consumers which also requires personalized media efforts.

There are five main categories of Web 2.0 and these are blogs and podcasts, social networks, content communities (websites that focus on a particular content, i.e. Facebook), forums/bulletin boards (websites that focus on idea exchanging) and content aggregators (i.e. RSS aggregates web content suited for the consumer) (Constantinides and Fountain, 2007). Kaplan and Haenlein (2010) consider Web 2.0 as a platform that sustained the growth of social media. The center of Web 2.0 is user participation, not only for consuming information but also by generating content. The authors claim that social media is a agglomerate of user generated content (UGC) which is all forms of media content created and made available by end-users (Kaplan & Haenlein, 2010).

Researchers have been studying why people use the Web 2.0 to share and consume information. For example, Sussman et al (2013) relied on the IAM model (Information Adoption Model) to argue that argument quality (relevance, timeliness, accuracy and comprehensiveness) and source credibility (source expertise and source trustworthiness) influence the usefulness of the information and consequently lead to its adoption on the Web by users. The IAM is based on the theory of reasoned action (TRA), by Azjen and Fishbein (1980), and the technology acceptance model (TAM), by Davis (1989). The theory of reasoned action (TRA) defends that behavioral intention of an individual stems from the evaluation of the behavior by that individual (attitude) and what they think is the evaluation of their behavior by others (subjective norms) (Azjen and Fishbein, 1980, as cited by Trafimow, 2010). Davis's model (1989) the technology acceptance model (TAM) is ultimately based on TRA as well, as it expands the view of TRA and focuses on technology. TAM sustains that the perceived usefulness (the belief that using the technology will increase performance) and the perceived ease of use (the belief that there are no obstacles in using technology) will motivate the consumer to use that technology. That attitude will trigger a behavioral intention and will ultimately lead to the actual system use.

In the recent years, Erkan and Evans (2016) added to IAM the need for information which, consequently, devised the IACM (Information acceptance model). The authors use the IACM to explain the influence of the information found in electronic word-of-mouth (e-WOM), in social media, on purchase intention (Figure 1). When users are in need of information and they find that the WOM's information is credible and of quality, they end up finding the information useful Cheung et al., 2009; Liu and Zhang, 2010; You et al, 2015; Erkan & Evans, 2016). Such model highlights the importance of e-WOM because the perceived usefulness of the its information will lead these users to adopt it and eventually make a purchase (Ismail Erkan & Evans, 2016).

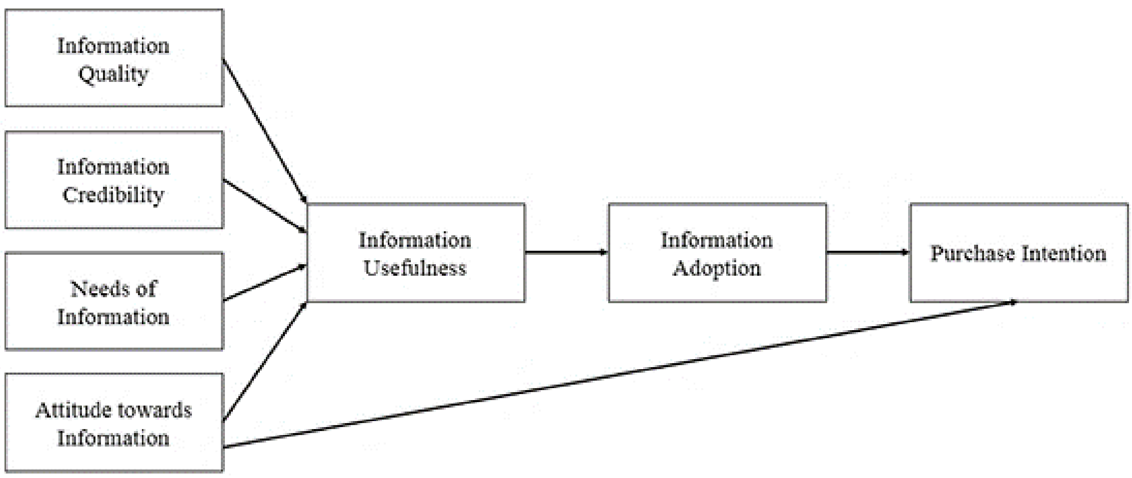

Figure 1 Proposed IACM model by Erkan and Evans (Source: (I. Erkan & Evans, 2016))

2.2. Word-of-Mouth and Electronic (WOM)

Word-of-mouth is not a new concept. Researchers for a long time have been giving the due interest in the topic because of its influence on consumer behavior (Laczniak, DeCarlo and Ramaswami, 2001; Park and Lee, 2009; Cheung and Thadani, 2012; You et al, 2015; Rosario et al 2016; Luo et al, 2018). Among many definitions, word-of-mouth or WOM is the *oral, person-to-person communication between a receiver and a communicator whom the receiver perceives as non-commercial, regarding a brand, product or service* (Arndt, 1967, as cited by Buttle, 1998, p.242).

According to Buttle (1998), the main idea that distinguishes WOM from traditional advertising is that it is made by sources that are independent from corporate influence. The author characterizes WOM by valence (it can either be positive or negative), focus (an objective to either convert the reader into a consumer or not), timing (the influence on different stages of the consumer journey), solicitation (WOM is not always sought however, when it is the input of an opinion leader is valuable), intervention (WOM is not always spontaneous, it can be intervened, for example when brands use celebrities to endorse them and create conversations).

Despite the importance of WOM for companies, the Web 2.0 has brought WOM to a new level by allowing consumers to express their opinions with others on a much wider platform: the Internet. Today, WOM moved from sharing an opinion with the consumer offline social network, to sharing the opinion over the online social network and is defined as electronic WOM (e-WOM) (Constantinides and Fountain, 2007).

Hennig-Thurau et al. (2004) defined electronic word-of-mouth (e-WOM) as any statement made by a customer (actual, potential or former) about a product, or company, and was made widely available on the internet. E-WOM is a very important tool for brands. It impacts recall and has high longevity, because it is stored on a platform and it can be accessed at any time by any user (van Doorn et al, 2010). If these e-WOM are positive and at high volumes, product sales are positively affected (You et al, 2015; Rosario et al 2016). For these users to make purchase the information must, not only be positive but also, be of relevance to them (Ismail Erkan & Evans, 2016).

Consumers like to get information from personal sources or people who are knowledgeable about the product such as opinion leaders (Solomon, 2010). With the growing use of internet and online forums to search for information, people seek a new kind of opinion leader. These opinion leaders are one of the external forces, the social influence, that directly encourages consumer purchase decision, just as explained by the theory of reasoned action (Solomon, 2010; Azjen and Fishbein, 1980). Some authors defend that even when seeking an opinion leader, the trust on the information of the e-WOM depends on what type of relationship the reader and the opinion leader have. This relationship aids e-WOM information adoption and purchase intention (Cheung and Thadani, 2012; Luo et al, 2018).

According to Cheung and Thadani's (2012) integrative model based on an extensive literature analysis, consumer's involvement has a moderating role in the relationship of e-WOM quality with information usefulness and purchase intention. Involvement is defined by *a motivational state induced by an association between an activated attitude and the self-concept* (Johnson and Eagly, 1980). This association is the identification the consumer feels with a particular product. Consumers with a high involvement are more attracted to the information quality in a e-WOM communication than with the product ratings. These consumers are in search of information, because they do not want to regret their decisions and therefore, they consider reading online word of mouth (Gu et al., 2012). Consumers with lower involvement are not as willing to make cognitive effort therefore information quality is not as important (Park and Lee, 2009).

Prospect consumers take more in consideration negative word-of-mouth (NWOM) than positive word-of-mouth (PWOM) (Yang and Mai, 2010; Park and Lee, 2009). This notion is highlighted by the fact that people are usually expecting to learn something new from these negative comments. If the information provided by the poster of NWOM is well organized and compelling it can influence the viewer's opinion about the brand (Laczniak, DeCarlo and Ramaswami, 2001). Having no negative reviews might incite suspicious looks from the consumers and they might question the trustworthiness of the source (Doh & Hwang, 2008).

Additionally, besides the source, consumers also care about the place and environment (platform) where the e-WOM communication is being distributed (Park and Lee, 2009). For a reader or a prospect consumer, when considering whether to buy or not a product, e-WOM builds expectations. Whenever the expectation created does not meet reality, the reader of the e-WOM comes to distrust the e-WOM communication and the website of the e-WOM. Consequently, this consumer turns into a NWOM writer as well. (Nam et al, 2018).

2.3 Negative Word-of-Mouth (NWOM)

2.3.1 Electronic Negative Word-of-Mouth (e-NWOM)

Negative electronic word of mouth (e-NWOM) takes many forms. It can either be a review of a product or service, a comment, a demand or furious accusations because of a company's actions. For example, in 2009, a video with the name "United Breaks Guitars" became viral and was watched by millions of people. An unknown singer called Dave Carroll rose to fame after seeking vengeance to United Airlines for his broken guitar. Dave uploaded the song on YouTube that shortly after generated negative, and somewhat humorous, buzz towards the airlines (Tran, 2009). A few days after its release the song gained nearly 4 million views and the airlines lost 180 million dollars due to it (Wrenn, 2009). Today the video was viewed by 18 million people, and still hunts the company. The company, when they could've learned from the effects of bad online negative word of mouth, failed again in 2017 when they dragged an Asian-American passenger, David Dao, by force off the plane (Selk & Aratani, 2017). This latter incident did not only cost United reputation in the USA but also traced all the way to China where furious Chinese netizens called for boycott of the company.

From a writer's perspective, to produce NWOM it often takes knowledge and experience in the brand's category as well a range of social contacts (East et al, 2007). The experience of the reviewer and the intensity of the negative emotions placed on a review or comment can damage a future consumer's attitude towards a product (Folse et al, 2016; Jones et al, 2018). If a consumer who does not have much experience (measured in the specific terms of each review website) writes a very negative review with intensely negative expressions, other consumers will be suspicious and may doubt the trustworthiness of their words. However, an expert (or experienced) reviewer will a massive influence on the readers' consumption intentions, since they are deemed as more rational and trustworthy (Folse et al, 2016).

Balaji et al (2016) studied the motivations to engage in NWOM in social networking sites (s-NWOM) from the poster perspective using the cognitive dissonance theory and social support theory. Cognitive dissonance happens through a state of inconsistency between attitudes and morals or beliefs (Festinger, 1957, cited by Kim et al, 2016). The motivations cited by the authors are: the feeling of injustice towards a service failure, the perception of self-image/reputation being damaged by the interaction had with the firm, the use intensity of social media and the strength of the relationship of the writer with the rest of users. Between peers, consumers trust their close relationships when it comes to actively sharing information about products on social media (Balaji et al, 2016; Chu & Kim, 2011; Wang et al, 2016).

From the reader's perspective, they seek communities that are formed in social networks which they identify themselves with. Simply put, different communities have different interaction goals, for that reason NWOM adoption differs (Relling et al, 2016). In social-goal communities, members are looking for peaceful coexistence and dialogue with like-minded people who share the same love for a brand or product. Therefore, NWOM is not welcome in these communities as it disrupts their environment. Whereas in functional goal communities, members seek to exchange objective and credible information about a brand and its products. NWOM in this type of community is sought for. Readers look for NWOM because they intend to collect new and diverse information. In these communities, readers and prospect consumers find the knowledgeable consumers, or opinion leaders, whom they trust and let themselves be influenced by (Chu & Kim, 2011). For these consumers, positive electronic word-of-mouth carries information to which they do not perceive as new. Which on the other hand, electronic NWOM is what helps them to make a rational decision (Relling et al, 2016).

The effect of e-NWOM was also proven to differ between hedonic and utilitarian products (Sen and Lerman, 2007). Hedonic products are the ones that seek to provide a consumption experience (i.e. concerts, luxury goods), and utilitarian products aim to be primarily functional (i.e. home appliances). Sen and Lerman's study (2007) do support that there is a negativity bias for utilitarian products. This means that for products that satisfy practical needs, consumers prefer to read more and trust more negative reviews than positive reviews. This can be reinforced by previous mentioned conclusions which defend that consumer search for e-NWOM because it is more likely to present new information. With hedonic products the situation is different. Although consumers read reviews, they do not take them to heart. The authors suggest that it is because of pre-existing expectations that are stronger from hedonic product consumers than for utilitarian products consumers (Sen and Lerman, 2007).

2.3.2 Sources of NWOM: Service Failure, Attribution Theory and Anger

Negative word-of-mouth (NWOM), as mentioned is present on social network communities and is needed for its value as an information source (Erkan & Evans, 2016; Relling et al, 2016). A consumer that writes and shares NWOM is mainly manifesting their dissatisfaction with the brand, the product or the service (Li & Stacks, 2017; Williams & Buttle, 2014; Hong & Yang, 2009). Often, this dissatisfaction is rooted on disconfirmation. Disconfirmation happens when the performance of a product or service does not meet expectations (Oliver, 1981). Seeing it like that, NWOM is a result of a service failure (Casidy & Shin, 2015; K. Gelbrich, 2010; Z. C. Li & Stacks, 2017).

Service failure affects individuals who weren't directly involved as well. Mattila et al (2014) reference them as observing consumers. The authors argue that even though these customers did not experience the service failure directly they did experience negative emotions towards the firm. Dissatisfied consumers still attribute some of the fault to the firm for the service failure, even if the consumer involved is to blame, and expect the company to make a service recovery regardless (Baker & Kim, 2018).

Attributing fault is a concept better explained by the *Attribution Theory*. Attribution theory is very much used to explain consumer behavior, including when writing or reading a negative comment or complaint (Hsin Hsin Chang & Wu, 2014; Esmark Jones, Stevens, Breazeale, & Spaid, 2018; Laczniak, DeCarlo, & Ramaswami, 2001; Zamani, Giaglis, & Kasimati, 2015). When it comes to the readers, when reading NWOM, the way it was written, the details, the expertise of the poster, the support of other consumers to that NWOM, will make the consumer attribute fault of the service failure to the brand, or company.(Hsin Hsin Chang & Wu, 2014; Laczniak et al., 2001).

Anger is another crucial lead to writing NWOM (Chung & Jiang, 2017). To relieve from disappointment, consumers start a negative evaluation of the company (Verhagen et al, 2013). This negative evaluation will lead the consumer to leave the company (exit - stop consuming), complain directly to the company (voicing), engage in NWOM or adhere to more extreme measures that aim to cause harm to the company (Li & Stacks, 2017; Trip & Grégoire, 2011).

This anger is not strictly seen on consumers of the brand. NWOM is not only communicated by consumers of a brand, non-consumers also engage in the act. This happens mainly when they do not agree with the brand's values and actions (Kähr et al, 2016). The reputation of the company is intrinsically connected to word-of-mouth. When a company has a good reputation and is seen in a good light by the public, positive WOM is very likely to be ensued among consumers and non-consumers (Hong & Yang, 2009). If they attempt an effort to service recovery, intentions of posting NWOM will decrease as reputation improves (Casidy & Shin, 2015; Hong & Yang, 2009). A bad reputation is regarded as a sign of bad quality service and products, customers will seize the part of communicating NWOM to warn other consumers (H.H. Chang et al., 2015)

Not only anger with a negative past experience leads to NWOM. Hegner et al (2017) defended that for other consumers non-identification with the brand and ideological (or moral) incompatibility also predict NWOM. For example, if brands are involved in moral situations to which the consumer is sensitive to, this consumer will develop negative feelings towards the brand. Consequently, the consumer will engage in anti-brand activism, such as NWOM (Grappi, Romani, & Bagozzi, 2013; Hegner, Fetscherin, & van Delzen, 2017).

When expressing their intense negative feelings (e.g. anger towards a brand) these writers prefer responses from companies and peers that support and approve their venting (Wetzer, Zeelenberg and Pieters, 2007, p.1321). For the actual consumer of a brand the intention varies. The consumer may want to end a relationship with a brand or not. In extreme cases, consumer brand sabotage (CBS), it happens when consumers plan a range of activities, they believe will harm the brand. This is a new construct conceptualized by Kähr et al (2016, p. 26), which signifies the extreme type of negative behaviors of consumers (and non-consumers) of a brand as they do not hope to restore their relationship with the brand or receive an apology.

In either case, we agree that the communication of negative WOM is associated with the emotions and intentions behind that communication. The writer of a NWOM might want to encourage or discourage the consumption of a product. They seek vengeance, to show off they are intelligent shoppers, or feel that they have the mission of preventing a bad experience of another consumer (Jayasimha and Billore, 2016; Sundaram et al, 1998). The latter motive shows consumer advocacy, and the more the consumer feels like an advocate the more they engage in NWOM and voicing (Chelminski and Coulter, 2011).

2.3.3 Literature-based typification of social media NWOM

The existent literature on social media and NWOM allowed us to group the common types of NWOM in social media. After a negative experience, consumers withstand a range of different feelings, catered to their individual ordeal, such as: anger, irritation, disappointment, dissatisfaction, regret, frustration, indignation and hate (Wetzer, Zeelenberg, & Pieters, 2007). These emotions will influence the content of the NWOM (Obeidat, Xiao, Iyer, & Nicholson, 2017; Wetzer et al., 2007; Z. C. Li & Stacks, 2017; Jayasimha & Srivastava, 2017).

The typification is organized from behaviors, motives or goals as of why a someone would write a negative comment or review to a brand on their social media page. Such behaviors can be distinguished as:

- **Revenge**: after a negative experience with a brand, consumers experience emotions like anger, frustration and irritation. These emotions make the consumer impulsive and are directly associated with venting and revenge (Obeidat, Xiao, Iyer, & Nicholson, 2017; Wetzer et al., 2007). They engage in online NWOM to release their frustrations by venting and using revenge as a coping behavior (Z. C. Li & Stacks, 2017; Zourrig, Chebat, & Toffoli, 2009).
- **Warning (consumer advocacy)**: regretful consumers after a negative consumption experience engage in online NWOM to warn other consumers and avoid others to experience the same (Jayasimha & Srivastava, 2017; Wetzer et al., 2007). This idea comes hand to hand to the meaning of consumer advocacy. Chelminski and Coulter (2011, p. 362) conceptualize consumer advocacy as “a generalized tendency to share market information to warn consumers so they can avoid negative marketplace experiences.”. Consumer advocacy leads to NWOM (Jayasimha & Billore, 2016). This tendency may be altruistic (Chelminski & Coulter, 2011), but it is mostly an egoistic motivation (Jayasimha & Billore, 2016). Because, they are doing it to feel better for themselves, therefore consumer advocacy is strongly motivated by egoistic reasons.
- **Threat (to leave):** Grégoire et al. (2009) illustrate online complaining as a divorce. They explain that these customers vow to leave or stop consuming the product and probably never will due to a grudge. And this grudge is held for a long period of time. These consumers experience regret and express the desire to switch (Jayasimha & Srivastava, 2017).

2.4 Managing NWOM

In an online environment the line that separates complaining (voicing) from negative word of mouth becomes a blur, because online complaining is very much expressed as NWOM. Despite having several ways to complain privately to the company, consumers choose to make their complaints public as a reference to other consumers of their situation (Ward and Ostrom, 2006; van Noort and Willemsen, 2012). Therefore, the question of how to manage public complaints and consumer venting is a relevant topic for businesses.

A study conducted by Matilla and Mount (2003), proved that when a consumer is complaining, he is expecting an immediate response from the company. When there is a delay in the response the upset consumer will readily share the dissatisfaction with others online through the complaint sites. The generated NWOM will have, as the authors described it, a snowball effect on the company's reputation. A snowball effect happens when at the beginning little damage is done to the company, and later it escalates in to a big and hazardous consequence. When consumers complain on websites, a more positive outcome comes from a positive response of another reviewer than from a brand or an employee (Jones et al, 2018). This explains a lack of trust from the reviewer to the brand after the service failure. Therefore, the brand may come better-off with brand advocates aiding in responding to negative reviews.

As mentioned earlier, deleting comments cannot be an option when managing NWOM (Relling et al, 2016). Take it from the Nestlé case in 2010. In the first semester of 2010, consumers and non-consumers of Nestlé's products stormed in their corporate page on Facebook complaining about the company's environmental mal-practice. The company had been sourcing palm oil from a local Indonesian company, which was retrieving palm oil from rainforests unsustainably (Lonescu-Somers and Enders, 2012). Nestlé responded by deleting comments and posts, and threatening trademark infringement (Keane, 2010; Fox, 2010). This action resulted in angrier responses by the online community. Greenpeace, the starter of the social media revolt, created a video denouncing the situation, which Nestlé accused it of copyright infringement on YouTube, attempting to take the video down. By the end of the day the issue only escalated. Later, Nestlé stopped deleting comments and threatening online NWOM posters and directly tackled the issue at hand. They severed ties with their palm oil source and partnered with Greenpeace and a non-profit organization, Forest Trust, to renew its palm oil supply chain (Lonescu-Somers and Enders, 2012). After these initiatives, positivity reigned once again on the corporate page where people thanked and congratulated Nestlé for doing what was right.

Nestlé's experience provides an important lesson in e-NWOM handling strategies. Deleting comments and threatening posters are not options, it may anger the online community and generate more NWOM. Management need to bear in mind that e-NWOM does not only affect future customers, it also affects current customers (Keane, 2010; Fox, 2010; Matilla and Mount, 2003).

2.4.1 Perceptions of Justice in service recovery

It is not only about noticing the consumer and responding to the service failure, but also it is about how it is delivered and how consumers perceive the fairness of service recovery effort (Joireman, Grégoire, & Tripp, 2016). Literature body on service failure and service recovery stress the importance of justice perceptions on the outcome of the recovery effort and customer satisfaction (Blodgett et al, 1997; Smith et al 1999; del Río-Lanza et al, 2009; Gelbrich & Roschk, 2011; Gursoy et al, 2007; Saleem et al , 2018; Schoefer & Ennew, 2005). There are three dimensions to the justice perception theory, and they all relate to the outcome of the service recovery to the failed consumer.

Perceptions of distributive, procedural and interactional justice improve customer satisfaction (del Río-Lanza et al., 2009; Homburg & Fürst, 2005; Smith et al, 1999). Del Río-Lanza et al (2009) studied the effects of justice perceptions on satisfaction and found that negative perceptions lead to dissatisfaction, where procedural justice (perception of the means used to resolve the conflict) proved to relay the strongest effect. Kau and Loh (2006) found that distributive justice (the perceived fairness of outcomes) had a high impact on satisfaction post-service recovery.

When a company encounters negative comments on their social media, they must act by performing an adequate service recovery. A successful, fast and effective service recovery improves levels of satisfaction and positive word-of-mouth (Istanbulluoglu, 2017; Kau & Loh, 2006; Maxham III, 2001). Many companies use the response to the NWOM as the first step to service recovery, the strategy used will influence consumer perceptions of interactional justice (Sugathan et al, 2018). Interactional justice refers to the perception of how the employees and the service provider treated the customer and it has strong effect on customer satisfaction

(Homburg & Fürst, 2005). The response to a complaint or rant online will have an effect on interactional justice, therefore it is important to review effective strategies of response in order to increase satisfaction (Homburg & Fürst, 2005; Jung & Seock, 2017).

2.4.2 Response strategies to NWOM

Marcus and Goodman (1991) grouped response strategies based on the accountability of firms to the problem: accommodative, defensive and no-action strategies. Accommodative strategies imply accepting responsibility, admitting the existence of the problem and taking actions. Defensive responses are responses denying any responsibility or implying that said problem does not exist.

When companies apply defensive response strategies consumers are most likely to attribute responsibility to the failure to the company alone (Lee & Song, 2010; Lee, 2005), they rather hear the company apologize than shifting the fault (H.H. Chang et al., 2015). On the other hand, if companies do not shift blame and sincerely take responsibility for the failure (accommodative approach) consumers will perceive the company in good light (Y. L. Lee & Song, 2010; Weitzl & Hutzinger, 2017). Other authors defend that firms should tailor each response type to each review type, for example for product service failure reviews and ordinary negative reviews (Li, Cui, & Peng, 2018; Sridhar & Srinivasan, 2012). Li et al (2018) justify that in a prospective customer point of view product failure reviews, accommodative responses had a positive impact and for ordinary negative reviews (related to dislikes, preferences, expectations and/or just a customer being unreasonable) defensive strategies worked best.

Davidow's strategies lean to the accommodative side, while Benoit's strategies support both defensive and accommodative dimensions. Benoit's image restoration theory and Marcus & Goodman's response strategies focus on the message the public should receive by the organization when the latter is attempting to fix a crisis.

Davidow's organizational response dimensions

Davidow (2000) formulated six dimensions of organizational response to complaints by consumers (Timeliness, Redress, Credibility, Facilitation, Apology and Attentiveness). Timeliness refers to the speed of response to complaints by an organization, which affects the valence of the word-of-mouth. Credibility is the organization's show of accountability to the problem and prevention of future problems Redress regards the compensation received by the company. The author found that it increases satisfaction and decreases the possibility for future NWOM. Many NWOM posters may be seeking redress when complaining. Facilitation is about leading the customer to complain through the organization's available tools. The organization facilitates complainants by creating untroublesome policies and procedures. This dimension refers to the easiness to complain and also includes the idea of empowering employees to make decisions and support the client on their own (Davidow, 2000).

On social media, companies often reply the consumer NWOM by asking them to send a private message or by sending them a link to the consumer complaint platform at their website. This type of diversion of platforms disconnects the consumer from the first employee who assists their problems by creating more hurdles for the consumer. Research defends that it is esteemed that the transference to another platform is done seamlessly and actively (Einwiller & Steilen, 2015). Consumers may feel that the company does worry about them, and consumers like when the company presents the tools to place complaints and be heard. Consumers perception of procedural justice increases (Karatepe, 2006), therefore increasing satisfaction. Therefore, we expect that in the case of social media NWOM:

- **H1: Facilitation has a positive effect on response satisfaction**

Apology is the most common dimension in most models of response to complaints and NWOM. Apology is commonly viewed as a form of psychological compensation (Davidow, 2000; Gelbrich & Roschk, 2011; Mattila & Patterson, 2004), with the objective of showing the customer that they care about their negative experience. Among his image restoration strategies, Benoit (1997) identified apology as mortification. In his point of view, apology was seen as a way to "confess and beg forgiveness" (Benoit, 1997, p. 181).

When a company apologizes, they are admitting full or partial responsibility towards the incident and, thus, apologies are included as a part of accommodative response strategies. Customers want to receive an apology (Karatepe, 2006) because they feel respected that way. Delivering apologies and recognizing the fault aids to safeguard or improve the organization's positive image (Chang et al., 2015; Lee & Song, 2010; Coombs & Holladay, 2008; Marcus & Goodman, 1991). Kim et al (2016) showed that apology had a better effect for the viewer of NWOM than for the actual consumer who experienced a service failure.

In the case of a service failure apologies are beneficial to reduce anger and desire for revenge, especially when it is combined with a compensation (Joireman et al, 2013; Jung & Seock, 2017). Other studies defended that apology alone is not enough to reduce NWOM intentions (Casidy & Shin, 2015; Duffy, Miller, & Bexley, 2006). However, in this particular study one cannot for certain know whether a compensation was delivered, for the way data was collected. The focus here is on the impact the apology has on the valence of the consequential conversation, because it is what the viewer of NWOM will see and conclude an evaluation of the company by the way it solves or cares about their consumers' problems. Therefore, we question if in a situation of online venting:

- **H2: Apology has a positive effect on response satisfaction**

Attentiveness refers to the interaction between the customer, who posted the complaint, and the employee who is addressing the complaint (Davidow, 2000, 2003). Davidow (2003, p. 243) further outlined four areas of attentiveness: respect, effort, empathy and willingness to listen. Gursoy et al (2007) defends the positive impact of attentiveness on interactional justice perceptions, which in turn has a positive effect on customer satisfaction (Homburg & Fürst, 2005; Sugathan, Rossmann, & Ranjan, 2018).

Einwiller and Steilen (2015) conducted a similar analysis but focused on corporate pages (Facebook and Twitter) and specific social media pages for complaints (i.e. Home Depot Customer Care and Microsoft Helps). The authors dissected Davidow's attentiveness dimension into: understanding, expressing gratitude, expressing regret, and inquiring further information. The results found showed that expressing gratitude increased satisfaction and expressing regret had no relevant impact on complaint satisfaction. However, when a company expressed understanding or inquired further explanation there was decrease in complaint satisfaction. Therefore, we suggest:

- **H3: Attentiveness has a negative effect on response satisfaction**

Benoit's Image Restoration Strategies

Benoit's (1997) strategies leaned to both accommodative and defensive forms. The author typified five strategies for companies in a crisis situation, the image restoration strategies. These strategies, as the author puts it, focus on the content of the communication to the public – what to say. Namely these strategies are denial, evasion of responsibility, reducing offensiveness of event, corrective action and mortification (Figure 2).

TABLE 1

Image Restoration Strategies

Strategy	*Key Characteristic*	*Illustration*
Denial		
Simple Denial	Did Not Perform Act	Coke Does Not Charge McDonald's Less
Shift the Blame	Act Performed by Another	Exxon: Alaska and Caused Delay
Evasion of Responsibility		
Provocation	Responded to Act of Another	Firm Moved Because of New State Laws
Defeasibility	Lack of Information or Ability	Executive Not Told Meeting Changed
Accident	Act Was a Mishap	Sears' Unneeded Repairs Inadvertent
Good Intentions	Meant Well in Act	Sears: No Willful Over-Charges
Reducing Offensiveness of Event		
Bolstering	Stress Good Traits	Exxon's Swift and Competent Action
Minimization	Act Not Serious	Exxon: Few Animals Killed
Differentiation	Act Less Offensive	Sears: Preventative Maintenance
Transcendence	More Important Considerations	Helping Humans Justifies Tests
Attack Accuser	Reduce Credibility of Accuser	Pepsi: Coke Charges McDonald's Less
Compensation	Reimburse Victim	Disabled Movie-Goers Given Free Passes
Corrective Action	Plan to Solve or Prevent Problem	AT&T Promised to Improve Service
Mortification	Apologize for Act	AT&T Apologized

Figure 2 Benoit's Image Restoration Strategies (Source: (Benoit, 1997))

The model for this research project considers Benoit's strategy: *Corrective Action*. This dimension has a great deal in common with Davidow's credibility dimension. However, the credibility dimension (Davidow, 2000) is about the company assuring that something will be done to prevent the problem from happening again, corrective action (Benoit, 1997a) consists in the company vowing to correct the problem. *Correcting,* as Benoit puts it, refers to the current problem at hand, opposite to Davidow's credibility dimension which looks at preventing future problems than the current problem. Therefore, for this particular project Benoit takes more in dept the definition and provides more sensical strategy for social media NWOM. Nevertheless, one has to not forget that Benoit's strategies were specifically made for a crisis situation and Davidow's dimensions for individual consumer complaints. However, companies do reply on social media vowing to correct the problem or showing interest to it (Einwiller & Steilen, 2015).

Corrective action is no doubt a crisis response strategy. A crisis being a problem of far bigger dimension than an individual service failure. On a scale crisis consumers are thankful and display positive online WOM intentions on social media when companies vow to correct the issue (Romenti, Murtarelli, & Valentini, 2014). Therefore, in this research project we want to know if the same condition applies to social media complaints and rants due to a service failure and dissatisfaction.

- **H4: Corrective Action has a positive effect on response satisfaction**

Polarity of NWOM and Industry

Expressing emotions verbally and in writing is powerful for relieving psychological stress and brings positive emotions to the individual. (Kahn et al, 2007; Cameron & Nichols, 1998; Esterling, L'Abate, Murray and Pennebaker, 1999). Different studies have tackled the issue of the intensely negative wording on NWOM, and recording the effect of it to a third-party (reader) trust in reviews and purchase intention (Folse, J. A. G., et al 2016; Luo et al, 2018). Jones et al (2018)'s research supported the argument that severely worded reviews do affect a third-party's satisfaction towards the product and the brand. However, no research article attempted to look at the side of the writer of the NWOM and how their initial emotions can affect their response satisfaction. Therefore, it is questioned:

- **H1a: The effect of facilitation on response satisfaction is moderated by NWOM's polarity.**
- **H2a: The effect of apology on response satisfaction is moderated by NWOM's polarity.**
- **H3a: The effect of attentiveness on response satisfaction is moderated by NWOM's polarity.**
- **H4a: The effect of corrective action on response satisfaction is moderated by NWOM's polarity.**

Last but not least, one needs to take into account the industries and the different types of consumers and service failure perceptions. NWOM volume and valence differ between industries with different levels of competition (You, Vadakkepatt, & Joshi, 2015). Gelbrich and Roschk (2011), asserted that interactional justice perceptions were different depending on industry type (service and non-service), when it comes to brand responses to NWOM. For service industries interactional justice had a higher impact on satisfaction (Katja Gelbrich & Roschk, 2011).

In literature a plethora of articles were published studying a specific industry when it comes to knowing the effects of NWOM or the effects of brand responses on satisfaction. Some commonly used industries are hospitality (C. Li et al., 2018; Xie, Zhang, Zhang, Singh, & Lee, 2016), e-commerce (Esmark Jones et al., 2018; Jung & Seock, 2017; Wu, 2013) or telecommunications (Ranaweera & Karjaluoto, 2017). However, little or nothing is being said about industry as moderator for response satisfaction, thus we propose studying the following:

- **H1b: The effect of facilitation on response satisfaction is moderated by the industry**
- **H2b: The effect of apology on response satisfaction is moderated by the industry**
- **H3b: The effect of attentiveness on response satisfaction is moderated by the industry**
- **H4b: The effect of corrective action on response satisfaction is moderated by the industry**

Considering the proposed hypotheses, the following model was assembled (Figure 2). Davidow's (2001) and Benoit's (1997) dimensions are considered as brand response types to predict response satisfaction. Polarity and industry serve as moderators for these relationships.

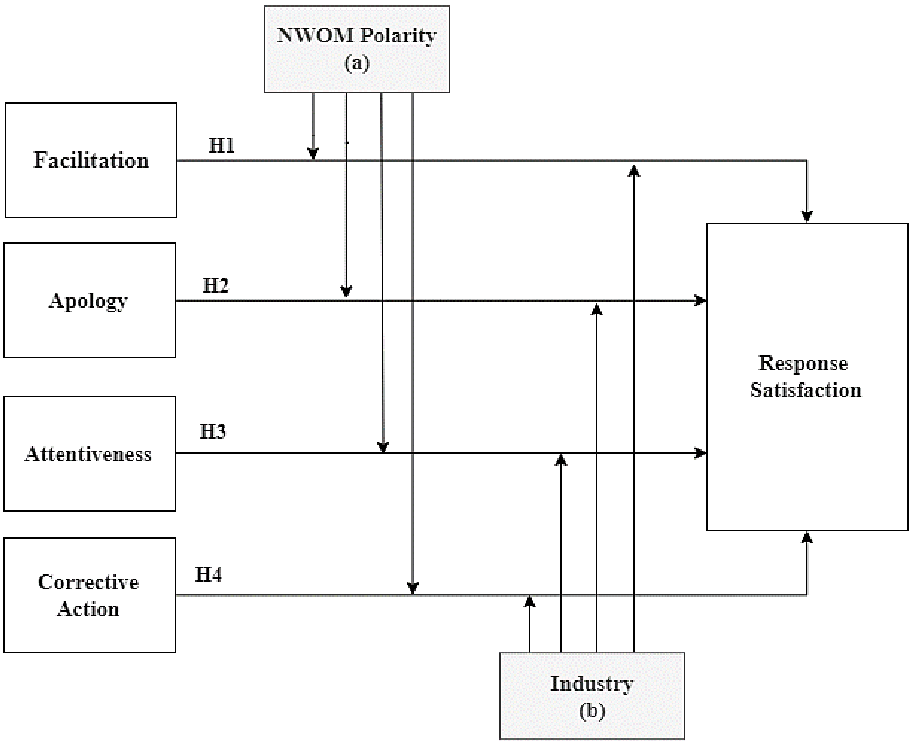

Figure 3 Main model derived from literature review

3. Methodology

3.1 Research Approach

To be able to study consumer behavior online we proceeded to extract conversations, publicly available, between them and the brand. This is a dataset of entries made of text, which is regarded to as unstructured data (Balducci & Marinova, 2018; I. Lee, 2017). Balducci and Marinova (2018) differentiate unstructured data from structured data by three characteristics: non-numeric (it is not represented by a numerical value, the researcher is the one to assign it), multifaceted (it can contain multiple types of information) and concurrent representation (one unit of data can contain multiple unique information, these information are intertwined and can be connected in different ways to show different knowledge). The rise in unstructured data comes with the emergence of Web 2.0. Vast amounts of information are stored online (I. Lee, 2017). Researchers and businesses want to work on unstructured data, transform it in to structured data so that they can learn more about consumer behavior and attitude. This complex work can be done through text mining (Miller, 2004).

By using text mining techniques, this research project purposes to ultimately learn about how brands can improve their consumer interaction skills and improve perceptions.

3.2 Secondary Data Extraction

We consider the data collected for this research project as secondary data. Secondary data refers to data collected by others, and it includes publicly available third-party data (Nachmias and Nachmias, 1992; Greener and Martelli, 2018). This data, consumer reviews, comments and reactions, and company responses, was collected through different Facebook brand pages (Facebook is the third-party making this data available). Facebook is a California-based company, has more than 2.38 billion users globally (as of 31st of March 2019) and has on average 1.56 billion active users (March 2019 average) (Source: Facebook). Facebook is a user-friendly platform for peer to peer communication or business promotion. One of the main features are company profile pages, brand pages. Anyone who wishes to communicate with the brand has different means to do it, for example: posting a comment below any posting of the company, send a private message, tag the brand on a posting made by themselves and, if they allow it, post a review with ratings on the brand page. Consumers have been increasingly using Facebook as a platform to send their reviews and complaints. Consumers have been migrating to Facebook and Google that initially were not review sites to do it, because they use these platforms on a regular basis more than they use TripAdvisor and Yelp (ReviewTrackers, 2019).

First, we proceeded a manual extraction of comments and reviews on Facebook with a negative connotation. Then, we retrieved the responses to each review and comment. Lastly, an interaction rating was given to the consumer’s response to the company’s response ranging from positive, neutral and negative reactions (Figure 4).

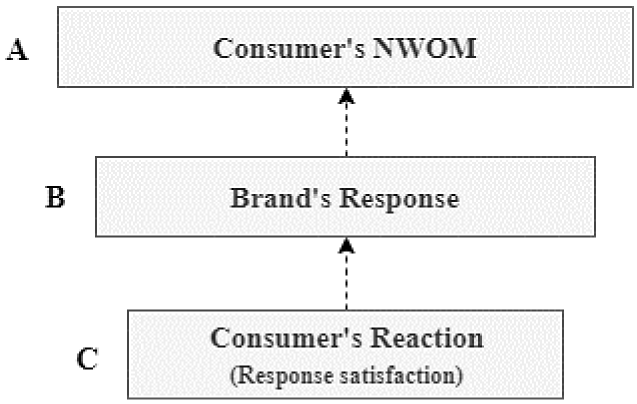

Figure 4 Types of data collected

Data in form of reviews and comments from different brand pages on Facebook were extracted to an excel file. USA-based brand pages were considered due to higher volume found and consistency with the software language. These reviews, comments and company responses were randomly selected among postings between 05 March 2018 to 05 March 2019. Several extraction rules were followed such as: only the English language was considered, no data included personal information (such as email, account number or tax identification number), only product-related or service-related comments/reviews (no mention of partner companies).

Fundamentally three columns of data were created: customer NWOM, brand response and customer reaction to the response. Customer NWOM (reviews and comments) and brand response were extracted in the form of text. Customer reaction (referred in this study as Response Satisfaction) was classified on a scale of -1 (negative), 0 (inexistent), 1 (positive). This variable regards the satisfaction of the consumer who wrote the NWOM with the brand's response. Satisfaction is a very complex concept, especially when one is talking about satisfaction with an online interaction. In this research project we are considering measuring satisfaction with the emotional outcome from the reaction the consumer had with the brand's reply to their NWOM. This reaction could either be negative, positive or inexistent. It was important to collect a data set where 0 was also an outcome to be fair and consistent. Consistent because, there are a plenty of factors that influence the emotional outcome of the reaction, for example response time, severity of the problem, the recurrence of the service failure, tone of voice, and more (Barcelos, Dantas, & Sénécal, 2018; Istanbulluoglu, 2017; Keyzer, Dens, & Pelsmacker, 2017; Tojib & Khajehzadeh, 2014).

3.3 Quantitative Research

3.3.1 Text Mining

The text mining method used reads and classifies what is communicated, either in the NWOM or in the response given by the brand. When gathering data in form of text it is considered unstructured. What text mining does is, through a diversity of techniques, it structures the data into meaningful information so that it is ready to be analyzed (Miller, 2004). Text mining combines a choice of techniques as text classification, text clustering, ontology and taxonomy creation, document summarization and latent corpus analysis (Meyer, Hornik, & Feinerer, 2008).

Sentiment Analysis is used to identify the polarity and emotion of the unstructured data (Cambria, Schuller, Xia, & Havasi, 2013). General sentiment dictionaries have been used frequently, however more researchers are opting to use object-oriented sentiment dictionary which is more accurate towards the specific object of study (Kim, Kang, & Jeong, 2018). Both techniques have had a place in literature to enlighten real consumer behavior

The software used to conduct text mining and sentiment analysis in this research project is MeaningCloud. MeaningCloud is a semantic analysis API product (application programming interface). An API allows the interaction between software components. In other words, it provides the service of one software integrated in another software. MeaningCloud uses natural language processing (NLP), or text analytics, solutions to extract insights from complex documents and interactions (unstructured data). The natural language processing technique, like the name conveys, it attempts to identify natural language. The NPL yields text mining techniques by identifying syntactic structures and natural logic in a group of words (Manning and Schutze, 1999; Gharehchopogh and Khalifelu, 2011). A text mining software supports machine learning, as well, to compliment NLP for better process automation (Gonzalez, 2019).

3.3.2 Design and Dictionaries

To enhance reliability a couple of user dictionaries were created to identify and classify keywords and lexicons most used among the data based on literature review. By uploading user dictionaries to MeaningCloud, we are able to do topic extractions and sentiment analysis. The topic extraction function in MeaningCloud, detects important generalized elements from unstructured texts such as named entities (i.e. people, organizations, places), concepts (significant keywords), time and money expressions, quantity expressions, relations and more. The sentiment analysis functionality identifies the polarity of the text submitted as data. As mentioned in MeaningCloud's website, this functionality has the ability to detect irony and polarity disagreement, differentiate facts from opinions and considers aspect-based sentiment. User dictionaries allow more precision to sentiment analysis and the detection of elements catered to what the researcher intends to study.

Dimension/Type	Description	Examples of words and expressions used	
Facilitation (Davidow, 2000; Einwiller & Steilen, 2015)	**Direct contact request**	Please send a private message	We messaged you
		Please call	We sent you an email
		Let's connect via private message	We will contact you
	Switching to platforms	Go to (link)	Reach us at
		Report at	Try these steps (link)
		Resolve tool	
Attentiveness (Davidow, 2000; Einwiller & Steilen, 2015)	**Listening and understanding**	We hear you	Customer satisfaction is our number one responsibility
		We completely understand	We want to offer the support you deserve
		We want to reassure you have a good experience	
	Inquiring further information	Can you share a little more	Can you please explain
		What happened	What issues are you experiencing
		More than happy to help	
	Expressing regret	We'd hate to see leave	Not the experience we want to hear
		It breaks my heart	We are sad to hear
		Don't want to see you go	Hate to lose you
		We are concerned	It is concerning
Apology (Davidow, 2000; Kim et al, 2016)	**Apologizing /Expressing regret**	We are sorry to hear	We are truly sorry
		Accept our most sincere apology	Regret the inconvenience
		Apologies for	Our sincerest apologies
Corrective Action (Benoit, 1997; Romenti, Murtarelli, & Valentini, 2014)	**Providing assistance**	We want to help	Do you need assistance
		We'd be happy to investigate	How can we help
		We would like to look into it	How can we turn things around
	Promising to solve the problem	Let's solve this	Let's have this resolved for you
		We want to do all we can	We're doing everything we can
		Let's get you a resolution	We can get started

Table 1 Company Response Types Dictionary

The dictionaries used for this research project were based on literature aid and what was defined by these articles as definition of each NWOM type and brand response type. We complimented these with used expressions and words from questionnaires and other research methods used in each article. For instance, Table 1 represents a summary of the words and expressions used to form a dictionary and that was derived from literature help: Facilitation: (Davidow, 2000), Apology: (Davidow, 2000; Joireman et al., 2013), Attentiveness: (Davidow, 2000), Corrective Action: (Benoit, 1997b; Romenti et al., 2014).

The focus of the project is definitely studying brand responses types, but one cannot fail to go more in depth and assist an analysis of the reviews/comments left by the customers. Therefore, we further designed a NWOM dictionary (Table 2) to help grasp the data's complexity. The dictionary was arranged combining the knowledge found in literature (Jayasimha & Srivastava, 2017; Z. C. Li & Stacks, 2017; Obeidat et al., 2017; Wetzer et al., 2007; Zourrig et al., 2009) and extracting some of the most common words for each type of NWOM. It is important to note that these dictionaries (Table 1 and 2) represent a brief summary of an extended word and expressions collection. There are various synonyms, aliases and variations of each entry that should be considered. It required partly manual work and partly machine work, from MeaningCloud, to create entries for a number of synonyms, aliases and variations.

Dimension/Type	Examples of words and expressions used	
Revenge (Obeidat, Xiao, Iyer, & Nicholson, 2017; Z. C. Li & Stacks, 2017)	It's ridiculous	Outrageous
	Thank you for nothing	Refund me
	Worst customer service	Shame on you
	Expensive	Crooks
	Frustrated	Disappointed
	A joke	Terrible Experience
Warning (Jayasimha & Billore, 2016)	Stay away!	Don't fly/shop
	Rip off	Don't go there
	Don't use	Go somewhere else
Threat (Jayasimha & Srivastava, 2017)	I'll never use again	Never again
	I am switching	Taking to court
	I am leaving	Will not go there again
	Losing a customer	I am cancelling

Table 2 Online NWOM Types Dictionary

3.3.3 Sample

Sample Size and Characteristics

The NWOM data was gathered from official brand pages of U.S-based companies where we could assure one language usage, the English language. In the period of one year, from March 2018 to March 2019, a total of 1157 random entries (reviews/comments, brand response and reactions). The telecommunications and the airlines industry had the higher amount of data collected because they demonstrated higher amount of negative reviews as they were also the most responsive industries to NWOM.

N=1157	
Country	U.S.A
Sample Time-Range	March 2018 – March 2019
Activity Sectors	Telecommunications (N=419) Airlines (N=396) Hospitality (N=167) E-Commerce (N=175)
User Typology	Writer of a negative connotated comment or review
Comment/Review Typology	Negative, with response from brand

Table 3 Sample characteristics and distribution

After collecting reviews and comments, we input the data on an excel sheet and ran the MeaningCloud program. Therefore, when considering the responses that were successfully identified in the dictionary and crossed with the reviews, the number of total entries considered for analysis decreased to 771 reviews and responses. The remaining 386 data entries were unable to match any of the words identified in the dictionaries and therefore no NWOM type or brand response type were attributed to them. For that reason, they were left out of the analysis.

N=771	
Activity Sectors	Telecommunications (N=311) Airlines (N=244) Hospitality (N=96) E-Commerce (N=120)

Table 4 Final sample distribution

Industry

Depending on the industry the consumer might have already pre-conceived expectations which can serve as bias to how they react to responses from companies. Four industries were chosen in order to obtain a more generalized conclusion of consumer behavior. Companies were carefully selected among the most popular and the highest ranking in the industry and in the US. The company list was retrieved from famed magazines, websites and associations such as The American Customer Satisfaction Index website (ACSI.org) , Forbes, Business Insider, U.S. News & World Report and eMarketer. Therefore, the entries estate from Facebook brand pages of companies such as Verizon, T-Mobile, AT&T (telecommunications), United, Delta, Southwest (airlines), Holiday Inn, Sheraton, Marriott (hospitality), Amazon and Wayfair (E-Commerce).

NWOM Polarity

Polarity is measured using MeaningCloud's sentiment analysis tool in NWOM reviews and comments. Sentiment analysis takes in to consideration the context of the text to determine whether it is positive or negative. The software analysis each word and attributes it a valence (positive, negative or neutral) and then it calculates global polarity index of that specific text entry. This variable transmits another useful piece of information that might aid to explain further NWOM posters' reactions to brand responses (Response Satisfaction). Sentiment Analysis allowed us to extract the global polarity each review. Polarity is measured from -2 to 2, being -2 equal to "Very negative" or "+N" and 2 equals to "Very positive" or "+P". Zero "0" is also included in the scale and considered as "Neutral".

3.3.4 Results

Exploratory Data Analysis

As an introduction to the research data analysis it is of relevance to study reviews first and then study the effect of the brand's response to the reviewer. We retrieved the top ten most used words by NWOM writers for each industry. By using the HTML5 Word Cloud platform we were able to get that information and after eliminating common stop words the table below (Table 5) was constructed. This analysis can be reflective of what these customers are most worried about. For the telecommunications, if we write-off the mentions of "phone" and "call", we can see that NWOM writers talked about the "service" (411 times), "customers" (383 times) and "bill" (156 times). The airlines industry had a great focus on "custom" (209 times), the "service" (161 times) and on "time" (137 times) and "hour" (148 times). The hospitality industry's customers had a focus in "service" (86 times) and the technicalities related to service such as "room", the "check" (referencing to check in or out; 80 times), the "staff" (58 times). Finally, the e-commerce industry was engrossed on service technicalities such as "order" (158 times), "delivery" (85 times), and "items" (71 times)

All industries did hold similar words related to time and service, which shows the importance of both elements on customer service and the impact on fostering NWOM.

	Telecom		Airlines		Hospitality		E-Commerce	
	Times used	Word	Times used	Word	Times used	Word	Times used	Word
1	411	service	511	flight	285	room	165	amazon
2	383	customer	240	United	153	hotel	158	order
3	377	phone	209	custom	112	stay	112	CUSTOM
4	271	call	206	airline	86	service	90	service
5	181	t-mobile	178	fly	80	check	89	day
6	156	bill	161	service	67	day	85	delivery
7	156	time	158	delta	63	time	74	time
8	150	month	148	hour	58	staff	71	item
9	129	company	137	time	54	ask	69	wayfair
10	127	now	122	seat	51	front	63	deliver

Table 5 Top 10 most used words on the retrieved data set of NWOM

Through text mining we were able to identify words and expressions linked to the NWOM types (*Revenge*, *Threat* and *Warning*) and brands' responses types (*Facilitation*, *Apology*, *Attentiveness* and *Corrective Action*). On each entry of a review and their respective response text mining is able to identify more than one word or expression linked to each type (Table 6). *Revenge* was the NWOM type that was more present in the data (942 words and expressions) meanwhile *Warning* was the least present (181 words and expressions). As for brands' response types, *Facilitation* lead with 557 words and expressions recorded and *Corrective Action* only counted with 134 words and expressions recorded in the data retrieved.

NWOM Types			Brand Response Types			
Revenge	**Threat**	**Warning**	**Facilitation**	**Apology**	**Attentiveness**	**C. Action**
942	250	181	557	347	145	134

Table 6 Total words used of NWOM types and brand response types

Starting off with NWOM types, *Revenge* type words and expressions were the most used among the NWOM attained (942 words). For each industry, *revenge* usage was above 60% (Graph 5). It was recorded on the hospitality industry that *Revenge* was used 1.5 times on average, which is the highest in comparison with the other industries.

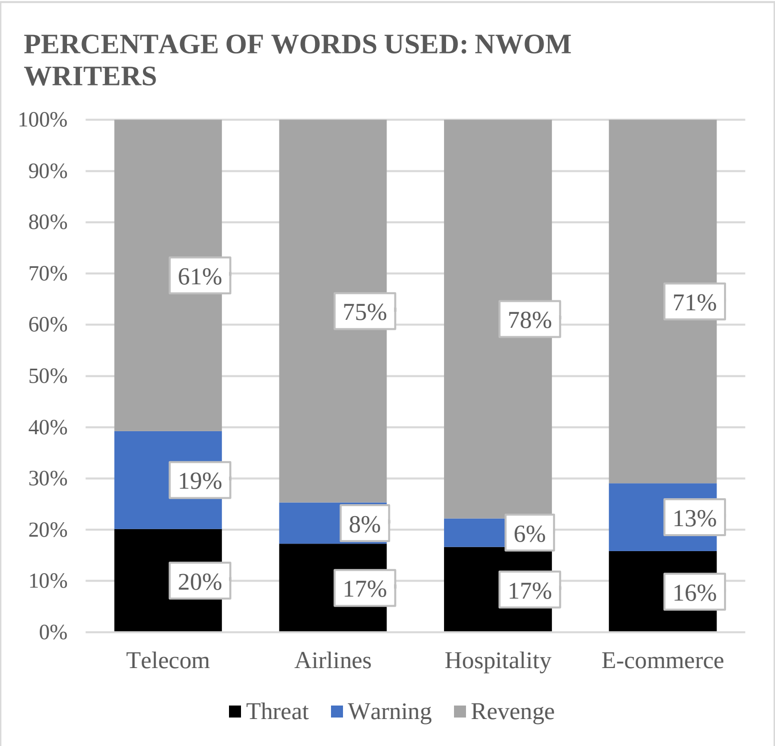

Figure 5 Percentage words used of NWOM types in each industry

Figure 6 Average revenge usage by industry

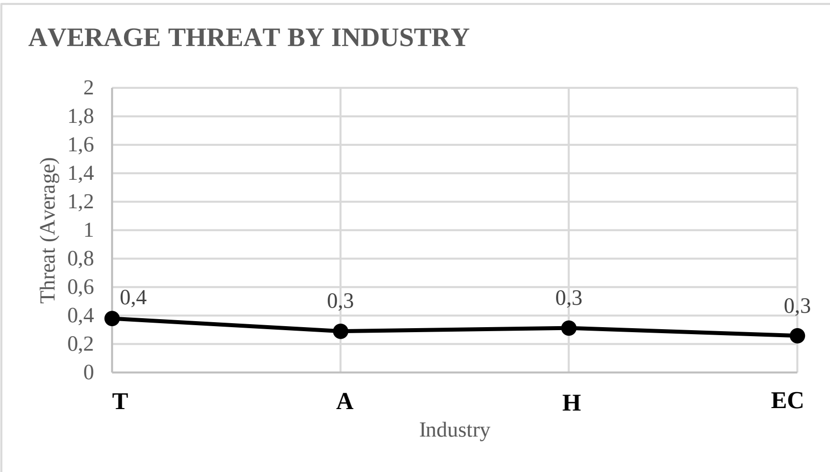

Figure 7 Average threat usage by industry

Threat and *warning* had the lowest average usage among the NWOM data in comparison to *revenge* (Graph 7 and 8). The telecommunication industry showed higher average usage of *threat* and *warning* (0.4 words). Airlines, hospitality and e-commerce presented the same average usage of threat (0.3 words). Warning was nearly non-existent for airlines and hospitality, presenting an average of 0.1 words.

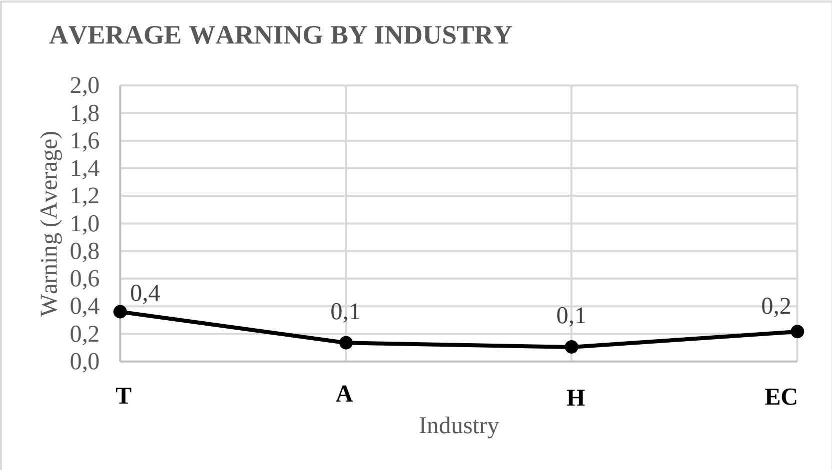

Figure 8 Average warning usage by industry

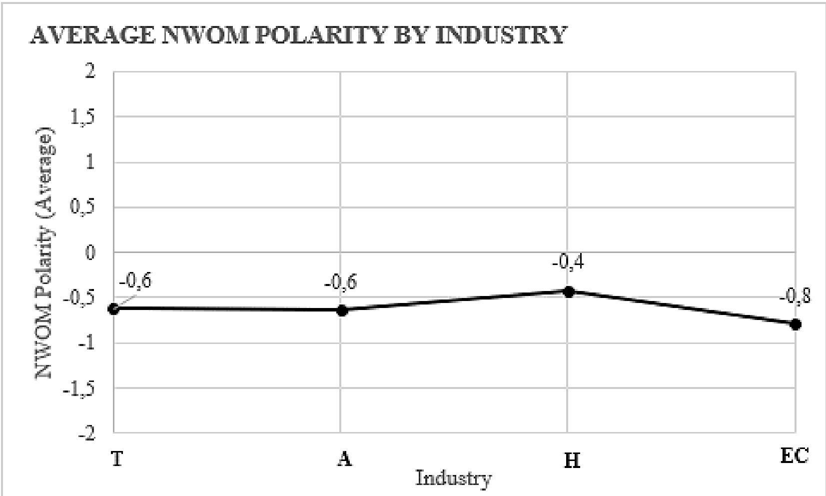

Figure 9 Average polarity usage by industry

Looking at the level of "angry" of each industry is also an interesting analysis. *Polarity* relays that information very well. As explained before, *polarity* ranges from -2 (Very negative) to +2 (Very positive). Among the complaints retrieved on average e-commerce had the most negative reviews (-0.8 words), whereas hospitality had the least angry reviews with and an average of -0.4 words.

When it comes to brand responses, there is a better distribution of strategies (Graph 3.4). *Facilitation* was the highest for telecommunications (63%) and hospitality (42%), meanwhile *Apology* was the highest for airlines (45%) and e-commerce (54%).

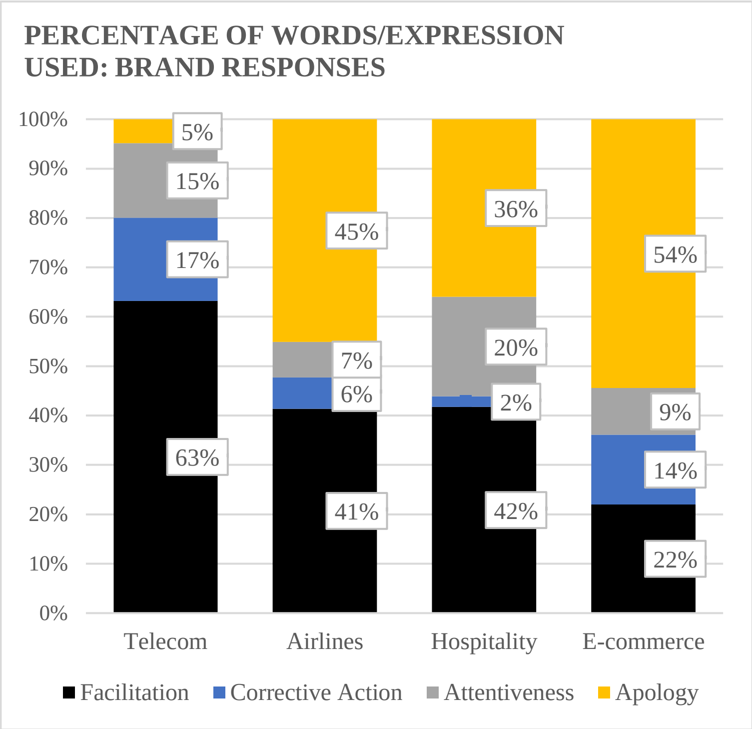

Figure 10 Percentage words used of brand responses types in each industry

The Correlation Matrix

Facilitation and Apology display a moderate negative Pearson correlation 0.47 ($r=-0.47$, $p<0.01$). This means that brands apologized less if they present the angry consumer with a mean to formally deliver their complaints. Del Río-Lanza et al (2009) mentioned how negative *procedural justice* perceptions had the highest effect on consumers' dissatisfaction among the justice perceptions. *Procedural justice* perceptions appertain to means or resources used by the brand to address their consumers' complaint or unhappiness with the service or product. Brands show a sensitivity to know that consumers desire to be listened to the most and these results reflect that.

Pearson Correlation (R)	Apology	Attentiveness	C. Action	Facilitation	R. Satisfaction
Apology	1	-0.166**	-0.047	-0.469**	-0.028
Attentiveness	-0.166**	1	-0.033	-0.132**	-0.063
C. Action	-0.047	-0.033	1	-0.024	0.003
Facilitation	-0.469**	-0.132**	-0.024	1	0.129**
R. Satisfaction	-0.028	-0.063	0.003	0.129**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Table 7 Correlation Matrix of corporate responses with Response Satisfaction

Attentiveness and Apology displayed an existent, however rather weak negative relationship between them ($r=-0.17$, $p<0.01$). Apology, Attentiveness and Corrective Action reflected nearly non-existent correlation with Response Satisfaction, which is not good for the literature-base model. This is a first step to understanding how the hypothesis test will play out. Facilitation exhibited a weak, however positive, correlation with Response Satisfaction ($r=-0.13$, $p<0.01$).

Hypothesis Testing

To test the hypothesis of the model two methods were chosen. The linear regression model and the moderation model through Andrew Hayes' PROCESS. The simple linear regression model differs from the correlation because its purpose is to measure strength and direction of the relationship between two variables (Zou, Tuncali, & Silverman, 2003). This relationship is a dependency relationship where one variable (Independent Variable or X) is used to explain the other (Dependent Variable or Y).

Andrew F. Hayes' method PROCESS was used in SPSS to measure moderation between variables. Moderation is the effect of the association or interaction of two variables. The independent variable X is paired with another variable or a set of variables W. Moderation happens when the relationship between the independent variable X and the dependent variable Y is influenced by a third variable W. The impact effect of that relationship depends on W (Hayes, 2017). A plethora of research projects have been using Hayes' PROCESS on SPSS to measure the effects of moderation and mediation in fields like education (Hanus & Fox, 2015; Risko, Buchanan, Medimorec, & Kingstone, 2013; M. Wang, 2017), psychology (Aschbacher et al., 2013; Burton, Marshal, Chisolm, Sucato, & Friedman, 2013; Goff, Jackson, Di Leone, Culotta, & DiTomasso, 2014; Sperry & Widom, 2013), management and business (Barrick, Thurgood, Smith, & Courtright, 2015; Sharif & Scandura, 2014), communication (Turcotte, York, Irving, Scholl, & Pingree, 2015) and health (Jones et al., 2015).

Considering the research project's model (Figure 3), corporate responses such as *Facilitation*, *Apology*, *Attentiveness* and *Corrective Action* are the independent variables (X). The dependent variable (Y) is *Response Satisfaction*, what we wish to predict. The moderators (W) are the NWOM's *Polarity* and *Industry*.

The interaction between *Facilitation* and *Response Satisfaction* was measured using a simple linear regression model (Table 8). The results reveal, consistently, that *Facilitation* is a statistically significant predictor of *Response Satisfaction* ($F(1,769)=13.069$, $p = 0.00 < 0.05$, $R^2=0.017$). Thus, confirming H_1. The slope of this relationship is positive ($\beta_1=0.174$), meaning that a unit increase in intentions of giving customers means of complaining increases satisfaction by 17.4%.

Path	Description	Hypothesis	Beta Coefficient	*t*-value	*p*-value
X1→Y	Facilitation → R. Satisfaction	H1	0.174	3.615	0.000
X1*Wa→Y	Facilitation*Polarity → R. Satisfaction	H1a	0.051	0.835	0.404
X1*Wb→Y	Facilitation*Industry→ R. Satisfaction	H1b	0.122	2.630	0.009
X2→Y	Apology → R. Satisfaction	H2	-0.039	-0.787	0.432
X2*Wa→Y	Apology*Polarity → R. Satisfaction	H2a	0.015	0.234	0.815
X2*Wb→Y	Apology*Industry→ R. Satisfaction	H2b	-0.154	-2.341	0.009
X3→Y	Attentiveness → R. Satisfaction	H3	-0.107	-1.761	0.079
X3*Wa→Y	Attentiveness*Polarity → R. Satisfaction	H3a	-0.137	-2.155	0.032
X3*Wb→Y	Attentiveness*Industry→ R. Satisfaction	H3b	0.105	1.791	0.074
X4→Y	C. Action → R. Satisfaction	H4	0.005	0.071	0.944
X4*Wa→Y	C. Action*Polarity → R. Satisfaction	H4a	0.014	0.185	0.854
X4*Wb→Y	C. Action*Industry→ R. Satisfaction	H4b	0.008	0.146	0.884

Table 8 Summarized results of linear relationships and moderation analysis

There is non-significant interaction between *Facilitation* with *Polarity* (X_1*W_a: F(1, 767)=0.6970, p = 0.404 > 0.05, R^2=0.009). H_{1a} is, therefore, not confirmed. However, our research also proved that the *Industry* plays a big part in the acceptance of *Facilitation* as a response technique (X_1*W_b: F(1, 767)=6.916, p = 0.009 < 0.05, R^2=0.009: H_{1b} confirmed). The moderation analysis showed that higher values of *Industry* showcased higher effects on the relationships of *Facilitation* with *Response Satisfaction*. *Industry*, however, is considered a categorical variable. Each industry was paired with a code number. To understand the impact better another linear regression analysis was done to the Hospitality and E-commerce industries (code numbers 3 and 4 respectively), considering the data from each industry individually (table 9 and table 10). Data revealed E-Commerce as the industry where *Facilitation* was significant to *Response Satisfaction*.

Description	**R^2**	**F (1,94)**	**Beta Coefficient**	***t-value***	***p-value***
Model*	0.27	2.642			
Facilitation (Y=R. Satisfaction)			0.210	1.625	0.107

*Only considering data from Hospitality

Table 9 Summarized results between Facilitation and R. Satisfaction on Hospitality

Description	**R^2**	**F (1,118)**	**Beta Coefficient**	***t-value***	***p-value***
Model*	0.65	8.269			
Facilitation (Y=R. Satisfaction)			0.412	2.876	0.005

*Only considering data from e-commerce

Table 10 Summarized results between Facilitation and R. Satisfaction on E-Commerce

When it comes to *Apology*, the influence proved non-significant (F(1, 769)=0.619, p = 0.432 > 0.05, R^2=0.001), concluding that H_2 is not confirmed (Table 3.2). The same conclusion applied to H_{2a} (X_2*W_a: F(1, 767)=0.055 p = 0.815 > 0.05, R^2=0.001). However, the moderation analysis with *Industry* tells us a different story. The interaction variable W_c (Apology*Industry) revealed to significantly influence the dependent variable *Response Satisfaction* (X_2*W_b: F(1, 767)=6.945, p = 0.009 < 0.05, R^2=0.010), showing that H_{2b} is confirmed. The independent variable *Apology* in itself does not have an effect on *Response Satisfaction,* however if paired with *Industry* as a moderator it proves important to the model. If we dig beyond *Apology* for all data and consider *Apology* among different industries, we can find a difference. This result is justifiable because it seems that for *Apology* in general (all industries) the effect cancels out, but not if we look in *Industry* as a moderator. Data tells us that as we move to the higher numbers of the *Industry* variable (likely for Hospitality and E-Commerce) the effect of *Apology* in *Response Satisfaction* is negative. In order to explain this, we computed another linear regression, but considering only data from E-commerce and Hospitality (Table 11). Indeed, there is some influence of these two industries in Response Satisfaction in comparison to the other two industries. The unstandardized beta is -0.247, which means if *Apology* increases by 1 unit, *Response Satisfaction* decreases by 0.247 units.

Description	**R**	**Beta Coefficient**	**t-value**	***p-value***
Model*	0,163			
Apology (Y=R. Satisfaction)		-0,247	-2,410	0,017

*Only considering data from E-commerce and Hospitality

Table 11 Summarized results between Apology and R. Satisfaction on E-Commerce and Hospitality

H_3 and H_4 were also not supported (H_3: F(1, 769)=3.102 p = 0.079 > 0.05, R^2=0.004; H_4: F(1, 769)=0.005 p = 0.944 > 0.05, R^2=0.003). For *Attentiveness* the moderation analysis was able to confirm *Polarity* as a moderator (H_{3a} is confirmed). The moderation model was significant (F(1,767)=4.493, p= 0.004 < 0.05, R^2=0.018) making it fit to be used. And, similarly to *Apology*, the moderator variable of the interaction between *Polarity* and *Attentiveness* is significant (X_3*W_a: F(1,767)=4.6429, p= 0.032<0.05, R^2=0.0053, β_{X3*Wa}=-0.137), despite *Attentiveness* not being a direct predictor of *Response Satisfaction*. The result show that at higher levels of *Polarity*, *Attentiveness* decreases *Response Satisfaction* (Table 12).

Polarity	**Effect**	**se(HC3)**	**t**	**p**	**LLCI**	**ULCI**
-0.821	0.005	0.08	0.058	0.956	-0.157	0.166
0	-0.108	0.061	-1.783	0.075	-0.227	0.011
0.821	-0.221	0.078	-2.839	0.005	-0.374	-0.068

Note: SPSS output from Andrew Hayes' PROCESS analysis

Table 12 Influence of Polarity in moderating Attentiveness and R. Satisfaction

As for H_{3b}, despite the moderation model turned out to be significant for (F(3,767)=3.831, p = 0.01 < 0.05, R^2=0.013), the moderator itself was not confirmed (X_3*W_b: F(1,767)= , p = 0.074 > 0.05, R^2=0.005, β_{X3*Wb}=0.105,). Therefore, we are not able to determine moderation for H_{3b}.

Corrective Action is the only variable we cannot derive any satisfiable result from. H_4 was not confirmed ($F(1,769)=0.005$, $p = 0.944 < 0.05$, $R^2=0.000$, $\beta_4= 0.005$) and neither any moderators. The moderation model A (*Polarity*): $F(3,767)=2.118$, $p=0.097>0.05$, $R^2=0.008$) and moderation model B (*Industry*): $F(3,767)=1.080$, $p = 0.357 > 0.05$, $R^2=0.004$) proved not significant and their interaction variables also proved not significant X_4*W_a: $F(1,767)=0.034$, $= 0.854 > 0.05$, $R^2=0.000$, $\beta_{X4*Wa}=0.014$) and X4*Wb: $F(1,767)=0.021$, $p = 0.884 > 0.05$, $R^2=0.000$, $\beta_{X4*Wb} =0.008$,).

	Model's Hypothesis	Result
H1	Facilitation has a positive effect on response satisfaction	<u>**Supported**</u>
H1a	The effect of Facilitation on Response Satisfaction is moderated by the polarity of the NWOM	Not Supported
H1b	The effect of Facilitation on Response Satisfaction is moderated by the industry	<u>**Supported**</u>
H2	Apology has a positive effect on response satisfaction	Not Supported
H2a	The effect of Apology on Response Satisfaction is moderated by the polarity of the NWOM	Not Supported
H2b	The effect of Apology on Response Satisfaction is moderated by the industry	<u>**Supported**</u>
H3	Attentiveness has a negative effect on response satisfaction	Not Supported
H3a	The effect of Attentiveness on Response Satisfaction is moderated by the polarity of the NWOM	<u>**Supported**</u>
H3b	The effect of Attentiveness on Response Satisfaction is moderated by the industry	Not Supported
H4	Corrective Action has a positive effect on response satisfaction	Not Supported
H4a	The effect of Corrective Action on Response Satisfaction is moderated by the polarity of the NWOM	Not Supported
H4b	The effect of Corrective Action on Response Satisfaction is moderated by the industry	Not Supported

Table 13 Hypothesis results summary

4. Conclusion

4.1 Discussion and Managerial Implications

The focus of this research project was to understand what type of company response to NWOM on social media, in this case Facebook, had the best impact on the poster of NWOM. This "impact" is being referred to, in this paper as response satisfaction. Response satisfaction is a relevant study item and of importance to brands, not only for the direct consumer, but also because of third-party observation. Just by responding to reviews and complaints company reputation or perception becomes more positive to other people that are simply reading these reviews (Rose & Blodgett, 2016). Therefore, a model based on elements of Davidow's (2000) and Benoit's (1997) frameworks was considered, along with other relevant elements characteristic of NWOM were added as moderators of the model.

Among NWOM types, revenge was reported as the predominant. This is very consistent with literature as the most agreed NWOM behavior among scholars in revenge and venting frustrations (Chung & Jiang, 2017; Z. C. Li & Stacks, 2017; Varela-Neira, Vázquez-Casielles, & Iglesias, 2014). At any type of NWOM, managers should be ultimately aware that response strategy is a sensitive topic which if done wrong brand reputation will be affected (H.H. Chang et al., 2015).

Consumers want to know that the company cares for their problem and want it solved, therefore brands need to facilitate the communication. The results confirmed this idea, facilitation was had some influence on response satisfaction which goes in hand what is defended by other research articles (Einwiller & Steilen, 2015; Gursoy, Ekiz, & Chi, 2007b; Karatepe, 2006). Brands that provide consumers resources to complain and to state their dissatisfaction have a better online reaction. This was particularly true to the e-commerce industry. Bystanders or prospective customers are vigilant of negative reviews and complaints, because it provides them important information for decision making such as shipping and online order problems (Ahmad & Laroche, 2017).

Managers should note that consumers are always aware of what means they are given to complain. They want companies to hear their frustrations and just then they can start to forgive (Harrison-Walker, 2019). Instead of eliminating ways for consumers to voice their dissatisfaction, easier and more effective means should be created. Facilitation comes hand in hand with procedural justice in concept. The perceptions of procedural justice rise when consumers think that the company is using the right means to solve conflict (Blodgett et al, 1997). A cheap use of facilitation techniques affects perceived procedural justice, which in turn decreases satisfaction (del Río-Lanza et al., 2009). Consumer satisfaction is key to retain consumers, driving repeat purchases and influence prospective customers for e-commerce businesses (Ahmad & Laroche, 2017; Sharma & Lijuan, 2015). Trust is important for e-commerce, therefore managers should attentive and implement creative, groundbreaking and effective consumer complaint mechanisms.

In the case of apology, we couldn’t support the connection to satisfaction. Apology as a response strategy has not been quite agreed in literature if consumers love it (Jung & Seock, 2017; Boshoff & Leong; 1998) or hate it (Einwiller & Steilen, 2015; Grégoire, Tripp, & Legoux, 2009). Specific circumstances warrant specific courses of actions. However, one thing agreed is that apology does work better when it is not provided individually. Previous researchers had claimed that apologies are best effective, or only effective, when paired with a compensation or a quick fix (Duffy et al., 2006; Grégoire et al., 2009; Joireman et al., 2013; Jung & Seock, 2017; Miller, Craighead, & Karwan, 2000). Apology, either alone or in combination with a compensation affects perceptions of distributive and interactional justice, which in turn are explanatory variables of satisfaction (Jung & Seock, 2017).

Our findings stipulate that for the hospitality and e-eommerce industries, consumers are not open to receive an apology or, assuming, *just* an apology is not enough (Casidy & Shin, 2015; Duffy et al., 2006). The implication for managers is simple: reward or compensate complaining customers. What’s at stake is not only losing the current customer but also not being able to attract new customers. Apologizing is a vicious cycle and customers are keener to see that they are valued more than they are “right”, because they know they are.

Attentiveness, as a response strategy, was also rejected by the data. Yet, when paired with a moderator we are told a different story. We observed that attentiveness will only predict response satisfaction if we take into account the polarity of the consumer's words. However, this only works for some levels of polarity. The moderation analysis showed that for high levels of polarity the effect of attentiveness is negative on response satisfaction. Our results on attentiveness showed that NWOM posters who delivered the least angry reviews/comments do not appreciate the efforts of the company to be attentive. It is categorized as attentiveness expressions and words that expressed understanding and inquired further information. These results are consistent with Einwiller and Steilen’s (2015) findings that whenever companies expressed understanding or inquired further information about the problem, satisfaction would decrease. Adding on, apology also demonstrated negative impact on response satisfaction for hospitality and e-commerce industries. For these consumers in particular, expressing concern is not enough. Therefore, companies should always be extra careful with how they respond to consumers. Managers should plan and strategize customer experience tools, for each customer's persona and focus on advocacy and retention stages. Studying the consumer on a deeper level, conducting interviews and tests, in order to understand what the best wording, compensation, or outcome, these consumers are waiting the most for.

Finally, no significant result could be retrieved from corrective action, which is a trickier element to analyze based on online interaction. According to Benoit (1997), a brand is promising a corrective action when they promise to address the problem. Einwiller and Steinlen (2015, p. 201) were able to find a link between corrective action and satisfaction corrective action is mainly used as a crisis communication measure (Benoit, 1997). To be able to adapt in a non-crisis environment more elements could be behind this dimension that are not easily measured through text mining on reviews/comments. In our data, corrective action was the least common response type. It is probable that firms do not want to engage in making promises. On a wider scale, corrective action is a very expensive strategy (Dutta & Pullig, 2011).

4.2 Limitations and Future Research Directions

This project sheds light on a very important topic which is the conversation of brands with their consumers. The way brands respond and handle the situation is critical to build and maintain reputation. This research project focused on the subsequent response of the consumer to the company's response, it would be of value to mediate conversations. The entire exchange between an angry consumer and the brand and evaluate response strategies.

Accessing review data through social media, or through a review site database gives us little knowledge about the consumer: Who, age, preferences, even gender cannot be assumed. Moreover, many of these reviews/comments were immediately re-directed to Facebook's private message chat which impedes independent researchers from investigating more distinguishing conclusions. Therefore, brands should also participate in these types of studies and aid research. This partnership would be of value to retrieve findings on specific socio-demographic data such as age group, gender and education and analyze how and why they write online NWOM. Further, researchers should study the impact of these socio-demographic groups' NWOM on third-party perception of the brand.

Another venue future research can delve into, is the distinction between complainers and brand haters and the impact on third party's perception of the brand. The distinction between the complainer and brand hater is not made clear in this research project as it would require further analysis to be done and, perhaps, supplement with interviews in order to acquire a deep understanding of each type.

When making a dictionary, it is hard work to collect words and expressions fitted for each dimension. One wants to represent every single review and collect every single word, but not always is possible. Therefore, it is easy to miss a set of words. This is especially concerning when a review or response has grammatical and typographical errors. It is not possible to predict what types of errors it will be found in the language used, therefore some aliases might be lost.

Future research should consider the differences of language specificities as "formal" and "informal" tones used by companies in their response. Among the data retrieved for this research project there is a record of the use of expressions like "Yikes!" and "Bummer!". Are consumers welcoming of these expressions or do they find it rude? It would be interesting to test this for different levels of anger and socio-demographic groups.

Finaly, Benoit’s strategies were primarily designed for crisis situations. Little information can be found regarding to the adaptation of Benoit’s, or similar, strategies for an individual customer on social media. Future research should dig deeper into the consequences of these promises to the individual consumer and their level of disappointment. It would be of interest to tackle further elements that could mediate this relationship such as past experiences, time of response, company’s past reputation and socio-demographic groups.

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6. Appendix

SPSS Outputs

Appendix 1

H1 – Linear Regression Facilitation → Response Satisfaction

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,129[a]	0,017	0,015	0,707

a. Predictors: (Constant), RS_Facilitation

b. Dependent Variable: Resp_Satisfaction

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6,529	1	6,529	13,069	,000[b]
	Residual	384,159	769	0,500		
	Total	390,687	770			

a. Dependent Variable: Resp_Satisfaction

b. Predictors: (Constant), RS_Facilitation

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-0,376	0,043		-8,719	0,000
	RS_Facilitation	0,174	0,048	0,129	3,615	0,000

a. Dependent Variable: Resp_Satisfaction

Appendix 2

H1a. Moderation analysis – Facilitation*Polarity→ Response Satisfaction

```
OUTCOME VARIABLE:
 Resp_Sat

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,1620      ,0262      ,4960     6,5114     3,0000   767,0000      ,0002

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     -,2501      ,0254    -9,8313      ,0000     -,3000     -,2001
RS_Facil      ,1771      ,0494     3,5833      ,0004      ,0801      ,2741
RV_Polar      ,0816      ,0316     2,5849      ,0099      ,0196      ,1435
Int_1         ,0510      ,0611      ,8349      ,4041     -,0690      ,1710

Product terms key:
 Int_1    :        RS_Facil x        RV_Polar

Covariance matrix of regression parameter estimates:
           constant   RS_Facil   RV_Polar      Int_1
constant      ,0006      ,0000      ,0000      ,0000
RS_Facil      ,0000      ,0024      ,0000      ,0002
RV_Polar      ,0000      ,0000      ,0010      ,0001
Int_1         ,0000      ,0002      ,0001      ,0037

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0009      ,6970     1,0000   767,0000      ,4041
```

Appendix 3

H1b - Moderation analysis – Facilitation*Industry→ Response Satisfaction

```
Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,2055      ,0422      ,4879    11,3086     3,0000   767,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     -,2223      ,0271    -8,2068      ,0000     -,2754     -,1691
RS_Facil      ,2540      ,0516     4,9231      ,0000      ,1527      ,3552
Industry      ,1080      ,0260     4,1494      ,0000      ,0569      ,1591
Int_1         ,1222      ,0465     2,6298      ,0087      ,0310      ,2134

Product terms key:
 Int_1    :        RS_Facil x        Industry

Covariance matrix of regression parameter estimates:
           constant   RS_Facil   Industry      Int_1
constant      ,0007      ,0001      ,0001      ,0005
RS_Facil      ,0001      ,0027      ,0005      ,0002
Industry      ,0001      ,0005      ,0007      ,0002
Int_1         ,0005      ,0002      ,0002      ,0022

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0090     6,9157     1,0000   767,0000      ,0087


     Focal predict: RS_Facil (X)
           Mod var: Industry (W)

 Conditional effects of the focal predictor at values of the moderator(s):

    Industry     Effect    se(HC3)          t          p       LLCI       ULCI
     -1,0324      ,1278      ,0676     1,8892      ,0592     -,0050      ,2606
      -,0324      ,2500      ,0515     4,8553      ,0000      ,1489      ,3511
       ,9676      ,3722      ,0710     5,2399      ,0000      ,2328      ,5117

 Moderator value(s) defining Johnson-Neyman significance region(s):
       Value    % below    % above
     -1,0048    40,3372    59,6628
```

Conditional effect of focal predictor at values of the moderator:

Industry	Effect	se(HC3)	t	p	LLCI	ULCI
-1,0324	,1278	,0676	1,8892	,0592	-,0050	,2606
-1,0048	,1312	,0668	1,9631	,0500	,0000	,2623
-,8824	,1461	,0633	2,3071	,0213	,0218	,2705
-,7324	,1645	,0595	2,7622	,0059	,0476	,2813
-,5824	,1828	,0563	3,2438	,0012	,0722	,2934
-,4324	,2011	,0539	3,7329	,0002	,0954	,3069
-,2824	,2195	,0522	4,2020	,0000	,1169	,3220
-,1324	,2378	,0515	4,6196	,0000	,1367	,3388
,0176	,2561	,0517	4,9580	,0000	,1547	,3575
,1676	,2744	,0528	5,2008	,0000	,1709	,3780
,3176	,2928	,0548	5,3470	,0000	,1853	,4003
,4676	,3111	,0575	5,4085	,0000	,1982	,4240
,6176	,3294	,0610	5,4039	,0000	,2098	,4491
,7676	,3478	,0650	5,3525	,0000	,2202	,4753
,9176	,3661	,0695	5,2713	,0000	,2298	,5024
1,0676	,3844	,0743	5,1729	,0000	,2385	,5303
1,2176	,4028	,0795	5,0665	,0000	,2467	,5588
1,3676	,4211	,0849	4,9581	,0000	,2544	,5878
1,5176	,4394	,0906	4,8515	,0000	,2616	,6172
1,6676	,4578	,0964	4,7487	,0000	,2685	,6470
1,8176	,4761	,1024	4,6512	,0000	,2752	,6770
1,9676	,4944	,1084	4,5593	,0000	,2815	,7073

Appendix 4

H2 – Linear Regression Apology → Response Satisfaction

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,028[a]	0,001	0,000	0,712

a. Predictors: (Constant), RS_Apology

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	0,314	1	0,314	0,619	,432[b]
	Residual	390,373	769	0,508		
	Total	390,687	770			

a. Dependent Variable: Resp_Satisfaction

b. Predictors: (Constant), RS_Apology

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-0,233	0,034		-6,881	0,000
	RS_Apology	-0,039	0,049	-0,028	-0,787	0,432

a. Dependent Variable: Resp_Satisfaction

Appendix 5

H2a - Moderation analysis – Apology*Polarity→ Response Satisfaction

OUTCOME VARIABLE:
Resp_Sat

Model Summary

R	R-sq	MSE	F(HC3)	df1	df2	p
,0962	,0093	,5047	2,2447	3,0000	767,0000	,0818

Model

	coeff	se(HC3)	t	p	LLCI	ULCI
constant	-,2504	,0257	-9,7573	,0000	-,3007	-,2000
RS_Apolo	-,0397	,0513	-,7742	,4390	-,1404	,0610
RV_Polar	,0800	,0322	2,4823	,0133	,0167	,1432
Int_1	,0150	,0641	,2341	,8150	-,1108	,1408

Product terms key:
Int_1 : RS_Apolo x RV_Polar

Covariance matrix of regression parameter estimates:

	constant	RS_Apolo	RV_Polar	Int_1
constant	,0007	,0001	,0000	,0000
RS_Apolo	,0001	,0026	,0000	,0001
RV_Polar	,0000	,0000	,0010	,0003
Int_1	,0000	,0001	,0003	,0041

Test(s) of highest order unconditional interaction(s):

	R2-chng	F(HC3)	df1	df2	p
X*W	,0001	,0548	1,0000	767,0000	,8150

Appendix 6

H2b. Moderation analysis – Apology*Industry→ Response Satisfaction

Model Summary

R	R-sq	MSE	F(HC3)	df1	df2	p
,1388	,0193	,4996	4,9104	3,0000	767,0000	,0022

Model

	coeff	se(HC3)	t	p	LLCI	ULCI
constant	-,2056	,0302	-6,8000	,0000	-,2650	-,1463
RS_Apolo	-,1106	,0594	-1,8617	,0630	-,2273	,0060
Industry	,0842	,0282	2,9809	,0030	,0287	,1396
Int_1	-,1540	,0584	-2,6354	,0086	-,2687	-,0393

Product terms key:
Int_1 : RS_Apolo x Industry

Covariance matrix of regression parameter estimates:

	constant	RS_Apolo	Industry	Int_1
constant	,0009	,0001	,0001	-,0009
RS_Apolo	,0001	,0035	-,0009	,0000
Industry	,0001	-,0009	,0008	-,0002
Int_1	-,0009	,0000	-,0002	,0034

Test(s) of highest order unconditional interaction(s):

	R2-chng	F(HC3)	df1	df2	p
X*W	,0098	6,9454	1,0000	767,0000	,0086

Conditional effects of the focal predictor at values of the moderator(s):

Industry	Effect	se(HC3)	t	p	LLCI	ULCI
-1,0324	,0484	,0845	,5720	,5675	-,1176	,2143
,0000	-,1106	,0594	-1,8617	,0630	-,2273	,0060
1,0728	-,2759	,0865	-3,1883	,0015	-,4457	-,1060

Moderator value(s) defining Johnson-Neyman significance region(s):

Value	% below	% above
,0398	71,9844	28,0156

Conditional effect of focal predictor at values of the moderator:

Industry	Effect	se(HC3)	t	p	LLCI	ULCI
-1,0324	,0484	,0845	,5720	,5675	-,1176	,2143
-,8824	,0253	,0786	,3216	,7478	-,1289	,1795
-,7324	,0022	,0731	,0296	,9764	-,1414	,1457
-,5824	-,0209	,0684	-,3061	,7596	-,1552	,1133
-,4324	-,0440	,0645	-,6827	,4950	-,1707	,0826
-,2824	-,0671	,0616	-1,0895	,2763	-,1881	,0538
-,1324	-,0902	,0599	-1,5064	,1324	-,2078	,0274
,0176	-,1133	,0594	-1,9068	,0569	-,2300	,0033
,0398	-,1168	,0595	-1,9631	,0500	-,2335	,0000
,1676	-,1364	,0603	-2,2643	,0238	-,2547	-,0181
,3176	-,1595	,0623	-2,5603	,0106	-,2819	-,0372
,4676	-,1826	,0655	-2,7890	,0054	-,3112	-,0541
,6176	-,2057	,0696	-2,9550	,0032	-,3424	-,0691
,7676	-,2288	,0746	-3,0689	,0022	-,3752	-,0825
,9176	-,2519	,0802	-3,1427	,0017	-,4093	-,0946
1,0676	-,2750	,0863	-3,1872	,0015	-,4445	-,1056
1,2176	-,2982	,0929	-3,2111	,0014	-,4804	-,1159
1,3676	-,3213	,0997	-3,2208	,0013	-,5171	-,1254
1,5176	-,3444	,1069	-3,2209	,0013	-,5542	-,1345
1,6676	-,3675	,1143	-3,2148	,0014	-,5918	-,1431
1,8176	-,3906	,1219	-3,2045	,0014	-,6298	-,1513
1,9676	-,4137	,1296	-3,1918	,0015	-,6681	-,1592

Appendix 7

H3 – Linear Regression Attentiveness → Response Satisfaction

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,063[a]	0,004	0,003	0,711

a. Predictors: (Constant), RS_Attentiveness

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,570	1	1,570	3,102	,079[b]
	Residual	389,118	769	0,506		
	Total	390,687	770			

a. Dependent Variable: Resp_Satisfaction

b. Predictors: (Constant), RS_Attentiveness

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-0,230	0,028		-8,211	0,000
	RS_Attentiveness	-0,107	0,061	-0,063	-1,761	0,079

a. Dependent Variable: Resp_Satisfaction

Appendix 8

H3a - Moderation analysis – Attentiveness*Polarity→ Response Satisfaction

OUTCOME VARIABLE:
Resp_Sat

Model Summary

R	R-sq	MSE	F(HC3)	df1	df2	p
,1339	,0179	,5002	4,4931	3,0000	767,0000	,0039

Model

	coeff	se(HC3)	t	p	LLCI	ULCI
constant	-,2491	,0256	-9,7450	,0000	-,2993	-,1989
RS_Atten	-,1082	,0607	-1,7827	,0750	-,2273	,0109
RV_Polar	,0850	,0317	2,6827	,0075	,0228	,1472
Int_1	-,1373	,0637	-2,1547	,0315	-,2625	-,0122

Product terms key:
Int_1 : RS_Atten x RV_Polar

Covariance matrix of regression parameter estimates:

	constant	RS_Atten	RV_Polar	Int_1
constant	,0007	,0000	,0000	-,0001
RS_Atten	,0000	,0037	-,0001	-,0002
RV_Polar	,0000	-,0001	,0010	-,0003
Int_1	-,0001	-,0002	-,0003	,0041

Test(s) of highest order unconditional interaction(s):

	R2-chng	F(HC3)	df1	df2	p
X*W	,0053	4,6429	1,0000	767,0000	,0315

Conditional effects of the focal predictor at values of the moderator(s):

RV_Polar	Effect	se(HC3)	t	p	LLCI	ULCI
-,8205	,0045	,0824	,0547	,9564	-,1572	,1662
,0000	-,1082	,0607	-1,7827	,0750	-,2273	,0109
,8205	-,2209	,0778	-2,8390	,0046	-,3736	-,0681

Moderator value(s) defining Johnson-Neyman significance region(s):

Value	% below	% above
,0785	67,8340	32,1660

Conditional effect of focal predictor at values of the moderator:

RV_Polar	Effect	se(HC3)	t	p	LLCI	ULCI
-1,3735	,0805	,1094	,7357	,4621	-,1342	,2951
-1,1735	,0530	,0990	,5353	,5926	-,1413	,2473
-,9735	,0255	,0893	,2859	,7750	-,1497	,2007
-,7735	-,0019	,0804	-,0242	,9807	-,1597	,1558
-,5735	-,0294	,0726	-,4050	,6856	-,1720	,1132
-,3735	-,0569	,0665	-,8560	,3923	-,1873	,0736
-,1735	-,0843	,0623	-1,3537	,1762	-,2067	,0380
,0265	-,1118	,0606	-1,8448	,0655	-,2308	,0072
,0785	-,1190	,0606	-1,9631	,0500	-,2379	,0000
,2265	-,1393	,0616	-2,2624	,0240	-,2601	-,0184
,4265	-,1668	,0651	-2,5633	,0106	-,2945	-,0390
,6265	-,1942	,0707	-2,7471	,0062	-,3330	-,0554
,8265	-,2217	,0780	-2,8408	,0046	-,3749	-,0685
1,0265	-,2492	,0866	-2,8758	,0041	-,4192	-,0791
1,2265	-,2766	,0962	-2,8765	,0041	-,4654	-,0878
1,4265	-,3041	,1064	-2,8588	,0044	-,5129	-,0953
1,6265	-,3316	,1171	-2,8321	,0047	-,5614	-,1017
1,8265	-,3590	,1281	-2,8016	,0052	-,6106	-,1075
2,0265	-,3865	,1395	-2,7703	,0057	-,6604	-,1126
2,2265	-,4140	,1511	-2,7397	,0063	-,7106	-,1173
2,4265	-,4414	,1629	-2,7106	,0069	-,7611	-,1217
2,6265	-,4689	,1748	-2,6832	,0074	-,8119	-,1258

Appendix 10

H3b - Moderation analysis – Attentiveness*Industry→ Response Satisfaction

Model Summary

R	R-sq	MSE	F(HC3)	df1	df2	p
,1121	,0126	,5030	3,8311	3,0000	767,0000	,0097

Model

	coeff	se(HC3)	t	p	LLCI	ULCI
constant	-,2486	,0257	-9,6890	,0000	-,2990	-,1982
RS_Atten	-,0888	,0596	-1,4904	,1365	-,2057	,0282
Industry	,0412	,0245	1,6805	,0933	-,0069	,0893
Int_1	,1050	,0586	1,7911	,0737	-,0101	,2201

Product terms key:
Int_1 : RS_Atten x Industry

Covariance matrix of regression parameter estimates:

	constant	RS_Atten	Industry	Int_1
constant	,0007	,0000	,0001	,0001
RS_Atten	,0000	,0035	,0001	,0012
Industry	,0001	,0001	,0006	,0000
Int_1	,0001	,0012	,0000	,0034

Test(s) of highest order unconditional interaction(s):

	R2-chng	F(HC3)	df1	df2	p
X*W	,0046	3,2081	1,0000	767,0000	,0737

Appendix 11

H4 – Linear Regression Corrective → Response Satisfaction

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,003[a]	0,000	-0,001	0,713

a. Predictors: (Constant), RS_Corrective Action

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	0,003	1	0,003	0,005	,944[b]
	Residual	390,685	769	0,508		
	Total	390,687	770			

a. Dependent Variable: Resp_Satisfaction

b. Predictors: (Constant), RS_Corrective Action

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-0,251	0,028		-8,933	0,000
	RS_Corrective Action	0,005	0,066	0,003	0,071	0,944

a. Dependent Variable: Resp_Satisfaction

Appendix 12

H4a. Moderation analysis – Corrective Action*Polarity→ Response Satisfaction

```
OUTCOME VARIABLE:
 Resp_Sat

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,0915      ,0084      ,5051     2,1181     3,0000   767,0000      ,0965

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     -,2503      ,0257    -9,7576      ,0000     -,3007     -,2000
RS_Corre      ,0045      ,0635      ,0707      ,9437     -,1201      ,1291
RV_Polar      ,0796      ,0318     2,5016      ,0126      ,0171      ,1420
Int_1         ,0139      ,0754      ,1845      ,8537     -,1341      ,1619

Product terms key:
 Int_1    :        RS_Corre x        RV_Polar

Covariance matrix of regression parameter estimates:
           constant   RS_Corre   RV_Polar      Int_1
constant      ,0007      ,0000      ,0000      ,0000
RS_Corre      ,0000      ,0040     -,0001     -,0002
RV_Polar      ,0000     -,0001      ,0010     -,0001
Int_1         ,0000     -,0002     -,0001      ,0057

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0000      ,0340     1,0000   767,0000      ,8537
```

Appendix 13

H4b - Moderation analysis – Corrective Action*Industry→ Response Satisfaction

Model Summary

R	R-sq	MSE	F(HC3)	df1	df2	p
,0657	,0043	,5072	1,0801	3,0000	767,0000	,3567

Model

	coeff	se(HC3)	t	p	LLCI	ULCI
constant	-,2500	,0257	-9,7263	,0000	-,3005	-,1996
RS_Corre	,0165	,0652	,2529	,8004	-,1116	,1446
Industry	,0433	,0248	1,7491	,0807	-,0053	,0919
Int_1	,0082	,0562	,1464	,8837	-,1022	,1186

Product terms key:

Int_1 : RS_Corre x Industry

Covariance matrix of regression parameter estimates:

	constant	RS_Corre	Industry	Int_1
constant	,0007	,0000	,0001	,0001
RS_Corre	,0000	,0043	,0000	,0008
Industry	,0001	,0000	,0006	-,0002
Int_1	,0001	,0008	-,0002	,0032

Test(s) of highest order unconditional interaction(s):

	R2-chng	F(HC3)	df1	df2	p
X*W	,0000	,0214	1,0000	767,0000	,8837