JUSTIFICATION DOCUMENT FAKE REVIEWS AND CORPORATE REPUTATION

Title: Justification document for fake review detection and corporate reputation
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1. Introduction

The aim of this report is to justify the focus of researching corporate reputation and to present the research questions that have been derived from the business problem. For this masterproject, the focus is to define, develop and present a model that has a practical application and generates new, unseen data that can improve the reputation of any organisation (HvA, 2020). This report is written with the belief of expanding the knowledge of online corporate reputation, and provides useful insights that can contribute to stronger and efficient reputation management for organisations. In this introduction, a kick-off of recent developments will be given that directly impacts the landscape of corporate reputation nowadays. Thereafter, the problem statement, goal of this study and research questions will be introduced.

COVID-19 and the business industry

The last few months have changed the landscape of the world drastically (McGrath & Ross, 2020). The outbreak of COVID-19, or the coronavirus, is already stamped as a human tragedy and has a growing impact on the global economy. Especially the business industry is facing a huge amount of challenges to cope with in order to sustain (Gerdeman, 2020). The latest article published by Harvard Business Review (2020) states that business leaders all over the world are struggling with a wide variety of problems from decreasing sales and stalling supply chains to keeping employees safe and ensure that the operational core can continue operating without too many obstacles from the coronavirus. Another recently published study from McKinsey (2020) shows that although the coronavirus has caused the biggest quarterly drops of shares since 1987, a record of unemployment claims and a crude drop of oil prices globally, it has turned more people to technology than ever. Governments around the world have urged people to work from home where possible, this together with the lockdown measures leads to a new way of using technologies in our daily lives. According to the Dutch Institute of International Relations (2020), *"COVID-19 is a digital pandemic in terms of its origin and it is also one in its effects"*. As workplaces instruct employees to work from home, universities shift fully to online teaching and the restaurant industry transitions faster than before to online ordering and delivering; one of the most rapid organizational transformations in the history of the modern firm is happening right now (Iansiti & Richards, 2020). In this huge digital transformation, organizations are forced to move to a fundamentally new operating architecture based on software, data and digital networks. With more digitally at stake for organisations, the online corporate reputation has become more important than ever, and can mean the deal breaker between surviving in times with the coronavirus or not.

Online corporate reputation

According to Forbes (2020), the coronavirus has driven a massive rise in the use of technology globally. In their recently published article is stated that *"the coronavirus boosted online spending and usage in Q1 of 2020 to the highest in history"*. It also shows that digital platforms are thriving as consumers seek more entertainment, shopping opportunities and new ways of connecting during the crisis. This increase of online behavior generates more data for organizations to work with improving their online corporate reputation. More organisations start to realize the importance of having an online strategy and strong digital visibility as part of corporate reputation. In times of the corona pandemic, organisations rely more than ever on strong online presence in terms of their websites and apps (Lincoln, 2020). Recent research from The New York Times (2020) stated that people are spending almost one hour a day extra on websites since the outbreak of COVID-19. This means that an important way to reach a broader audience is by having a multi-channel strategy including an app, social media pages and websites. However, with more organisations strengthen their digital strategies; the online market becomes more crowded in terms of competitors. Also, organisations that shift from a traditional marketing toolbox to multi-channel become more vulnerable in terms of corporate reputation. The rise of social media and reviewing websites has empowered consumers and weakened the position of organisation by exposing them to negative publicity, customer attacks and reputation damage (Horn, Taros & Dirkes, 2015). In order to provide a very actual and up-to-date research, this study will focus on the rising concern of fake reviews and its relationship with corporate reputation.

Fake reviews and corporate reputation

Fake reviews can be easily written by anyone on the Internet. Martens and Maalej (2019) state that this feedback is often used by managers for business decisions and to measure corporate reputation. Research shows that positive feedback improves app downloads, sales and the reputation of the company. However, as a side effect, a market for fake reviews has emerged with can turn into very negative consequences for organisations (Martens & Maalej, 2019). For several years now, there has been done extensive research on the effect of negative and fake reviews on online corporate reputation. Many researchers indicate that small insignificant comments or reviews can have a far-reaching impact on an organisation (Bulmar & DiMauro, 2014). According to research from Otar (2018), negative and fake reviews can damage corporate reputation online and business growth. Stats show that only four negative or fake reviews can cost an organisation 70% of potential customers (Otar, 2018). Especially fake reviews are recognized as a real challenge by both the research community and the e-commerce industry. As many giant app stores as Google and Apple try to combat against fake reviews, almost 15-30% of all reviews are estimated to be fake per product or services (Barbado et al., 2019). Therefore, fake reviews in app stores can be seen as an actual, critical business problem that affects all layers of businesses.

For this research, the important factor of fake reviews that can damage corporate reputation will be taken into account. In times with the coronavirus, organisations need to put extra focus on online presence and limit the amount of negative input that affects their competitive position which can even lead to business loss. Therefore, by using a dataset scrapped from Google and obtained from Kaggle, a machine-learning technique will be used to detect fake reviews that can have a negative effect on online corporate reputation.

Problem statement

In a recent official statement, Google highlighted the negative effects of fake reviews on review websites and specifically requested companies not to buy and users not to accept payments to provide fake reviews (Google, 2019). The Digital Trend Report (2018) shows that also governmental authorities started taking action against organisations that show to have a high number of fake reviews on their apps. However, while the phenomenon of fake reviews is well-known in industries as online journalism and business and travel portals, it remains a difficult challenge in software engineering (Martens & Maalej, 2019). Fake reviews threaten the reputation of an organisation and lead to a disvalued source to determine the public opinion about brands. Negative fake reviews can lead to confusion for customers and a loss of sales. Positive fake reviews might also lead to wrong insights about real users' needs and requirements (Martens & Maalej, 2019). Although fake reviews have been studied for a while now, there are limit spam detection models available for companies to protect their corporate reputation.

Goal of this study

Aiming at the problem described above, the goal of this study is to research fake reviews by focusing on the suppliers of fake reviews, how fake reviews differ from regular reviews and how fake reviews can be automatically detected best. To detect fake reviews, a supervised classifier will be developed that includes the machine-learning technique of Support Vector Machines. The main goal of this study is therefore to provide more useful insights in fake reviews and provide a system to automatically detect these reviews. To main the goal of this study specific, the main contribution of this study will be to provide researchers and practitioners with valuable insight and further improvements on the fake review detection problem.

Academic relevance
Fake review detection has been a hot topic in the research industry for many years now (Li, Lui & Qin, 2018). However, as few studies show that there is an urgent need for technology that detects fake reviews with high accuracy, not many studies have passed so far. Also, because of low accuracy of detecting fake reviews by people, it has a far-reaching significance in academic research. Therefore, it is interesting to analyse the background and effect of fake reviews and how these can be detected using machine learning methods.

Practical relevance
With the rising market for apps, organisations have become more vulnerable to user feedback in form of app ratings and reviews. As research shows that one negative or fake review can have a significant impact on the business, it will be important to take this problem serious and analyse in more detail. In addition, the outcomes of this study will be made available for other companies in the future to tackle the issue of fake app reviews.

Research questions

In this research, fake reviews will be studied according to three research questions:

RQ1: How are fake reviews created?
RQ2: What are the characteristics of fake reviews?
RQ3: How accurate can fake reviews be detected?

These research questions are designed in order to give more background on fake reviews and how these are used, together with a focus on how fake reviews can be detected for practical implication.

The conclude, the report will be structured by a literature review, which will explain more about the current knowledge that is available on this research topic and how it has been dealt with in academic papers. After this, the research methodology will outline the research methods that are chosen, in order to be transparent and understandable. The actual research will be carried out over a timeframe of eight weeks, and research findings, discussion and conclusion will be presented in a deck of slides and verbal presentation.

2. Literature review

This chapter will be dedicated to the literature review of online corporate reputation and fake app reviews. It will provide an overview of the current knowledge including relevant theories, methods and gaps in the existing research. This chapter involves collecting, evaluating and analyzing academic publications related to corporate reputation and fake reviews.

2.1 Definition of key variables

In order to provide a clear overview of the literature review, two main key variables are determined which include corporate reputation and the phenomenon of fake reviews. Firstly, an in-depth description and background of corporate reputation will be provided. Secondly, the developments of fake reviews will be discussed, where after a conceptual model is presented to help understand the research subjects.

2.1.1 Corporate reputation

Before explaining the role of fake reviews in online corporate reputation, this sub-chapter will discusses the concept of corporate reputation in the context of this research. The definition of corporate reputation has been widely discussed over the years in the research industry and is in continual change. Although it is a hot topic, this concept is still vague and has many different definitions that sometimes even contradict each other. According to Giovanni (2010, p.74), *"the reputation of a company can be considered one of the most valued organizational assets"*. Chun (2005) and Dowling (2016) both agree that corporate reputation has one aligning element; the term is often described as a reflection of the company to insiders and outsiders. Also, corporate reputation is often linked with terms as corporate identity, corporate image and corporate goodwill (Wartick, 2002; Barnett et al., 2005).

For this study, it will be important to set one straight direction for corporate reputation; therefore the definition from Fomburn and van Riel (1997) will be maintained throughout the report. According to their early days research corporate reputation can be identified as *"a perceptual representation of a company's past actions and future prospects that describes the firm's overall appeal to all of its key constituents when compared with other leading rivals"*. Another important finding that comes across in most academic papers on corporate reputation is that many researchers define corporate reputation as a collective concept; it is seen as the sum of the perception of external stakeholders (Barbado et al., 2019; Barnett et al., 2005; Horn et al., 2015). Chun (2005) states that corporate reputation can be seen as an umbrella construct for corporate image and corporate identity.

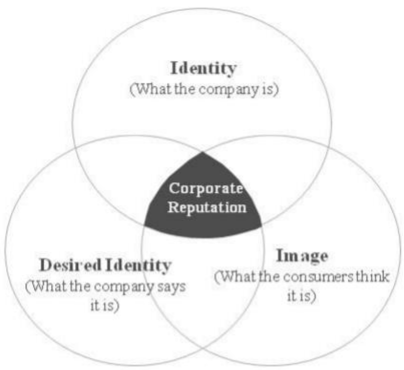

FIGURE 1: KEY ELEMENTS OF CORPORATE REPUTATION (CHUN,

Figure 1 shows the statement from Chun (2005) that identity and desired identify are independent variables that form corporate reputation. Image can be described as the perception of others of a company or how is formulated *"how others see us"* (Chun, 2005). Identity can be described as an internal view of the company what means how members of the organization perceive, feel and think about the company (*"how we see ourselves")*. The third variable refers to the desired identity and describes how an organisation wants to be perceived which refers to the name, logo, symbol as well as strategic actions and philosophy (*"how we want others to perceive ourselves"*). The gap in the middle represents how an organisation is actually perceived internally and externally, as well as how it wants to be perceived (Chun, 2005). A wide gap indicates inconsistencies in strategy or communication and can damage the organisation corporate reputation. Walker (2010) states that alignment between these variables can lead to strategic benefits, such as increasing profitability, lower costs and a competitive advantage.

Online corporate reputation
A-concept that often simultaneously appears with corporate reputation is online reputation. According to Jones, Temperley and Lima (2010), *"online corporate reputation is a reputation, which involves a corporate reputation created in the online environment"*. Online reputation is not only created on social media but is also created by groups of people sharing and collaborating online and through search engines as Google, Ask and Yahoo (Weber Shandwick & KRC Research, 2019). In this digital era, online corporate reputation is as important as offline reputation (Ambimbola & Vallaster, 2009). The emergence of social media platforms and review websites allow people to have new tools to publically judge companies at a much greater and faster pace than before. On these platforms, consumers do not only discuss content from companies, they also create it (Barnett et al., 2009). Fournier and Avery (2011) have defined social media as *"a venue for open source branding"* in which consumers can co-create the nature of reputations of a brand. Companies try to influence this process of co-creation by creating solid online presence and strong online marketing strategies. The online presence, according to Waters et al. (2009), *"offers various benefits to companies like the opportunity to communicate directly with customers, strengthen relationships, stimulates co-creation and to assess consumer's brand attitudes"*. Nowadays, companies experience more pressure from outside to take part in online conversations in order to influence the corporate reputation. Therefore, the online corporate reputation is associated with increased loss of control and increased need for active monitoring (Gensler et al., 2015).

Corporate reputation management
The overall goal of this research is to research and detect fake reviews in order to contribute to online reputation management for companies; therefore it is important to understand the meaning behind reputation management.

According to Hutton et al. (2001), reputation management, which is considered a business function, is based on the traditional term "public relations" or also known as "corporate affairs". Beal & Strauss (2009) state that online reputation management is placed between marketing communications, public relations and search engine optimization (SEO). Jones et al. (2009, p. 943) agree with this definition as they list *"online reputation management is the process of positioning, monitoring, measuring, talking and listening as the organization engages in a transparent and ethical dialogue with its various online stakeholders"*. What comes across from different literatures is that in order to build and maintain corporate reputation, it is important for companies to understand who their stakeholders are and how they perceive the company (Beal & Strauss, 2009). This can be linked to the umbrella theory of Chun (2005) and is aligned with the perception that reputation is formed by a collective perception of different individuals. The more the perceptions of several individuals are aligned with each other, the stronger the corporate reputation of a company (Gensler et al., 2015).

When looking at how corporate reputation can best be maintained, research from Page and Fearn (2005) indicates that organisations should focus on aligning the perceptions of different stakeholders. In order to do so, organisations should focus on clear communication about leadership and successes of the organisation and the organisation's perspective on consumer fairness in

advertisement, marketing, websites, reviews and other forms of communication. To go more in-depth on this:
1. Leadership and success: this reflects that the reputation of an organisation is reflected by the leadership style and its successes from the CEO. A clear example of this is Tesla, an automotive company that is mainly known for its famous CEO, Elon Musk (Wollaerts, 2020).
2. Consumer fairness: this includes the fair treatment of consumers regarding pricing, quality of products and services and transparency in advertisement which also include reviews.

To conclude reputation management, literature indicates that it is important for organisations to measure, monitor and co-ordinate the different stakeholder reputations with the overall goal to align these as much as possible. Page and Fearn (2005) and (Gensler et al., 2015) emphasize strongly that the more different stakeholder reputations are similar, the stronger the corporate reputations of an organisation is. In order to create alignment, organisations should focus on creating clear and transparent messages with regards to leadership style, successes of an organisation, advertisement and marketing communication. It is important for an organisation to create be authentic and transparent towards all its stakeholders.

EWOM (electronic word-of-mouth)
The Internet and social media platforms have added a new element to the traditional word-of-mouth (WOM) term. Electronic word-of-mouth, or eWOM, refers to any positive or negative content made by potential, actual, or previous customers about a product or company, which is made available to an audience of people and institutions via the web 2.0 (Mishra & Satish, 2016). EWOM is expressed in different forms of communication such as opinions, online ratings, online feedback, reviews, comments and experience sharing via online communication channels. A study from Mishra & Satish (2016) on e-WOM, it plays a critical factor in marketing efforts and has an impact on different stages of consumer purchase decision process. The following table shows how consumers are in touch with eWOM during the purchasing process (Dewey, 1910; Mishra & Satish, 2016).

Stage	Touch points of eWOM
Problem or interest	External stimuli (ads on websites, social media personalization and recommendations)
Information search	Search engines, social media, product websites, e-retailers
Evaluation of alternatives	Websites with compare options, social media for feedback, online reviews and rating websites
Purchase decision	Channels (e-commerce websites), discussion and feedback on social media
Post-purchase behaviour	Review sites, social media, online rating and reviews, feedback on social media or product sites

Table 1: Touch points of eWom (Mishra & Satish, 2016)

Although there seems to be a clear link between eWOM and corporate reputation, there is little literature on this connection. Hoyer and MacInnis (2001) found out that WOM is the most credible and objective influence on corporate reputation. Other researchers agree that in meeting or exceeding customers’ expectations, customer satisfaction is achieved, eWOM is uttered and good reputations are built (Davies et al. 2010). However, the corporate reputation of companies is considered fragile; while it may take time to build it can be easily destroyed.

2.1.2 Spam reviews

In today's tech-savvy world, review websites, social media and mobile applications have become the most important source for consumers to express themselves. It is considered very easy for people to share their views about products and services using e-commerce websites as TripAdvisor and Trustpilot, forums and blogs (Hussain, Mirza, Rasool, Hussain & Kaleem, 2019). In app stores in particularly, users can rate downloaded apps on a scale from 1 to 5 stars and write a review message in which they can express satisfaction, report bugs or make suggestions (Martens & Maalej, 2019). Recent study on online consumer buying behaviour confirms the statement that most people read these reviews about products and services before buying them (Xhema, 2019). In case of apps, consumers often read through the reviews before deciding to download the app. Harman, Jia and Zhang (2012) identified in their research that there is a positive relationship between the number of positive ratings and reviews to sales and download ranks of apps. As is stated *"stable numerous ratings lead to higher downloads and sales numbers"*, which will have a positive effect on corporate reputation (Barnett et al., 2005).

As result of the positive connection between reviews and sales, a new illegal market focused on producing fake reviews has emerged. This phenomenon of fake reviews on product and services with the goal to boost sales is also referred to in academic studies as "spam attack" (Hussain et al., 2019). In regular situations, real users are motivated by their satisfaction level to provide feedback on apps; however, fake reviewers get paid or similarly rewarded to submit reviews (Martens & Maalej, 2019). An important distinction between real users and fake reviewers is that fake reviewers might not even be real users of the app and the review might not be truly reflecting their opinion. According to Martens and Maalej (2019) fake reviews can be defined as non-spontaneous, requested and rewarded reviews. Another definition provided by Fontanarava et al. (2017) states that a fake review is a positive, neutral or negative review that is not an actual consumer's honest and impartial opinion or that does not reflect a consumer's genuine experience of a product, service or business (European Parliament, 2015).

Spam detection approaches

As fake reviews are becoming much more of a problem with more reviews sites popping up and consumers' ability to produce feedback at anytime, demand for spam detection methods is rising. However, as much more research appears on the topic of spam detection, the practical implication seems to be a challenge. Major review websites as Yelp and Amazon have already taken first steps in detection fake reviews on their websites; however there seems to be a lot of room for improvement. Hussain et al. (2019) researched several spam detection techniques and how these can be applicable for corporate reputation. According to their paper, spam detection consists out of the following steps:

1. Gathering a review dataset
2. Select feature engineering
3. Apply machine learning technique

In order to answer the research questions properly, it is important to analyze this process much more in-depth. Therefore, each step will be separately discussed in order to generate useful findings for creating an own spam detection model.

Gathering a review dataset

In order to set-up any machine learning model, it is important to have a dataset to work with. However, in terms of spam detection it is considered difficult to find an available, labelled dataset (Hussain et al., 2019). Multiple researches on spam detection models indicate that there is only one labelled hotel review dataset available with only review text and no other features available (Kaggle, 2020). Many of the studies used to analyze spam detection methods do no publish their used datasets publicly, which makes it difficult for new researchers to continue optimizing spam detection models. It can be stated that after researching multiple studies on spam detection, a limited amount of labelled datasets are available which is contradicting the high urgency for spam detection methods.

Feature engineering
According to Hussain et al. (2019), the linguistic approach is the most common approach for feature extraction from review datasets. As they explain in their research, this approach focuses on review text and includes data pre-processing, tokenization, transformation and feature selection. In appendix 1 an example of how the first three steps can be executed for spam detection will be given. For the purpose of literature review, feature selection will be discussed in this chapter as previous research on this topic shows to have significant value for the spam detection model of this study. Previous research, according to Hussain et al. (2019), shows that the following spammer features are used to detect spam and non-spam reviews.
1. Maximum number of reviews: previous research indicates that spammers write often more than one review per day.
2. Percentage of positive reviews: most spammers write positive and favourable reviews, therefore a high percentage of positive reviews could indicate spam reviews.
3. Review length: most spammers do not write very lengthy reviews with a lot of details. Therefore, short reviews can indicate spam reviews.
4. Reviewer deviation: spammers give often very high ratings, therefore this rating deviate from the average review rating.
5. Maximum content similarity: research shows that similar reviews are used for multiple product/services and different organisations.

After analyzing several sources in the study of Hussain et al. (2019) it shows that the linguistic approach shows to have the highest accuracy in terms of spam detection method. However, it all depends on the feature selection as these become the input for the spam review detection method.

Machine learning techniques
In order to classify the reviews for spam or non-spam, it will be needed to choose the appropriate classification model. Hussain et al. (2019) published a model for the taxonomy of spam detection techniques. This model is created for other researchers, *"to classify existing approaches and to figure out the most appropriate technique to solve a spam detection problem"*.

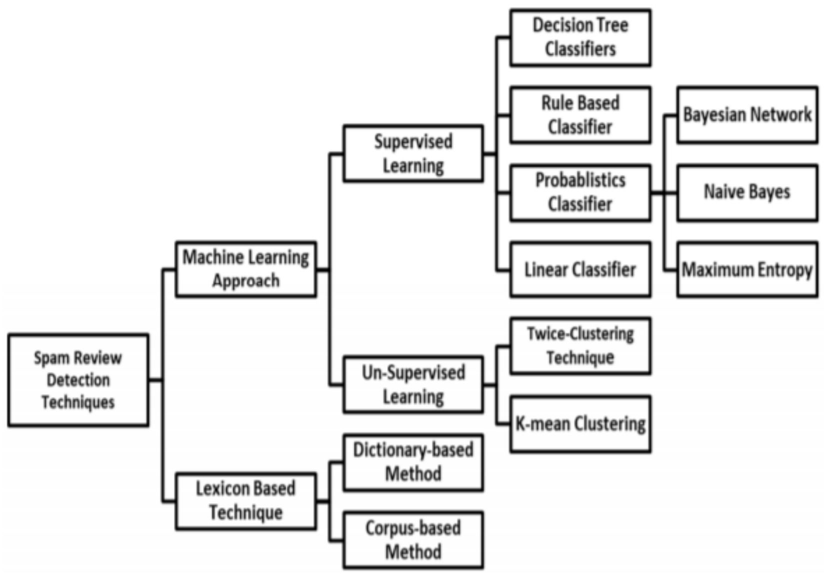

FIGURE 2: TAXONOMY OF SPAM REVIEW DETECTION TECHNIQUES (HUSSAIN ET AL., 2019, P. 13)

According to existing literature on spam detection, generally spam detection models can fall into two categories: machine-learning based methods and lexicon-based approach. The first approach, machine learning techniques, can be classified into supervised and unsupervised learning. Research shows that the accuracy of supervised-learning in terms of Support Vector Machine and Naïve Bayes performs best. For unsupervised learning, Aspect based and K-nearest neighbour approaches outperform in this approach. In this study, the focus will lie on machine learning techniques therefore the Lexicon-based approach will not be further discussed in this literature review. For an overview of accuracy rate per approach, please see appendix 1.

2.1.3 The role of fake reviews in corporate reputation

Many studies agree that fake and negative reviews have a negative effect on the online corporate reputation of a company (Horn et al., 2015; Barbado et al., 2019; Xhema, 2019; Hussain et al.,2020). One of the main issues with opinion sharing websites and apps is that fake reviews can easily create hype about a particular product based on misleading information. These fake reviews can become the key factor for consumer in their buying decision and thus lead to negative financial consequences. Although it seems clear for people that not everything on the Internet is believable, research from shows that almost 84% of consumers consider online reviews to be as trustworthy as personal recommendations. However, for organisations to make use of fake reviews or have fake reviewers can harm the corporate reputation by creating false expectations. Also, true reviews can help organisation learn where to improve and can be beneficial tools in increasing success and business. Secondly, if an organisation gets caught buying fake reviews for its own products or to decrease the value of its competitors, it will lead to much more reputation loss than it could gain. An example from 2013 is Samsung which was fined for paying people to negatively review HTC products. Also, a report from BBC showed that fake online reviews are openly bought and sold were shoppers get in return for a fake review a product for free.

Benefits of corporate reputation management

The above-mentioned examples indicate what can happen if organisations do not put effort in strong reputation management and alignment of stakeholder reputations as discussed by Page and Fearn (2005). For the interest of this research and why it is important to limit fake reviews and focus on strong reputation management, this section will describe the benefits of reputation management. Positive reputation can strengthen the overall performance of an organisation, while negative reputation is considered a competitive disadvantage (Aula, 2010).

According to Helm and Klode (2007) there are five major benefits that strong corporate reputation can bring to an organisations. These are as follows:

1. Increased financial performance
2. Greater competiveness
3. Higher satisfaction and loyalty among consumers
4. Attract and retain employees
5. Support in crisis

The first benefit, increased financial performance can result by increased stock value. According to Helm and Klode (2007) strong reputation indicates limit risk for investors, who are more willing to spend money on the organisation. The second benefit, greater competiveness goes hand-in-hand with increased financial performance. Helm and Klode (2007) identify that organisations with strong corporate reputation can easily charge higher prices due to the fact that consumers perceive the quality of product and services as better. Thirdly, several studies indicate that a good corporate reputation can increase customer satisfaction and loyalty (Helm and Klode, 2007; Chun, 2005; van

Riel & Fountain; 2008). Fourthly, a positive company image attracts more highly skilled employees hence the benefit of attracting and retaining employees (Helm & Klode, 2007). Lastly, according to Helm and Klode (2007) in times of crisis for an organisation, a positive reputation can help companies to overcome economic consequences. Organisations with a strong image experience less market decline compared to organisations with a weak reputation (van Riel & Fombrun, 2008).

To conclude, according to the discussed literature sources, strong corporate reputation can bring several major benefits to an organisation. These benefits are linked to financial, strategic and competitive advantages that all have a positive effect on the performance of an organisation. Therefore, it is highly advisable and important for an organisation to focus on strengthens its corporate reputation and limit threats as fake reviews.

Fake reviews in consumer buying behaviour

Study from Constantinides and Fountain (2008) also describe an important relationship between how consumers are exposed to information of organisations. They identified four stimulating factors; each communication means that affect the purchasing decision. Although purchasing behaviour should be threatened separately from corporate reputation; it is chosen to describe the theory from Constantinides and Fountain (2018) shortly, to emphasize on the importance of fake reviews on purchasing behaviour.

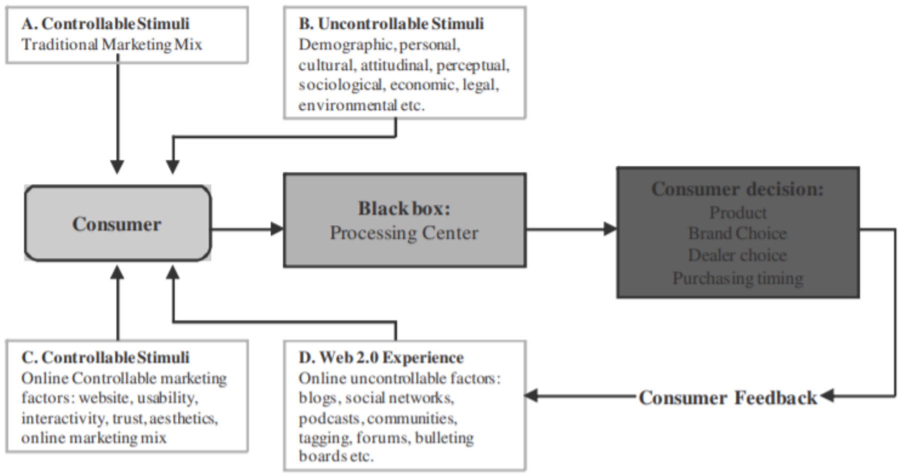

Figure 3: Four stimuli on consumer behaviour (Constantinides and Fountain, 2018)

The model shows four stimulating factors, that according to the study, *"influence consumers equally"* (Constantinides & Fountain, 2018).

A) Controllable stimuli as traditional marketing
B) Uncontrollable stimuli as demographics, culture, economic situation, environment of a person (external factors)
C) Online, controllable factors on the Internet, which is considered the created web experience for consumers
D) Online, uncontrollable factors on the Internet, as input from others (reviews)

Organisations that use fake reviews, attempt to make from stimuli D a controllable stimulating factor. According Constantinides and Fountain (2018), all stimulating factors are equally distributed, this can explain why organisations with bad reputation or as part of sales strategy, focus on making the uncontrollable controllable (Grutzmacher, 2011).

2.2 Conceptual model

This section combines the variables identified of corporate reputation as discussed in the above literature frame. The goal of this conceptual model is to visualize the study and indicate the connection between fake reviews and corporate reputation. The model, inspired by Fombrun (1997), shows how several variables are related to each other and eventually create corporate reputation. According to Dowling (2001) corporate identity is in short how people recognize an organisation (Dowling, 2001). Secondly, corporate image is defined as *“a set of beliefs and feelings an audience has about an organization”*. This all lead to corporate reputation, that is formed by the judgement about the organisation’s attributes as is indicated in the model. This is were fake reviews play an important part on the perception of customer and community image.

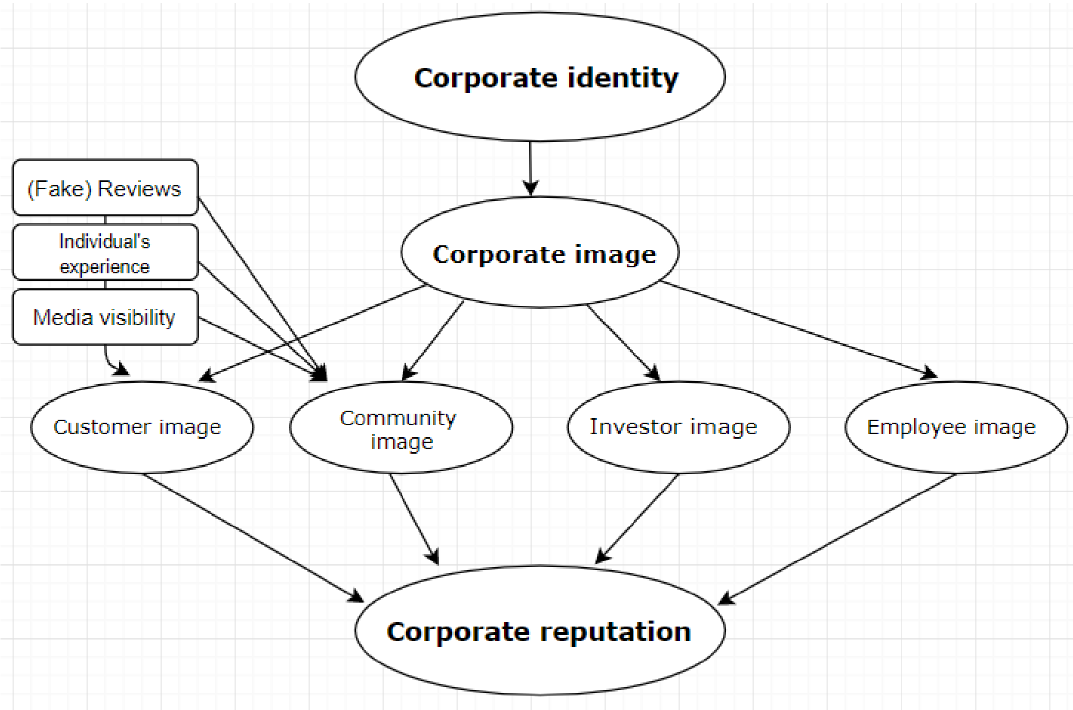

FIGURE 4: FAKE REVIEWS AND CORPORATE REPUTATION, A CONCEPTUAL FRAMEWORK

3. Research methodology

This section will focus on the research design of the project. An explanation will be provided about the research methods used; which included data collection, preparation, and analysis. For this study, suitable methodological techniques are chosen carefully with the understanding of their limitations. All decisions made for are underpinned by scholars and suited this study on reasoned choice (Saunders et al., 2009). This research methodology is created to provide a clear overview of all actions taken, in order to fulfil the goal of building a spam detection model to strengthen corporate reputation for companies.

3.1 Research design

In this methodology, the research design refers to the overall strategy that targets different components of the study, in a coherent and logical way, to effectively address the research problem (Williamson, 2002). This research design will follow exploratory research, as it intends to explore fake reviews by making use of machine learning methods and their respective research areas. The overall goal of the exploratory search is to generate insights about the online reputation problem the e-commerce industry is dealing with. Brown (2006) describes exploratory research as *"tends to tackle new problems on which little or no previous research has been done"*. One of the main reasons that this type of research design has been chosen is due to the flexibility and adaptability of change.

In order to explore information, primary and secondary data sources will be used. Primary data is defined as "*data which is collected to serve a particular research*" (Kumar, 2002). Primary data will be obtained to use as raw dataset to work with for developing a spam detection model (RQ3). Primary data is collected in two forms; a scraper is built to subtract customer reviews from Google Play. One major drawback from this primary data source is that this dataset will be unsupervised, which makes it more challenging to work with. Therefore, another alternative is thought of; information provided by Kaggle (2020) will be used as primary data source, this data is later processes into an own dataset for the spam detection model. The primary data is considered qualitative data, as it contains text rather than numbers. Secondary data is defined as *"data which is readily available and not originally collected by the researchers but rather obtained from published or unpublished sources"* (Fraenkel & Wallen, 2000, p.346). Throughout this research, secondary sources are used by the means of academic articles, reports and books together with literature provided by the Amsterdam University of Applied Science. In order to ensure the reliability and validity of these secondary sources, only academic articles from the last ten years in scientific journals of Q1-level are used. These articles are obtained via the CMI of HvA (2020), and via the website Scimago (2020).

3.2 Data collection

Data collection is a process of collecting information from all the relevant sources that targets answering the research problem and evaluate the outcomes. For this study, two datasets are collected: a dataset scraped from Google Play including product metadata and reviews from customers; as well as a supervised dataset from Kaggle with 400 deceptive reviews.

The scraped dataset was created April 2020 and consist out of 200.000 products, their metadata, and reviews. To collect this data, a crawling tool using Google Play Scraper was used. The data collection included of the following steps three steps. Firstly, a list of companies was chosen which included 10 food & beverage retailers. Then, the data was retrieved via a Python built code in Jupyter Notebook. Lastly, all metadata was converted to a csv file for further use. The second dataset is obtained from Kaggle (2020), this is an open-source data platform. The data that is obtained concerned a dataset from Amazon Mechanical Turk in combination with TripAdvisor. This dataset is created for researchers to work with supervised data in order to provide new solutions on the fake review issue. For this dataset, a group of people were paid to write 400 fake positive and 400 fake negative reviews. In order to make this dataset still primary data, the data was cleaned and processed before it was used for building a model. The dataset from Kaggle was obtained April 2020, via their website.

3.3 Data preparation

For this phase, the data was first observed. All data was obtained in a CSV-file and consisted out of text and numbers. Then, data was cleaned and validated, this included removing data outliers, filling in missing values, confirming data to standardized patterns, filter to English reviews and remove duplicated. After this, all data was transformed to CSV-format again and stored on the machine for further use. As it turns out the unsupervised dataset from Google Play was too sophisticated to use for spam review detection, the chose was made to continue the study further with the dataset obtained from Kaggle.

3.4 Data analysis

The data analysis phase consists out of two steps which respectively answer the research questions. To answer RQ2, the data was used to explore characteristics of fake reviews. Three hypotheses were created to describe the dataset which included the differences in length of words from between multiple variables. Also, POS, polarity and weighting meaningful words and form into topics was used to create features that can be used as input for the model. The second step, to answer the final research question, the data was used to implement into a machine-learning model, Support Vector Machines, to train the model. Overall, by using this data, it was possible to develop a model with an accuracy rate of 0.98 with only 5 out of 320 test samples misclassified.

The following diagram represent the research method consisting the data collection, preparation and analysis process.

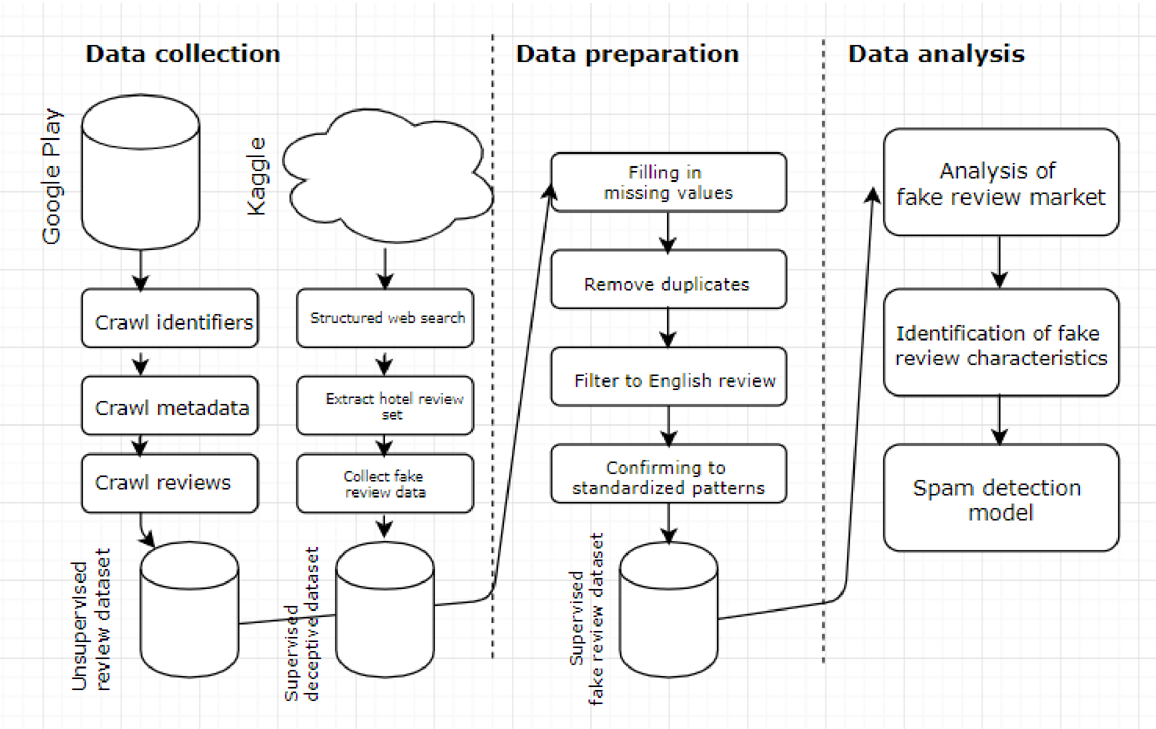

DIAGRAM 1: RESEARCH DESIGN PROCESS

3.5 Reliability and validity

For this project, the reliability and validity will be described to ensure the quality of the research. Reliability is described as *"the extent to which the results can be reproduced when the research is repeated under the same conditions"* (Saunders et al., 2009). Reliability of this study can be ensured as other people have used the same dataset for spam detection and achieved also an accuracy in the same range. Also, when running the Notebooks again, the results stay similar. It will be easy to reproduce this research as all steps are presented in the project documentation and can be copied and run on every machine.

Validity refers to *"the extend to which the results really measure what they supposed to measure"* (Saunders et al., 2009). The results of the research show to be accurate, therefore reproducible. This study has focused on testing the existing knowledge of spam detection using the machine-learning technique Support Vector Machines. The concept that tested was spam detection, which shows to be fulfilled by presenting a model that can automatically detect deceptive from truthful reviews. For these reasons, it is stated that the validity of this project is ensured.

3.6 Limitations

In their research, Hussain et al., (2019) already stated some key limitations that can occur when developing a spam review method. One of these statements was the limited amount of supervised dataset available; during this research this statement become true. It was very hard to find a supervised dataset to work with. One way to create a primary dataset with labelled is to find fake review websites with fake reviews and scrape this data into one fake review dataset. However, due to time limitations and lack of resources, it was difficult to achieve for this research. The scarcity of labelled datasets forms a real challenge for further researchers, with limit resources, to fasten the progress of spam detection.

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5. Appendices

5.1 Appendix 1: Comparison of different supervised learning techniques

Source: Hussain et al., (2019)

Dataset	Learner	Accuracy
Amazon.com	Logistic Regression (LR)	78%
Epinions.com	Naive Bayes (NB)	63%
Hotel reviews through Amazon Mechanical Turk (AMT)	Support Vector Machine (SVM)	89.9%
Amazon.com	Support Vector Machine (SVM)	71%
Yelp's real-life data	Support Vector Machine (SVM)	86.1%
Hotel reviews through Amazon Mechanical Turk (AMT)	Support Vector Machine (SVM)	84%
Arabic reviews from Tripadvisor.com and Booking.com	Naive Bayes (NB)	99%
IMDb movie	Decision Tree (DT)	75%
Chinese Language micro-blog	Random Forest (RF)	65%
	Logistic Regression (LR)	79%
	Naive Bayes (NB)	72%
Yelp restaurant reviews	Random Forest (RF)	76%
	Support Vector Machine (SVM)	78%
Amazon product reviews	Random Forest (RF)	91%