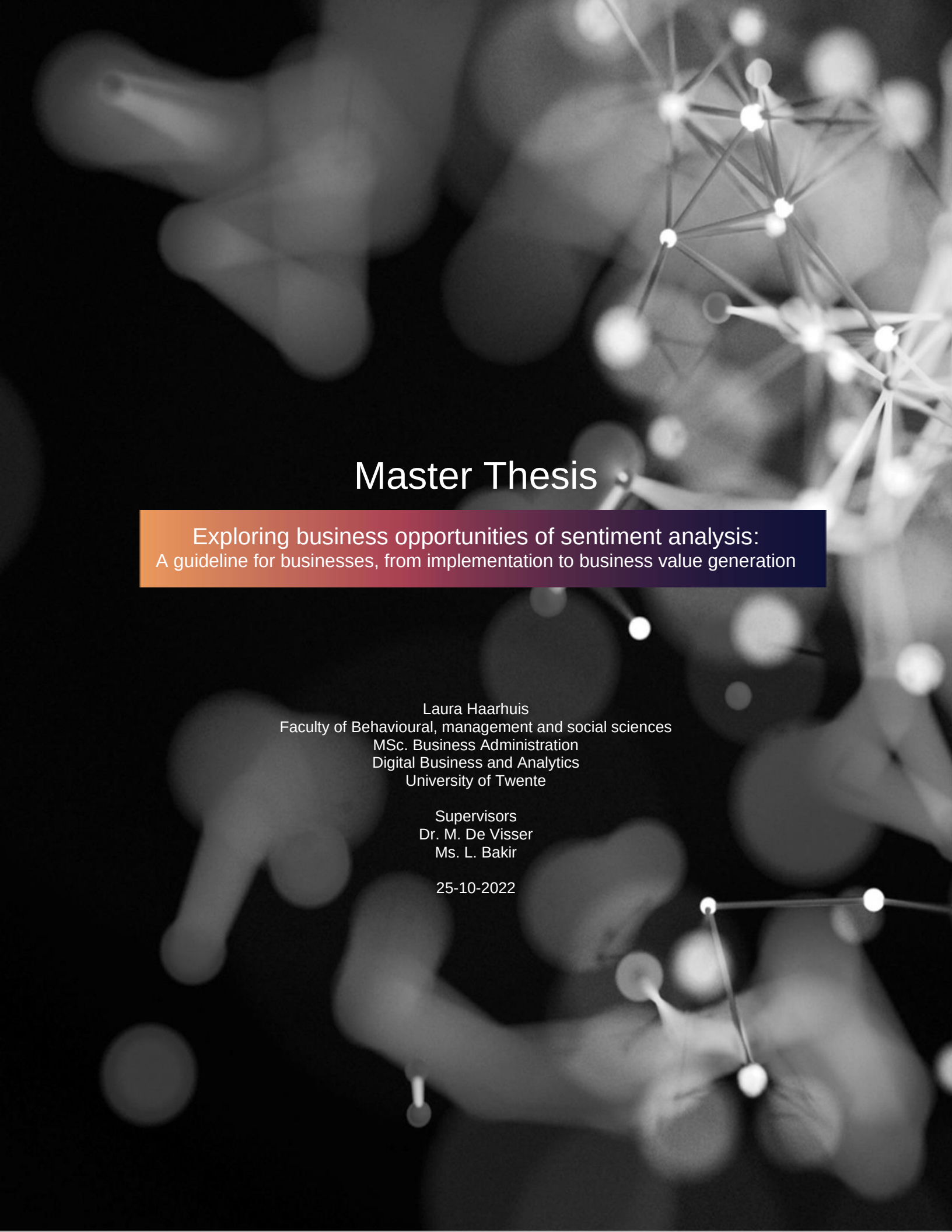

Master Thesis

Exploring business opportunities of sentiment analysis:
A guideline for businesses, from implementation to business value generation

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Abstract

Machine-learning conquers the world as this emerging new technology offers great opportunities not only for science but also for businesses. One interesting machine-learning application is sentiment analysis. Sentiment analysis is an interesting and upcoming machine-learning application which measures sentiment. This machine-learning method can obtain sentiment from stakeholders like customers and employees. Research papers describe that sentiment analysis is used to predict the sentiment of Twitter users (Pozzi et al., 2016). Literature also discusses several sentiment analysis applications for businesses but the full potential of sentiment analysis for business has thus far not been examined extensively. Therefore, this research provides a comprehensive guideline for businesses on if and how they should implement and utilize sentiment analysis. The first steps (step 1 to 4) within the guideline explain how businesses can implement sentiment by utilizing pre-trained sentiment analysis models. Therefore, this research first examines which input is suitable for sentiment analysis and how this data should be cleaned in order to obtain accurate sentiment analysis scores. Next, an overview of pre-trained sentiment analysis models for the Dutch language will be presented. The research examines considerations in order to provide a guideline for businesses to select an appropriate sentiment analysis model. This research utilizes interviews to help answer step 1 to 4. The up-following steps (step 5 to 8) describe how businesses can utilize a systematic approach to explore new value-generating sentiment analysis applications for their business. The systematic approach explores new sentiment analysis applications in a business setting. This method examines the goals of several departments. It develops business metrics which can be derived from sentiment analysis. After this, applications can be developed by analyzing which metrics help each division to reach their goals. Lastly, this research ranks the applications based on business value. This helps companies to determine if they should or should not invest in sentiment analysis. In step 5 to 8 the research utilizes a case study at company X to determine how well the systematic approach of exploring new sentiment analysis applications works. Company X is a big insurance company in the Netherlands and would like to utilize the full potential of sentiment analysis for their organization. The case study entails interviews and a survey to examine sentiment analysis inputs, models, considerations, goals, metrics and applications. It compares literature to the results of the interviews and surveys and determines how companies can best implement and utilize sentiment analysis. The sentiment analysis applications are categorized in the following business divisions: board of directors, business intelligence, customer relationship management, customer support, external Affairs, human resource management, marketing, purchase department and sales department. The research shows that the case study provides valuable information for companies on how to best implement and utilize sentiment analysis. New methods are explained related to sentiment analysis input, metrics and applications. The results show the importance of defining the purpose of the sentiment analysis as the input needs to fit the purpose. Next to this, the research presents newer and broader sentiment analysis metrics like shareholder sentiment KPIs and supplier sentiment KPIs. KPIs can also be more focused like measuring the sentiment within contact moments to analyze why sentiment is going up or down during contact moments. The results also present new applications. The most valuable application presented in this research is the prioritization tool. The prioritization tool creates business value by identifying which business processes create lots of negative customer sentiment. Companies should also take into consideration that there are also limitations to sentiment analysis. Companies should examine data privacy and data security legislation in order to determine if the data can be used for sentiment analysis.

1. Introduction

1.1 Current situation

Innovation is key in highly competitive markets and companies in the Netherlands are becoming more innovative by the day. Machine-learning and AI are widely used methods and new models are developed every day. Nowadays, new machine-learning methods are examined by researchers but new machine-learning methods can also be utilized by businesses to generate value. Machine-learning models can for instance help businesses to automate operations, to fasten processes and to evaluate their performances.

Customer satisfaction is of utmost importance in highly competitive markets. As 91% of the customers will leave if they are unsatisfied and they will never buy anything from you again (Live Work Studio, 2018)(Macdonald, 2021). This statistic shows the importance of having happy customers. Customer satisfaction is key to measuring their happiness and there are various methods to measure it. Hydock and Carlson (2017) explain how companies can utilize customer satisfaction metrics to get a better understanding of customer behaviour like engagement, word-of-mouth communication, loyalty, and purchase behaviour. In addition to this paper, Capuano et al. (2020) mention that sentiment analysis is of utmost importance for measuring customer satisfaction, tracking consumer opinion, interacting with consumers and building customer loyalty. Sentiment analysis can provide value for businesses as the sentiment of the customer tells a lot about the performance of the business. The sentiment measured in sentiment analysis models is often labelled as negative, neutral or positive sentiment (Martínez-Camára et al., 2012). This helps companies to determine if the customers are happy.

Measuring customer satisfaction is only one way of utilizing sentiment analysis in a business setting. There are many business opportunities which can be explored in order to determine what sentiment analysis has to offer for businesses. Sentiment analysis measures the sentiment of entities. For customer satisfaction, the entity is the customer but sentiment analysis can for instance also measure employee satisfaction by utilizing employee data as input for sentiment analysis models. Therefore, sentiment analysis can provide business value not only by obtaining the sentiment of the customer but also by obtaining the sentiment of other entities within a business.

1.2 Problem statement

Studies mention that sentiment analysis offers a wide range of opportunities for businesses as it provides opportunities to measure the sentiment of various entities. Bianchi (2021), Roldós (2020) and Fairly (2022) mention that companies can obtain and utilize the sentiment of entities to obtain business value. This means that the sentiment can be obtained from the market, customers, participants of events and employees by utilizing sentiment analysis. The sentiment of these entities can be used by businesses to improve their business performance. Capuano et al. (2020) explain for instance that sentiment analysis is of utmost importance for businesses as it helps businesses to measure customer satisfaction, track consumer opinion, interact with consumers and build customer loyalty. Róldos (2020) and IrisAgent (2022) mention that sentiment analysis can also be used to order customer support tickets based on urgency. The urgency of how fast a ticket should be handled will be based on the sentiment of the customer. When a ticket shows highly negative sentiment then the ticket will be labelled faster. This research presents an overview of sentiment analysis applications and how much business value these applications generate. It is important to measure how much business value the existing applications generate in order to examine if companies should invest in implementing sentiment analysis.

As sentiment analysis is a newly developed technique, it is possible that not all sentiment analysis applications are identified for business. Bianchi (2021) and Roldós (2020) mention that for businesses the sentiment of the market, customers, participants of events and employees can be measured but they do not mention that sentiment analysis can obtain sentiment from other business stakeholders as well. Therefore, this paper identifies from which stakeholders in business the sentiment can be acquired via sentiment analysis. New sentiment analysis applications are explored by analyzing the possibility of obtaining the sentiment of various stakeholders. This research presents an overview of all sentiment analysis applications for businesses and their business value. It presents newly developed sentiment analysis applications and already existing sentiment analysis applications and the research compares them based on business value.

Currently, the internet provides various guidelines for businesses to utilize sentiment analysis but none of these guidelines are comprehensive. This creates a knowledge gap. The guideline by Das (2022) for instance provides a step-by-step method for businesses to utilize sentiment analysis but instead of referring to methods for businesses how they can develop a sentiment analysis model themselves, the guideline refers to tools and applications which measure the sentiment for you. The guideline is written in a very commercial way and tries to create new leads for these sentiment analysis tools. Rojewska provides a guideline for business to implement sentiment analysis (2022). She explains which steps companies have to take in order to utilize sentiment analysis but she explains the steps very generally. After reading the guideline, it is not clear yet what companies first have to do to. Rojewska mentioned, for instance, to “train the model” but she does not mention how companies can do this. This research provides a guideline of how businesses can best obtain sentiment by utilizing pre-trained sentiment analysis models and how they can utilize this to improve their business performance by using sentiment analysis. It discusses based on business value if implementing sentiment analysis is worth the investment.

1.3 The research question

This research will examine how companies can best utilize sentiment analysis to obtain the sentiment of the customer. It additionally examines how companies can utilize this sentiment analysis to create business value. By measuring the business value, companies can decide if they should or should not invest in sentiment analysis based on their business value. The following research question will be answered in this research:

How can companies best obtain and utilize sentiment via a pre-trained sentiment analysis model in order to improve business performance?

This research provides a guideline to help companies exploit the full potential of sentiment analysis. Therefor, the research question is divided in steps a company should take to fully exploit the potential of sentiment analysis. Step 1 to 4 are focused on how companies can best implement sentiment analysis. Step 5 to 8 are focused on the business value of implementing sentiment analysis and if the company should invest in sentiment analysis based on the business value.

Step 1: Evaluate if the data is suitable for sentiment analysis

Step 2: Prepare the data for the sentiment analysis

Step 3: Develop an overview of available sentiment analysis models

Step 4: Choose a sentiment analysis model

Step 5: Define the goals of the departments

Step 6: Define which metrics can be obtained from sentiment analysis

Step 7: Develop an overview of sentiment analysis applications

Step 8: Prioritize the sentiment analysis applications based on business value

1.4 Theoretical contribution

This research proposes a guideline for businesses on how to best implement and utilize sentiment analysis. Next to this, this research presents a newly developed approach on how business can explore new sentiment analysis applications. This systematic approach helps businesses to examine sentiment analysis applications by analyzing the goals and the available sentiment analysis metrics.

As the newly developed approach to explore new sentiment analysis applications in business was executed at Company X, the research additionally obtained various new sentiment analysis applications for company X. The newly developed applications generate business value as the survey at company X shows.

This research is of importance as it helps business to decide if they should invest in sentiment analysis based on the business value that is generated by the sentiment analysis applications. Additionally, this research is valuable as it proposes a new way of obtaining sentiment analysis applications. The newly developed method is built in a systematic way. All businesses can utilize the systematic approach to explore new sentiment analysis applications for their business.

The guideline proposed in this research was developed by executing interviews. The systematic approach to explore new sentiment analysis applications was developed by the researcher. The systematic approach was developed by comparing what is relevant (by looking at the goals and the tasks fitting to these goals) with what is possible (possible sentiment analysis metrics which can be obtained). In this way, new sentiment analysis applications could be developed.

This research is relevant as sentiment analysis is a newly developed method with lots of business opportunities but if companies do not examine new sentiment analysis applications then they cannot utilize the full potential of sentiment analysis. As not all sentiment analysis applications are yet discovered, which is often the case with newly developed techniques.

This thesis is valuable for companies which are in doubt on how they can implement sentiment analysis and how sentiment analysis can create business value for their company.

1.5 Practical contribution

This research provides a guideline to businesses on how and if they should utilize sentiment analysis for their business. In this way, the research fills the knowledge gap discussed in the problem statement. First (in step 1 to 4), the guideline explains how companies can best obtain the sentiment of stakeholders (customers, employees et cetera). It discusses how companies can select data, prepare data, explore pre-trained sentiment analysis models and choose between pre-trained sentiment analysis models. Next (in step 5 to 8), the guideline describes how companies can best utilize sentiment analysis. In this section, the research describes how companies can explore sentiment analysis metrics and applications. The research additionally helps companies to decide if they should or should not invest in sentiment analysis. The research does this by determining how much business value can be obtained from implementing sentiment analysis and its applications.

There are already various applications of sentiment analysis in business (Fairlie, 2022). It can for instance be used as a purchase tool or an evaluation tool (Fairlie, 2022). This research examines all possible business applications of sentiment analysis and ranks the applications based on business value. In order to provide recommendations to companies on which applications they should implement to obtain business value.

2. Theoretical Framework

This chapter provides a clear theoretical framework of the research. In order to fully understand the research question, the theoretical framework first defines sentiment. This paragraph will be followed by the paragraphs 2.2 “Studies on the importance of obtaining (customer) sentiment” which explains the importance of sentiment in business. The following paragraphs 2.3 “Studies on common methods of obtaining sentiment” and 2.4 “Studies on new methods of obtaining sentiment” explain which methods can be utilized to obtain sentiment in a business setting. As this research provides a guideline, the theoretical framework discusses studies about the development of guidelines. Next,

2.1 Definition of Sentiment

The American definition of sentiment is the general feeling, attitude or opinion about something (Cambridge Dictionary, 2022). Emotions such as love, hate, sympathy, disgust show sentiment. The definition of sentiment in a business English setting is the following: sentiment be defined as a though, opinion or idea based on a feeling about a situation or a way of thinking about something (Cambridge Dictionary, 2022). Measuring the sentiment of customers is widely used in business.

2.2 Studies on the Importance of Obtaining (Customer) Sentiment for Businesses

According to Live Work Studio (2018) and Macdonald (2021), it is important for companies to measure the sentiment of customers. As 91% of the customers will leave the company if they are unsatisfied and they will never buy anything from you again. This statistic shows the importance of having happy customers. Customer satisfaction is key to measuring their happiness and there are various methods to measure it. Hydock and Carlson (2017) explain how companies can utilize customer satisfaction metrics to get a better understanding of customer behaviour like engagement, word-of-mouth communication, loyalty, and purchase behaviour. In addition to this paper, Capuano et al. (2020) mention that sentiment analysis is of utmost importance for measuring customer satisfaction, tracking consumer opinion, interacting with consumers and building customer loyalty. Sentiment analysis can provide value for businesses as the sentiment of the customer tells a lot about the performance of the business. This research also provides a new method to explore sentiment analysis applications. In this method, the goals, metrics (KPIs), business applications and business value will be analyzed. Therefore, these topics will be explained. Lastly, the theoretical framework defines important concepts in order to get a better understanding of this research.

2.3 Methods of Obtaining Sentiment

2.3.1 Surveys

According to Segwick (2014), surveys are widely used to measure customer satisfaction, but this method might be biased. Not all customers answer the questions in the customer satisfaction survey and this could lead to an inaccurate representation of the actual customer satisfaction scores. When companies measure the sentiment by analyzing the amount of complaint emails they should keep in mind that that only 4% of the unhappy customers actually complain to the company according to Macdonald (2021). 91% of the customers whom are unhappy and do not complain cancel their membership or stop buying the product (Macdonald, 2021). Therefore, companies should look to alternative methods to measure the sentiment of the customers.

2.3.2 Sentiment Analysis

Nowadays, AI and machine-learning models provide new ways of obtaining customer satisfaction scores like sentiment analysis models (Al-Otaibi et al., 2018). Sentiment analysis models can be split into two approaches the machine-learning approach and the lexicon-based approach (Medhat et al., 2014). Figure 1 displays the categories within sentiment analysis approaches. According to Liu (2012) “sentiment analysis, also called opinion mining, is the field of study that analyzes people’s opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes”. Sentiment analysis mainly focuses on opinions that express or imply positive or negative sentiments (Liu, 2012). Figure 1 displays NLP techniques that can be used to execute a sentiment analysis. Sentiment analysis is one of the most studied research areas of natural language processing (NLP). It is widely used in marketing for instance when analyzing the sentiment of the social media users (Liu, 2012). Social media performances can be evaluated by using sentiment analysis. Which posts generated a negative sentiment and which post generated a positive sentiment? These posts can be compared in order to predict if future posts will generate positive or negative sentiment. Sentiment analysis models are nowadays able to measure sentiment not only in written but also in facial and voice expressions. In the future, the facial and voice expression might be used to measure the customer sentiment in a better way. Attention should be paid to the fact that the customer first has to give their permission so that companies can utilize this private data in their sentiment analysis models (Fairly, 2022).

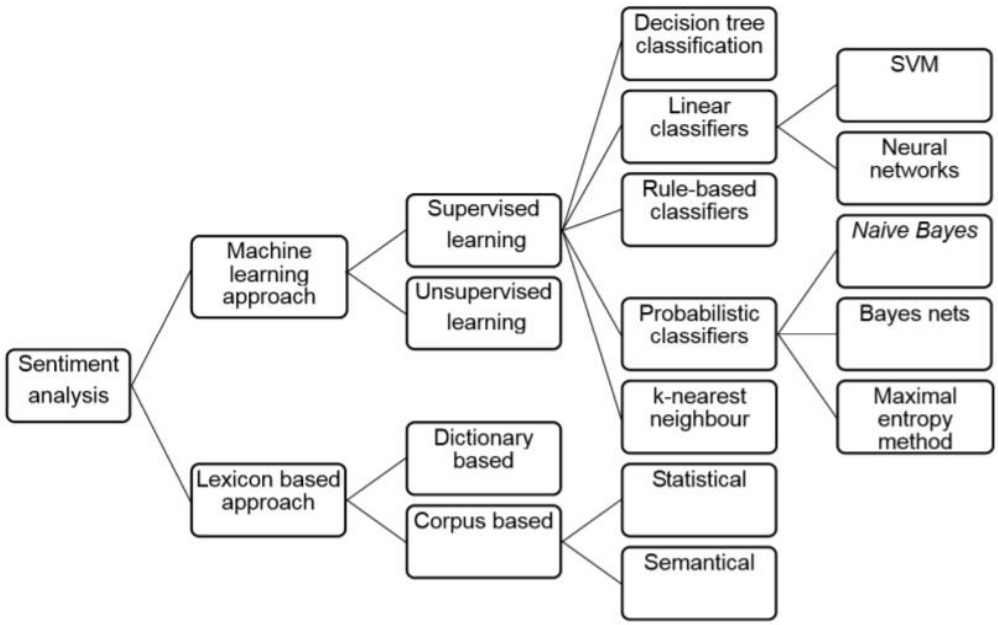

Figure 1: Sentiment classification techniques (Medhat et al., 2014)

Companies can choose to train and develop sentiment analysis models themselves but they can also utilize pre-trained sentiment analysis models. Pre-trained sentiment analysis models contain training data. Therefore, a company does not need to provide large dataset themselves. Another benefit is that pre-trained models can score content immediately into positive, negative or neutral sentiment. Depending on the pre-trained sentiment analysis model, the text input will be scored differently. A text can be given a score from 0 to 1, where 0 is negative and 1 is positive but this can also be a scale from 1 to 5 or a scale from -1 to +1.

2.3.3 Emotion-detection Analysis

Emotion-detection analysis is another method to obtain the sentiment of customers. This analytics method assigns the text to certain emotion-detection categories like “wicked”, “bad”, “sad”, “relief”, “upset”, “angry”, “surprised”, “happy” and much more (Fairlie, 2022). In this way, they can obtain sentiment of customer in emotion-detection categories.

2.4 Studies on Structuring a Guideline

Lester (2015) proposes a methodology to develop a good guideline. In this methodology, she describes that a guideline must contain the following steps to be considered a good guideline. The first step is that the purpose of the guideline must be defined. The second step is that the guideline must be written for the specified audience. This means that the author of the guideline should first establish the audience and then utilize the writing style corresponding with this audience. The third step is to write objectively by stepping in the shoes of your audience. This steps helps the author to understand what the audience needs to know. The fourth step is to develop the guideline in a step-by-step order. The actions should be broken down in instructions which are concise, single-tasked and actionable. The fourth step is to use plain English. The guideline should be clear, concise and the audience should understand it easily. The fifth step is to be direct and to start the steps with the verb first. This means that the author should drop the usage of the word “should” and should start using words like “choose”, “prioritize” et cetera. The sixth step is to establish a clear pattern in the guideline. Use headings and questions which answer what the audience should do, why they should do it and how they should do it. The seventh step is to include images where appropriate. Images can be used to explain certain steps better. The eight step is to add an example. Some steps might be hard to understand. An example can help to better understand the step. The ninth step is to not add specific details. The guideline can add chapters related to the background, history or context of specific steps but the steps itself should not provide all background and history related to the topic as this slows down the guideline. Adding topics like background, history and context can give the audience additional information but it is not necessary to read this information if the audience would like to utilize the guideline. The last step that Lester (2015) recommends to establish a good guideline is to ask feedback. Ask people to give feedback about the guideline. Did they understand everything?

2.5 Explanation of Important Concepts

2.5.1 Explanation of Business Goals

Businesses establish business goals. Business goals are goals that a company would like to accomplish (Herrity, 2022). According to Herrity (2022), business goals can be defined for the overall business, departments, employees, managers and/or customers. Employees work towards business goals, this means that employees try to achieve their business goals. Business goals are developed in a broad sense. Business goals have various objectives. Business goals for instance provide businesses with a way to measure their success. Business goals help employees to focus on a specific purpose. Business goals show how decision-making can affect the business goal and business goals ensure that the company is going in the right direction (achieving its goals) (Herrity, 2022).

Herrity (2022) mentions in her paper that business goals are different from business objectives. As business objectives consist out of clearly defined steps which are measurable. Business objectives are the steps which ensure that the business achieves their goal. Business objectives are always specific and can be easily measured and defined. In order for a business to achieve their goals, they first have

to manage how they will achieve their plan by creating business objectives. Therefore, the main difference between business goals and business objectives are that the business goals define what the company wants to achieve whereas the business objectives define how the company will achieve their business goal.

2.5.2 Explanation of KPIs

According to Bauer (2004) Key Performance Indicators (KPIs) are quantifiable metrics which reflect the performance of an organization in achieving its goals and objectives. KPIs focus on providing strategic value. KPIs are metrics but not all metrics are KPIs as KPIs focus on providing strategic value. Other metrics can also provide value but these metrics measure non-critical business activities and processes. Therefore, companies should base the selection of their KPIs based on their critical business activities and processes. When companies establish a KPI they should think about the following thing: what will be measured? When, how and by whom will the KPI be measured? The number and the complexity, benchmarking and normalization of the KPI (Bauer, 2004).

2.5.3 Explanation of Applications

According to the Cambridge dictionary (2022), the definition of application varies. An application can be defined in general as a way in which something can be used for a particular purpose. In this context, it can be viewed as a synonym of utilization. In relation to computer science, the Cambridge dictionary (2022) proposes another definition of application. In this context, an application can be a computer program that is designed for a particular purpose.

2.5.4 Explanation of Business Value

According to literature, applications can be ranked based on business value. According to Nurkiewic (2022), business value can be utilized as a tool for people with different perspectives to understand each other and identify what is important in a product or service. Business value can be presented in various ways. Business value can present itself as economic profit, cost reduction, risk minimalization, ensuring customer/stakeholder satisfaction, innovation, fastening delivery times, simplification and increasing quality. Another way of measuring the business value is by conducting a company survey to acquire how much business value the employees think that an application can generate.

2.5.5 Explanation of Natural Language Processing Techniques

Natural Language Processing (NLP) Techniques is a sub-branch of Artificial Intelligence (Thanaki, 2017). These techniques process natural language. Natural languages are the thoughts and feelings people express. When people speak, read, write or listen they use natural language. Examples of natural language are for instance this thesis but also WhatsApp conversations. According to Thanaki (2017) “Natural language processing is the ability of computational technologies and/or computational linguistics to process human natural language”. It can be defined as the automatic processing of human natural language (Thanaki, 2017). NLP techniques can be split into various systems; speech recognition system, question answering system, translation, text summarization, template-based chatbots, text classification, topic segmentation and sentiment analysis. NLP techniques have spread across various research fields. Sentiment analysis for instance has become important in various fields like managerial and social sciences due to its importance to business and society (Thanaki, 2017).

2.5.6 Explanation of Internal and External data

Internal data is data obtained by the company itself. It can be WhatsApp conversations, emails and phone calls (Techopedia, 2012). It can be data of customer contact data but it can also be data about their employees, partners, shareholders or other stakeholders. External data is data obtained by utilizing a tool like a web scraper. A web scraper is a data mining tool as it gathers data (Techopedia, 2012). There are various web scraping methods and the goal of a web scraper is to collect information from across the internet. Often, this is executed by utilizing software that simulates human web surfing to gather specific information from different websites (Techopedia, 2012). External data can be data from several websites like social media platforms, rating platforms, blogs, news articles et cetera.

3. Research methods

This chapter explains how the research will be conducted by defining the data strategy, data collection and data analysis methods.

3.1 Data strategy

This research examines the research question “How can companies best obtain and utilize sentiment via a sentiment analysis in order to improve business performance?”. The research question is split into several steps to produce a valuable sentiment analysis guideline for businesses.

Step 1 to 4 focus on the sentiment analysis method. It explains if the company can utilize sentiment analysis based on the data input and the sentiment analysis models. The steps are the following: step 1: Evaluate if the data is suitable for sentiment analysis, step 2: Prepare the data for the sentiment analysis, step 3: Develop an overview of available sentiment analysis models and step 4: Choose a sentiment analysis model. Step 1 to 4 are important as the accuracy of the sentiment analysis output depends on it. Step 1 examines if the dataset input for the sentiment analysis is suitable. If a company uses a biased dataset for the sentiment analysis then the sentiment analysis cannot produce accurate outputs. If the output is not accurate then the outputs are biased and a company might change direction to a biased sentiment analysis KPI. Step 2 was determined in order to examine how the dataset should be prepared in order to generate accurate outputs. This step is next to step 1 important to examine as it also ensures that the output of the sentiment analysis is accurate. Step 3 was developed to give an overview of Dutch sentiment analysis models companies can utilize to obtain sentiment. This overview shows companies from which sentiment analysis models they can choose to obtain sentiment. Step 4 determines how companies can choose a suitable sentiment analysis model from the overview in order to choose the best sentiment analysis model for their organization.

The next steps (step 5 to 8) help companies to determine which applications create business value for the company. This is necessary because before companies implement sentiment analysis they should first know if sentiment analysis is worth investing in. Will enough business value be derived from sentiment analysis? If the applications do not create business value then a company should not invest in sentiment analysis. The steps 5 to 8 are executed for company X in order to show how the steps can help the company to develop new sentiment analysis applications and to rank them based on business value. These steps help to determine if company X should invest in sentiment analysis. Step 5 to 8 are the following: step 5: Define the goals of the company and of the departments, step 6: Define which metrics can be obtained from sentiment analysis, step 7: Develop an overview of sentiment analysis applications and step 8: Prioritize the sentiment analysis applications based on business value. Step 5 was developed in order to determine what the goals are of the company. It examines the goals per division (Board of Directors, Business Intelligence, Customer Relationship Management, Customer Support, External Affairs, Human Resource Management, Marketing, Purchase Department, Sales Department) in order to examine if metrics like KPIs can be valuable for these divisions and how these metrics can be utilized to create value-generating applications. Step 6 was developed to give an overview of metrics (KPIs) which companies can derive from sentiment analysis. A company can determine if it is possible to develop these KPIs. Step 7 analysis if these KPIs can derive business value for divisions. It analysis which applications can be developed based on the possible KPIs and goals of the divisions. Lastly, step 8 determines how much business value each application generates. This helps companies to determine how valuable the applications are and if they should implement the application.

3.2 Data collection

The research first gathers literature in order to determine a baseline. Next, the literature will be compared next to new data which will be developed via a case study. This case study will be executed by executing 4 interviews and a survey at company X. Table 1 in the appendix shows the interview questions figure 30 in the appendix shows the survey.

A data scientist at the company will be interviewed to answer the steps 1 to 4. This gives insight if the literature proposes different methods than the data scientist on how to best obtain sentiment via a sentiment analysis model. Figure 2 shows that this research question will be answered by comparing the literature with the interview.

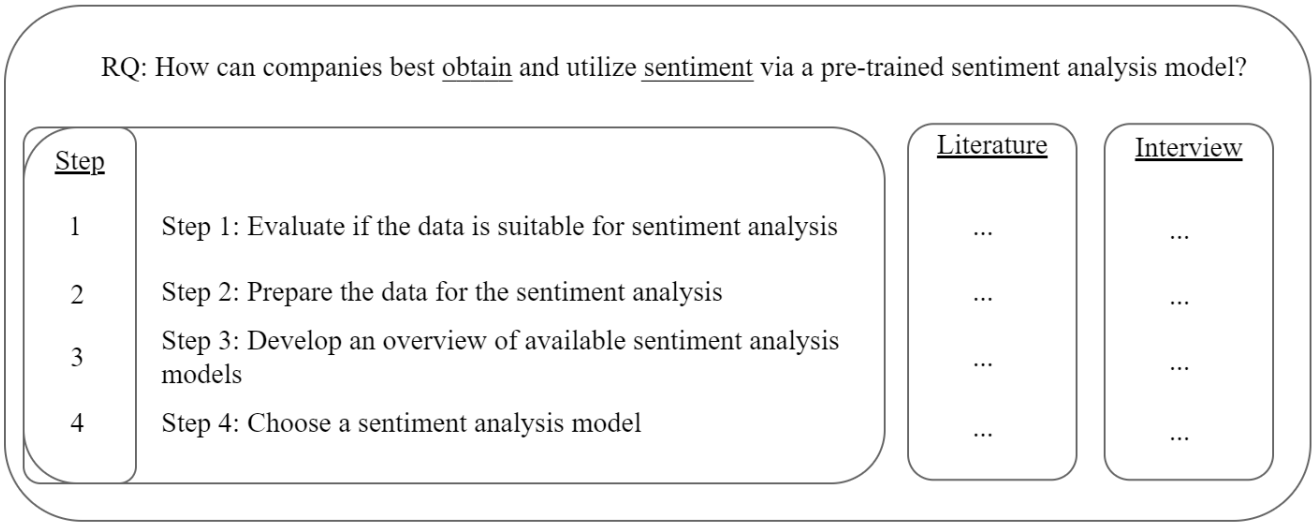

Figure 2: Visualisation of how step 1 to 4 will be answered

The steps 5 to 8 will be answered by doing 3 interviews. An interview with the customer service vision, strategy and innovation manager, an interview with the marketing intelligence analyst and an interview with the business intelligence team leader. These interviews help to identify possible sentiment analysis applications for the company. To examine the business value of all applications separately a survey will be conducted. The survey determines the business value per application. This is valuable information for an organisation in order to determine if they should or should not implement an application. Figure 3 shows how steps 5 to 8 will be answered.

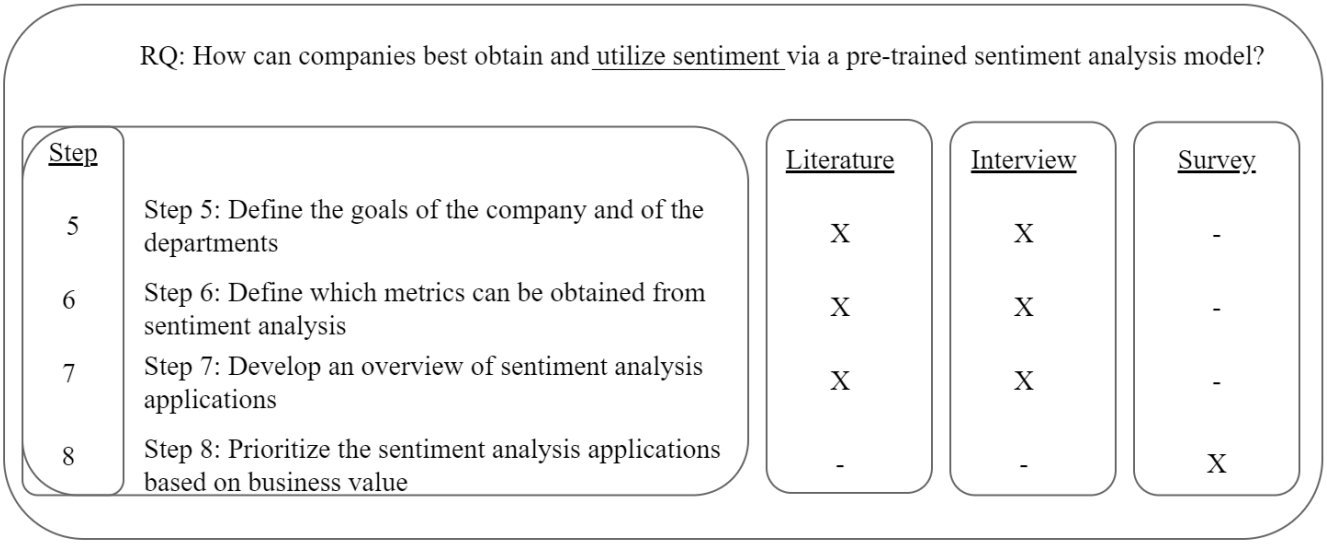

Figure 3: Visualisation of how steps 5 to 8 will be answered

The case study will be conducted at company X. Company X is a big insurance company in the Netherlands. The company offers insurance and financial services like mortgages, pensions and investments. Customer satisfaction and customer sentiment are of utmost importance for the company as they want customer satisfaction to become the most important KPI in the company. Therefore it is important to examine how this company can best obtain and utilize sentiment analysis in order to gain business value. The company has in-house IT knowledge concerning machine-learning and AI. They are very innovative and utilize machine-learning models to optimize their business performance. Now they would like to examine what opportunities sentiment analysis offers and how they can best implement sentiment analysis.

3.3 Data analysis

The research examines the data collected by the literature and the case study (4 interviews and a survey). It compares the results between the literature and the case study. It examines the value of existing sentiment analysis applications for organizations and new sentiment analysis applications for organizations. New sentiment analysis applications are proposed in this research by utilizing the systematic approach in figure 4. The approach in figure 4 shows that new applications could be developed by analysing the possible stakeholder metrics and linking them to department goals.

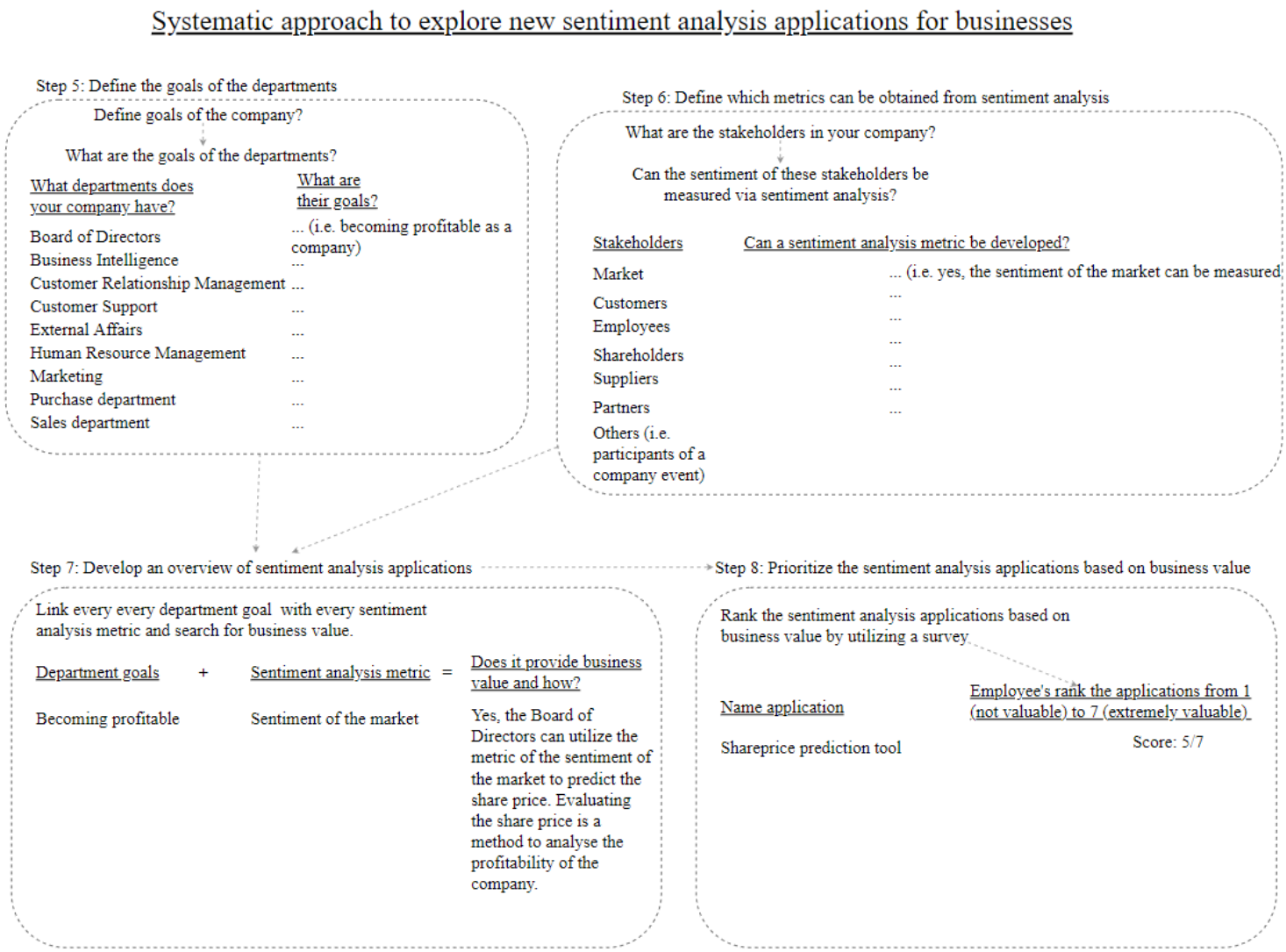

Figure 4: Systematic approach to explore new sentiment analysis applications for businesses.

4. Results

This chapter presents a guideline for companies to obtain and utilize sentiment analysis to obtain business value. The results of step 1 to 4 are developed by gathering data via literature and by executing interviews at company X. The results discussed in step 5 to 8 describe how companies can explore new sentiment analysis applications by utilizing the systematic approach (figure 4). Next to this, step 5 to 8 help companies decide if they should or should not invest in sentiment analysis based on the business value of the sentiment analysis. applications. To give an example of how the systematic approach works, this research answers step 5 to 8 for company X. Hereby, it shows how the systematic approach can explore new sentiment analysis applications and how it helps to decide if the company should invest in sentiment analysis.

The guideline proposed in this research is developed in the following way. Step 1 to 4 discuss how companies can best implement sentiment analysis. Step 5 to 8 focus on the business value of sentiment analysis and if a company should invest in sentiment analysis. The first step of the research discusses how companies can select suitable data for the sentiment analysis model (step 1). The next step explains how this data should be prepared before it will be used as input for the sentiment analysis (step 2). Next, it discusses several sentiment analysis models (step 3). Additionally, this research explains how companies can decide which sentiment analysis model is suitable for them (step 4). This research furthermore provides a method of how companies can develop new sentiment analysis applications by using the systematic approach explained at figure 4. This systematic approach defines the company goals (step 5), and links them to sentiment analysis metrics (step 6), this results in the development of sentiment analysis applications for departments (step 7). Lastly, the sentiment analysis applications are ranked based on business value (step 8). This helps to understand which applications provide the most business value and if the company should or should not invest in sentiment analysis.

Step 1: Evaluate if the data is suitable for sentiment analysis

WHAT: The first step is to obtain sentiment via a sentiment analysis model is to evaluate if the data is suitable for sentiment analysis. WHY: It is important to select suitable datasets to accurately predict the sentiment as the input in a sentiment analysis model automatically affects the output. HOW: The following paragraph discusses what aspects data scientists at companies should take into account when choosing a dataset for sentiment analysis.

Literature

Literature mentions the following aspects for selecting suitable sentiment analysis input data.

Companies need to fine-tune their sentiment analysis model to obtain more accurate sentiment analysis scores. When companies label the training dataset for finetuning purposes, they should first determine what a positive and what a negative text looks like (Vallantin, 2021). Sentiment analysis models often need to be trained. As the model first needs to establish what positive and negative sentiment is. It is important to determine what texts are positive and what texts are negative before labelling the data as some data input have more subtle distinctions between sentiment. Product review sentiment is easy to determine because these text inputs have strong sentiment relationships. When analyzing customer service sentiment, the input sentiment for the models are less distinct. Therefore the company first needs to decide what input is negative and what input is positive (Vallantin, 2021). The following text for instance: “Thank you for calling me back this fast, I would like to claim a refund for how I was handled when I wanted to submit the last damage claim”. A pre-trained model, which was trained on product reviews would probably rate this as a neutral score, although it can be valued as positive as the customer is happy that the

customer support employee called the customer back this fast. Thus, the model first needs to be fine-tuned for what is positive and what is negative input.

The size of the fine-tuning dataset is of importance as a bigger dataset generates more accurate sentiment analysis scores (Reddy, 2018). When firms fine-tune sentiment analysis models attention should be paid to the accuracy. As already mentioned earlier in this paper, human analysts accurately predict the sentiment of the customer 80-85% of the time (Richards, 2022). Additionally, Naylor describes in the interview with Rhodes (2020) that the accuracy scores should be at least 80%. Naylor recommends in the paper of Rhodes (2022) to develop fine-tuned sentiment analysis models with an accuracy score above the 80% threshold to ensure good performance of the machine-learning model. This means that the machine-learning model can predict 80 out of 100 outputs correctly from the sentiment analysis model.

It is important to establish the accuracy of the dataset when it will be utilized as input for models (Tayi & Ballou, 1998). As an accurate dataset can result in accurate sentiment analysis scores and an inaccurate dataset will result in inaccurate sentiment analysis scores. Some datasets are established by software and therefore companies first need to examine if the software established an accurate dataset. An example is the software by Contexta360. Contexta360 has developed a software which creates transcripts from audio records (Contexta360, 2022). The step of transcribing the audio records is needed when companies want to utilize audio records as input for sentiment analysis models. The audio records first need to be transformed to text before it can be utilized as input for sentiment analysis models. As most sentiment analysis models like BERT and Pattern.nl utilize text as input for the sentiment analysis (Yalçın, 2021), (University of Antwerp, 2010). The software which transcribes the audio records has an accuracy score. This accuracy score is a percentage which predicts how much of the transcript is transcribed correctly and matches with the audio records (Contexta360, 2022). According to Rhodes (2022), when a text is transcribed the average transcription score should be above 70%. Every text below 70% needs improvement. In the same article, Naylor (an analytic expert) explains that companies should still aim to have an accuracy score of above 80% (Rhodes, 2022). With an accuracy score of above 80% companies can still utilize the text developed by the transcription software for other models like sentiment analysis. Datasets which are generated by transcription software should not only take into account the overall score of the transcribed text but also the confidence scores of every word within the dataset. The confidence score is a score per word of what the probability is that the word from the audio records is accurately predicted and written down in the dataset (Rhodes, 2022). The confidence score ranges from 0 to 1 (Tonye, 2022). When transcribing software like Contexta360 transcribes audio records to written transcripts it is never 100% accurate (Rhodes, 2022). Therefore, the input for the sentiment analysis model should be examined. Are the confidence scores high enough of the words that valuable information can be obtained from the dataset? Microsoft determined that a confidence score of over 0.7 should predict the value correctly for AI purposes (Tonye, 2022). Therefore, Tonye (2022) recommends deleting words within the dataset with a confidence score of below 0.7. A dataset should thus be cleaned by deleting for instance all words with a confidence score of below 0.7 so that the input for the sentiment analysis model is still valuable (Tonye, 2022).

Next to the accuracy scores of the data set, companies should also take NaN values into consideration as many machine-learning models do not support NaN values (Kumar, 2021). Nan-values are cells within the dataset which are empty. This means that a dataset can have multiple NaN values which means that there are multiple rows within the dataset which do not contain information. Kumar (2021) recommends examining the percentage of rows which contains NaN values in the dataset. There are various ways of dealing with NaN values. Either delete the rows with missing values or use an imputation method to predict and replace the missing value. Imputation methods add new features to the dataset which may result in a poor dataset and a poor machine-learning performance (Kumar, 2021).

When assessing if the dataset is suitable for sentiment analysis, firms should also examine if the conversations or emails (depending on what the input is for the sentiment analysis) contain lots of sarcasm (Eremyan, 2018). Sentiment analysis models hardly detect sarcasm and therefore analysts should first assess if customers often use

sarcasm (Eremyan, 2018). There is a possible workaround for this limitation. Researchers in Jerusalem developed a NLP model which determines how sarcastic texts are (Data News, 2010). This sarcasm prediction model could be run prior to the sentiment analysis to determine how sarcastic texts are and if the texts are suitable as input for the sentiment analysis (Eremyan, 2018).

To summarize, the literature mentions that data scientists at companies should first determine if the input dataset is suitable for sentiment analysis. They should pay attention to the size and accuracy of the dataset. This means that they should examine if the data within the data set is gathered in a reliable and accurate way and if the dataset is big enough to produce accurate sentiment analysis outputs. Data scientists should pay attention if other software was used to develop the dataset. When data scientists utilize other software to develop the dataset, confidence scores should be examined to ensure the accuracy of the dataset. Furthermore, NaN values have to be investigated and deleted. Too many NaN values result in a biased dataset. To improve the quality of the dataset it might be better to first utilize a sarcasm detection model to determine how much sarcasm exists in the dataset. If the dataset contains too much sarcasm then the dataset is not suitable as input for sentiment analysis models. Lastly, it is not only important to determine what data is suitable but companies should also determine what positive and negative sentiment is as sentiment is subjective.

Case study

In the interview with the data scientist, she mentions that companies need to label a dataset in order to fine-tune sentiment analysis models. The data scientists explained that when companies label datasets, they should keep in mind to first establish what positive and negative sentiment is. As positive and negative sentiment is subjective. For example, when a company utilizes BERT as a sentiment analysis model then they categorize the input based on the sentiment scores 1 (negative), 2 (somewhat negative), 3 (neutral), 4 (somewhat positive) and 5 (positive). Some data scientists could label the input “This is a helpful service” with a sentiment score of 4 (somewhat positive), another data scientist could label the same input with a sentiment score of 5 (positive). The data scientists who labelled this input with the score 4 might label input like “I love this service so much, thank you so much for your help” with a sentiment score of 5 (positive). Whereas the other data scientist also labels the same text with a sentiment score of 5. Therefore, data scientists should first define what positive and negative sentiment is. How strongly positive or how strongly negative should a text input be to be labelled as a 1, 2, 3, 4 or 5? Next to the importance of determining what positive and negative sentiment is, the data scientist mentions the importance of a big and accurate dataset. Furthermore, she mentions that companies should take into account if they are allowed to utilize this data as input for sentiment analysis. Is the company allowed to utilize customer contact data for instance for sentiment analysis purposes or does the company violate data privacy and data security legislation? Lastly, she mentions that companies should examine the amount of Nan-values.

The interview shows lots of similarities with the literature but there is one addition which is important to companies. When companies want to select a suitable dataset for sentiment analysis they should first determine if using the dataset does not violate data privacy and data security legislation as internal data can be utilized for sentiment analysis.

To conclude, companies need to evaluate if the data is suitable for sentiment analysis by examining the accuracy of the dataset, the amount of sarcasm, the confidence scores of the data set, the number of NaN values, the purpose and the size of the labelled dataset. Next to this, companies should first establish what positive and negative sentiment is when they need to label a dataset.

Step 2: Prepare the data for the sentiment analysis

WHAT: This chapter discusses how the data should be prepared (cleaned) in order to be suitable input for sentiment analysis models. WHY: This is important in order to obtain valid sentiment analysis scores from the sentiment analysis. HOW: The following paragraph discusses how data scientists at companies should prepare data for sentiment analysis.

Literature

The literature mentions that when companies first utilize pre-trained sentiment analysis models, they need to fine-tune the pre-trained model to fit it to the company's purpose/topic (Hugging Face, 2021). Pre-trained sentiment analysis models are often trained on a general dataset from for instance Facebook and Twitter but this input data is often not suited for company use cases as companies operate in a specific market (Magdani, 2020). This is the reason why pre-trained sentiment analysis models should be fine-tuned. When companies fine-tune pre-trained sentiment analysis models, they first need to label a large dataset. This means that as input for finetuning, they need to create a dataset which contains an “x” column as an independent variable which contains the text as input and they need to create a ‘Y” column (dependent variable) where the sentiment score is given (Sharrow, 2020). This labelled dataset can be used to train the sentiment analysis model in order to obtain more accurate sentiment analysis scores. Companies need to manually label the sentiment analysis scores in order to fine-tune sentiment analysis models (Sharrow, 2020).

It is difficult to manually label the dataset as sentiment is subjective. Two people can appoint different sentiment scores based on how they interpret the text (Vallantin, 2021). If it is hard to determine and label a dataset then Siddhaling and Urolagin (2018) recommend using a summarization model first. Summarization models are machine-learning models which generate a summary of a specific text. This could be a phone conversation summary for instance. In this way, it is easier to predict the sentiment of the text input (Siddhaling & Urolagin, 2018).

When data will be utilized for sentiment analysis companies should first clean the data before they use the dataset as input. The amount of data preparation depends on the pre-trained sentiment analysis model. Multiple sentiment analysis models like for instance BERT have multiple pre-trained sentiment analysis models. They have for instance cased and uncased sentiment analysis models (Kiao, 2022). Cased pre-trained sentiment analysis models include capital letters in the model. Capital letters are used as extra information about the words (Kiao, 2022). Uncased pre-trained models require only text data with text that does not contain capital letters therefore the input text should be transformed into text without capital letters (Kiao, 2022). Other special characters should also be deleted as machine-learning models often do not interpret special characters (Sharrow, 2020). Special characters are for instance “@” signs. Additionally, Sharrow (2022) recommends removing excessive data which does not generate a more negative or more positive sentiment. Customer support call records often start with “good morning, this is the customer support department, Laura speaking”. Then the other person introduces him or herself. This text could for instance be deleted as this intro is considered as a sentence of stop words. It namely always has the same way of introduction and it does not generate a more negative or more positive sentiment per conversation (Sharow, 2020).

Furthermore, it is important in which data type object (dtype) the input for the sentiment analysis is stored. A dtype describes multiple aspects of data like how the bytes in the fixed-size block of memory corresponding to an array item should be interpreted (Numpy, 2022). It describes aspects of the data Is it for example stored as an integer or a string? Depending on the sentiment analysis model, the dtypes need to be adapted.

Lastly, attention should be paid to the output. How do you want to present the sentiment? Some pre-trained models already have a scale. The pre-trained model BERT has for instance a scale from 1 to 5, where 1 represents strong

negative sentiment and 5 represents strong positive sentiment (Hugging Face, 2021). Pattern.nl presents the sentiment with a score between minus 1 and 1 (University of Antwerp, 2010). The score will be given with 2 decimal places behind the comma, where minus 1 is strongly negative and 1 is strongly positive (University of Antwerp, 2010).

To summarize, the literature mentioned various steps data scientists should undertake in order to select and prepare their data for machine-learning models. Data scientists need to clean datasets before utilizing them in sentiment analysis models. Dtypes need to be converted to the right dtype, special characters need to be deleted and the text input needs to be cased or uncased depending on the sentiment analysis model. If the sentiment analysis model does not predict the sentiment accurately then the input could be prepared more extensively. The data scientist could utilize summarization models. Summarization models are machine-learning models which generate a summary of a specific text. In this way, it is easier to predict the sentiment of the text input. Next to this, stop words can be deleted to ensure higher accuracy of the sentiment analysis model. The accuracy can also be improved by finetuning the sentiment analysis model. It is important to think about the purpose of the sentiment analysis model when preparing the dataset. As the dataset might need to be adapted due to the purpose of the sentiment analysis model.

Case study

According to the interview with the data scientist at company X, data scientists might not understand what a target (customer, employee, stakeholder, depending from who you measure the sentiment) meant by reading the input for the sentiment analysis model. This depends on how much the input for a sentiment analysis model was cleaned. This makes it hard to examine if a sentiment model works well as data scientists can in this case not manually examine if the input matches the predicted sentiment score measured by the machine-learning model. Therefore, the data scientist proposed in the interview to develop one column with the full text without cleaning or deleting data from the text (see table 2, column “Text”), create another column which is used as input for the sentiment analysis model (see table 2, column “Cleaned text”). In this way, the data scientists can still read the whole conversation at the column “Text” but can additionally measure the sentiment of the text based on the column “Cleaned text”. By developing a column “Text” and “Cleaned text”, data scientists can examine if the sentiment score output, column “Sentiment”, actually matches the input text “Cleaned text” by examining the column “Text”.

Conversation ID	Part of conversation	Text	Cleaned text	Sentiment (1-5)
1	1	I had a car accident last week and I broke my hip. My car is damaged and I don’t know what to do with my insurance.	i had a car accident last week and i broke my hip my car is damaged and i do not know what to do with my insurance	2
1	2	A friend told me that I would never get my money back because I did not pay the last term of my car insurance.	a friend told me that i would never get my money back because i did not pay the last term of my car insurance	2

1	3	I am furious because I always pay my car insurance on time and I accidentally forget to pay one term and now I am not insured anymore.	i am furious because i always pay my car insurance on time and i accidentally forget to pay one term and now i am not insured anymore	1
2	1	I already waited 30 minutes before somebody received me. Why did I have to wait this long?	i already waited 30 minutes before somebody received me why did i have to wait this long	1
2	2	Anyhow, I wanted to ask if the money will be refunded before the end of this week.	Anyhow i wanted to ask if the money will be refunded before the end of this week	3
2	3	Thank you for reaching out to us! Give me one second, I will check the refund administration. Thank you for your patience! I have good news! You will receive the refund today.	thank you for reaching out to us give me one second i will check the refund administration thank you for your patience i have good news you will receive the refund today	5
2	4	It's great to hear that the money will be transferred today. Thank you so much for your help. I did not expect it to be transferred this fast!	it is great to hear that the money will be transferred today thank you so much for your help i did not expect it to be transferred this fast	5

Table 2: Data frame example for sentiment analysis

Next to adding a "text" column and a "cleaned text" (input) column, data scientists can additionally choose what input they want to utilize for the sentiment analysis. Data scientists should first determine the purpose of the sentiment analysis before they choose the input. Data scientists can for instance choose to include a whole conversation as input for sentiment analysis but they can also choose to only utilize what the customer said as input for the sentiment analysis. During a phone call for instance; first, the customer support employees talks, then the customer responds and then the customer support employees talks again. Data scientists can choose to delete the text of the customer support employee in order to get unbiased sentiment from the customer. Therefore, it is important to first establish the purpose of the sentiment analysis. If the sentiment needs to be obtained for a customer metric then the customer support employee text can best be deleted. If the sentiment of the overall conversation or the sentiment of the customer support employee needs to be measured. Then it's better to include the text of the customer support employee as input for the sentiment analysis. 3 displays at conversation ID 1 input without the customer support employee. At conversation ID 2 table 2 shows input when the customer support employee has not been deleted.

Next to this, the data scientists mention in the interview that rows in the dataset might need to be split into several rows as pre-trained sentiment analysis models often have a maximum amount of characters or words that they can

predict the sentiment of per row. BERT has for instance a maximum of 512 per row which the dataset needs to predict the sentiment of (Peltarion Knowledge Center, 2022). Therefore, it is sometimes necessary to split conversation over multiple rows in order to predict the sentiment. Table 2 displays this in the following way: the column “conversation ID”, displays the whole conversation. As the whole conversation exceeds the maximum amount of characters per row. The conversation is split in 3 rows. All 3 rows have in the “conversation ID” column, the same conversation ID but in column 2 “Part of conversation”, the number in the column shows the order of the conversation. In the column “Part of conversation”, “1” means that the conversation starts with this input text. “2” means that this input is the up-following input after “1” and so on per conversation ID.

The data scientist at company X proposed various new techniques to prepare the sentiment analysis model. She shows methods which can be utilized to split datasets in a way which helps data scientists to ensure the accuracy of the sentiment analysis model. The method of creating a “cleaned text input” and a “text input” helps data scientists to manually examine if the output fits with the input. A method to improve the accuracy of the model is by executing A/B tests by examining if the sentiment analysis outputs are more accurate if the data scientist includes or excludes some text (i.e. includes customer support employee response to the customer or excludes his response). Next to this, the data scientist shows the importance of knowing your input. If the input is too big for the sentiment analysis model then the input needs to be modified and divided over several rows in order to determine the sentiment analysis scores. In comparison to the literature, the data scientist does mention the finetuning of the sentiment analysis model, casing or uncasing input, deleting special characters, deleting stop words, adapting dtypes and thinking about the output. The only method she does not mention is the method of utilizing a summarization model to obtain more accurate sentiment analysis scores. She mentions about this technique that summarization models might create too much noise as summarization models often have accuracy scores as well of how accurate the text was summarized. So then the input for the sentiment analysis model is less accurate depending on the accuracy of the summarization model. This is the same disadvantage which was mentioned in step 1 (“Evaluate if the data is suitable for sentiment analysis”) with the transcription software The confidence scores of transcription software need to be taken into account when this data will be utilized for sentiment analysis models. In this case, the dataset will be modified by a summarization model instead of transcription software but both methods decrease the accuracy of the original dataset.

To conclude, companies need to prepare the data for the sentiment analysis by examining how the dataset should be cleaned fitting to the sentiment analysis model. Data scientists (at the company) might need to change the dtypes, include or exclude capital letters and delete special characters. A summarization tool might be needed to change the input in order to obtain more accurate sentiment analysis scores but this can also backfire as software like transcription software or summarization models have their own accuracy scores for producing output. It is recommended to add a “cleaned text” column as data scientists can then manually examine if the output of the sentiment analysis models is accurate. Next to this, data scientists have to decide what the purpose is to define if they want to include all text of the conversation or only text from the target (for example: only text from the customer, not the text from the customer and the customer support employee). Lastly, the data scientist might need to split conversations over multiple rows as sentiment analysis models have a maximum number of characters per row whereof they can predict the sentiment.

Step 3: Develop an overview of available sentiment analysis models

WHAT: This chapter discusses the available pre-trained sentiment analysis models. WHY: It is important to establish what pre-trained sentiment analysis models are available for the Dutch language in order to determine which sentiment analysis model a company should implement. HOW: This step gives an overview of these sentiment analysis models by doing literature research.

Literature

Literature mentions the pre-trained sentiment analysis model named Pattern.nl. Pattern.nl is a sentiment analysis model which can be utilized to extract Dutch sentiment via a lexicon-based approach (University of Antwerp, 2010). The model has an accuracy of 82% and Github users saved the webpage about Pattern.nl more than 8.300 times. Pattern.nl is a rule-based sentiment analyzer, which is based on a built-in lexicon of about 4,000 Dutch lemmas. Lemma's are the base of a word. It is the way words are defined in the dictionary. The model determines 2 scores; the polarity and subjectivity scores. The polarity score is a score between -1 and +1. This is the sentiment score stated with 2 numbers behind the comma. If the score is close to -1 for instance -0.88 then the input is categorized as negative sentiment. If the score is closer to 1 then the sentiment is positive. A score around 0 states that the sentiment is neutral. The subjectivity score determines how subjective the polarity score is. It is a score between 0 and 1. The higher the number the more subjective the outcome of the model is.

The second pre-trained sentiment analysis model mentioned in literature is BERT. BERT is a sentiment analysis model which can be utilized to extract Dutch sentiment via a machine-learning-based approach (Hugging Face, 2021). BERT has multiple variations of its machine-learning model. The most popular pre-trained model is the bert-base-multilingual-uncased-sentiment model. BERT utilizes neural networks to categorize the sentiment from 1 to 5, where 1 is extremely negative and 5 is extremely positive sentiment. This model was downloaded 369.005 times in July 2022 (Hugging Face, 2022) and has an accuracy for the Dutch model of 57%. The Dutch model does predict the sentiment way more accurate when the sentiment score is allowed to be off by 1 degree than the accuracy is 93% for the Dutch model. The BERT model recognizes patterns like for instance "this is not bad". It recognizes that "not" is connected to "bad" and it understands that the combination of these 2 words generates a positive sentiment rather than a negative sentiment. Lexicon-based sentiment analysis models would categorize "not bad" as extremely negative. Lexicon-based sentiment analysis models generate a sentiment score for every word. In this way "not bad" will be classified as two words that both generate negative sentiment. The BERT pre-trained model is multilingual and applicable for English, Dutch, German, French, Italian and Spanish inputs. The input for the pre-trained model where 80.000 product reviews. Sentiment is easily extractable from product reviews as product reviews contain strong signal words like "I hate this product" and "This product is great". It is harder to obtain the sentiment from customer support records as these conversations are more nuanced (Magdani, 2020). Therefore, this paper recommends to first fine-tune BERT.

To summarize, the literature describes 2 sentiment analysis models. Sentiment analysis can be executed by a machine-learning approach or by a lexicon-based approach. BERT is a machine-learning-based approach which is a suitable method to obtain the sentiment for Dutch sentiment analysis models. Pattern.nl is a lexicion based approach to obtaining the sentiment of Dutch sentiment analysis models.

Case study

In the interview with the data scientist at company X, she mentioned BERT as a suitable sentiment analysis method for the Dutch language. Company X had already had a tutorial on the possibilities of BERT and how BERT can be utilized to obtain sentiment from texts. The IT department at company X already established that BERT is a safe model to use for the company. By first establishing how safe the model is, the company does not have to deal with cyber security or privacy threats due to the download of the BERT pre-trained model.

The model proposed in the interview (BERT) was also mentioned in literature as a suitable method for sentiment analysis for the Dutch language. The data scientist had not heard of Pattern.nl, the lexicon-based sentiment analysis model.

To conclude, companies need to develop an overview of available sentiment analysis models by examining current pre-trained sentiment analysis models. Currently, the literature and the interview identified 2 sentiment analysis models for the Dutch language: BERT and Pattern.nl.

Step 4: Choose a sentiment analysis model

WHAT: How accurate the sentiment can be predicted depends on the sentiment analysis model. WHY: It is important to select a suitable sentiment analysis model fitting to the organisation. HOW: Which consideration should companies take into account before choosing a sentiment analysis model? This step defines multiple considerations companies can take into account to select a suitable sentiment analysis model.

Literature

The literature mentions that it is important to utilize the best sentiment analysis model for your organization. As it depends on the model how accurate the sentiment analysis is. Valdarrama (2022) proposes 7 considerations of how a machine-learning model should be chosen. Figure 5 displays the 7 considerations.

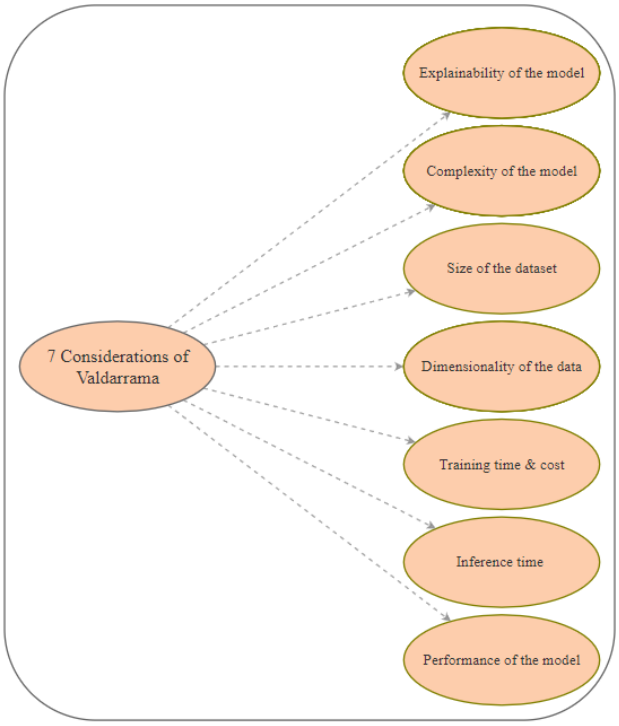

Figure 5: 7 Considerations to choose an appropriate machine-learning model ofValdarrama (2022)

The first consideration of Valdarrama is the explainability of the model. When data scientists cannot understand how the model works then it is hard to understand how the sentiment scores are developed by the model. A model which is not explainable to data scientists is likely to be turned down as a suitable model by the management as they prefer a transparent model which can be easily explained as incorrect sentiment scores can then be easily explained. Linear regression and decision trees are sentiment analysis methods which provide more explainability. Next to machine-learning-based sentiment analysis methods, there are lexicon-based sentiment analysis methods. The benefit of lexicon-based sentiment analysis methods is that they have a high explainability.

The second consideration of Valdarrama is complexity of the model. As mentioned before, lexicon-based sentiment analysis models are easily explainable. This is because these sentiment analysis models are not complex. They do not have multiple layers like machine-learning-based sentiment analysis models. Complex sentiment analysis models can have multiple layer. Layers can improve the accuracy of the model but layers also make the model more complex. Layers also increase the computing time of machine-learning models and this can increase the cost.

The third consideration of Valdarrama when a machine-learning model will be chosen is the size of the dataset. Lots of machine-learning-based sentiment analysis models need a training set to train the machine-learning model. The size of the training set depends on which sentiment analysis model a company chooses. Neural networks are able to process large datasets. K-Nearest Neighbors can already train the model with only a few rows. The amount of training data is dependent on the method and on accurate the model should be. Most of the time, more training data causes more accurate sentiment analysis predictions. Van Overmeire (2018) proposes a way to obtain training data without manually labelling the data. He proposes that companies can use reviews of their website to train their sentiment analysis model on. When a customer reviews a company they can rate the company for instance by selecting an amount of starts (Trustpilot) or then leaving a comment with the stars. The stars can be used as the label and the comment can be used as the input for the training data set. A disadvantage of this method is that it utilizes reviews. Reviews have a stronger sentiment then a regular customer support phone call. Therefore, the accuracy may not match. Lexicon-based machine-learning models do not need to be trained therefore the size of the dataset does not matter as much.

The dimensionality of the data is as well important when companies select a suitable sentiment analysis method. The dimensionality consists of the vertical size and the horizontal size. The vertical size represents how much data the company has. The horizontal size represents the number of features. Features are ways to examine the accuracy of the model like Pearson's R, Spearman's Rho, ANOVA and Kendall's Tau). More features can create a more accurate model but it will also increase the complexity and increase the computing time. Thus, companies have to examine how many features the machine-learning model needs. Lexicon-based machine-learning models do not have features, thus the dimensionality is not a consideration for lexicon-based sentiment analysis models.

The trainings time of the model depends as mentioned above on the amount of features and the machine-learning model. A machine-learning-based sentiment analysis model needs to be trained on trainings data to predict the sentiment accurately. It is important to establish a good threshold of how accurate the model should be as there is a difference in training time between a 99% accurate model and a 95% accurate model.

Additionally, the computing time is very important. The computing time is how long the sentiment analysis model needs to run to predict sentiment scores. When companies want to developed a dashboard with real-time sentiment metrics than it is of utmost importance that the computing time of models is fast. When a company chooses a slow machine-learning model than CPU's can provide a solution. Companies can buy CPU power to fasten the computing times of sentiment analysis models.

The last consideration is the performance of the model. A sentiment analysis model needs to be accurate. Accuracy is an important criteria to determine if the model is working well. This research recommends that the accuracy of sentiment analysis models should be above 80-85%. This means that the model can predict the sentiment with a certainty of 80-85%. This research proposes this threshold as Richards (2022) mentions that human analysts predict 80-85% of the time sentiment accurately. The accuracy of pre-trained models is often given but as insurance companies might have more keywords that are considered "neutral" the model should still be fine-tuned and tested on its accuracy.

Furthermore, there are multiple ways to further improve the accuracy of models. Companies can for instance choose to do A/B test to check when the model is more accurate. English models are for instance often better trained and

are therefore more accurate. It is a possibility to translate customer support records, to use them as input for English sentiment analysis models and to obtain the sentiment in this way. Companies could compare these two models (the Dutch model and the English model) to determine which model is more accurate for predicting the sentiment.

Another method to measure the sentiment accurately is to incorporate a sarcasm score. Sarcasm models predict how sarcastic texts are. The higher the score the more sarcastic the text is. Sentiment analysis models do not recognize sarcasm. Therefore, the customer support records can be categorized in sentiment (1-5) but also on sarcasm score. With this function, companies could filter texts based on the sarcasm score. For instance: I would like to obtain the sentiment of the average customer who calls the customer support. The company then first filters all inputs with a high sarcasm score as these conversations are highly sarcastic, the sentiment will be predicted inaccurately.

Companies could also utilize a summarizing model before using the dataset as input. As customer support records consist of long conversations the conversations can first be summarized to obtain the sentiment of the customer easier. An A/B test could be executed to compare the accuracy scores of the model. The two models can be compared (the model with the whole text as input and the model which utilizes the summarized text as input).

When a sentiment score is not accurate than the model cannot be used as a metric in business. But it is also important to balance the accuracy, computing time and costs when choosing for a sentiment analysis model. When the accuracy should be really high than either the computing time or the cost will increase. When the cost needs to be low than the either the computing time or the accuracy will be lower. When the computing time needs to be fast than either the cost or the accuracy will be lower. Therefore, it is all about balancing these considerations.

To summarize, the literature proposes to utilize the 7 consideration of Valderrama to determine which sentiment analysis model is suitable for a company. The 7 considerations of Valderrama propose that data scientists should pay attention to the explainability of the model, the complexity of the model, the size of the dataset, the dimensionality of the data, the training time and cost, the inference time and last but not least the performance of the model. These 7 considerations provide guidance to data scientists who need to select a sentiment analysis model.

Case study

During the interview with the data scientist at company X, she mentioned the importance of safe sentiment analysis models. She mentions the performance of the model, the size of the dataset, the training time and cost and the inference time as considerations. These considerations are also part of the 7 considerations of Valderrama. But the data scientist also mentions that there are more considerations when selecting a sentiment analysis model for a company. Individuals who utilize sentiment analysis are less prone to be hacked or to be cyber attacked then companies. Big companies on the other hand, should be aware of cyber security and data privacy threats. Therefore, safety of a sentiment analysis model is also an important consideration for company when they select a sentiment analysis model. A safe sentiment analysis model means that the company is less prone to data security or data privacy threats when a certain sentiment analysis model will be used. The IT department of firms should thus first assess if the sentiment analysis model creates data security or data privacy threats.

The interview shows similarities with the literature as both acknowledge the importance of the accuracy of the model, the size of the dataset, the training time and training cost of the model. The literature does not specifically focus on considerations for selecting a machine-learning model for business. It only focuses on general considerations for selecting a machine-learning model like sentiment analysis. Therefore, the interview shows additionally the importance of safety of the model. Attention should be paid to data privacy and data security when

selecting a sentiment analysis model as violating this consideration could lead to significant fines by the government.

To conclude, companies need to choose a sentiment analysis model by evaluating all pre-trained sentiment analysis models via considerations. The literature and the interview identified 8 considerations for data scientists at companies to take into account. The considerations which companies should consider are the explainability of the model, the complexity of the model, the size of the dataset, the dimensionality of the data, the training time and the cost, the inference time, the performance of the model and the safety of the model.

Step 5: Define the goals of the departments

WHAT: Step 5 to 8 provide companies with a complete overview of sentiment analysis applications for their business. The steps help to determine existing and new sentiment analysis applications. Additionally, the applications will be ranked by business value. WHY: This will be done to help companies decide if they should or should not invest in sentiment analysis. HOW: By utilizing the systematic approach (figure 4) mentioned in the research methods, companies can explore new sentiment analysis applications in their business. Literature will be studied to establish existing sentiment analysis applications for businesses. Lastly, a survey helps to determine the business value of business applications. Step 5-8 are answered for company X to provide an example of how new sentiment analysis applications can be explored. Next to this, it shows if the systematic approach helps to determine new sentiment analysis applications.

WHAT: Step 5 in the guideline is to define the company and department goals. WHY: Step 5 is a necessary step in the systematic approach in order to explore new sentiment analysis applications. HOW: The goals of company X are defined by executing interviews with the customer service vision, strategy and innovations manager, the marketing intelligence analyst and the team leader of a business intelligence unit. Next to this, literature provides insight on general company and department goals to establish a clear overview of possible goals per department. In the following paragraphs, step 5 will be answered for company X in order to provide an example for the systematic approach. Therefore, the goals of company X are defined by doing literature and by gathering data via interviews. The goals are defined per department.

2.6.1 Board of Directors

According to the literature, the function of the board of directors is to protect the interests of the shareholders, to select top executives and review their performance, to review and approve big decisions and strategies and develop new committees (Beaver et al., 2007). It is important to be a successful company for the Board of Directors as a successful company is one of the interests of the investors. Measuring the success of a company can be measured by the stock price (Massari et al., 2016). If the stocks are going up then a company performs well, if a stock goes down a company does not perform well.

2.6.2 Business Intelligence

Literature mentions that business intelligence is a department which provides the company with by analysing data (Nelson, 2015). The goal of business intelligence departments is to provide the company with valuable insight which can help the company to make strategic decisions (Nelson, 2015). Business Intelligence can for instance give insight into operational goals. Operational goals are of utmost importance as smooth operations are often the reason why business are so successful (Bitley,2020). Operational goals are related to for instance customer satisfaction, process consistency, turnaround time, team growth and administrative efficiency (Bitley,2020).

There are several business intelligence divisions within company X according to the interview with the marketing intelligence analyst at company X. The business intelligence departments are split based on their goals. Within

company X the goals of these departments are the following: creating happy customers and improving business processes. The first business intelligence department examines what creates happy customers. The other business intelligence department examines what business processes to optimize.

2.6.3 Customer Relationship Management

According to literature, the goal of the customer relations department is to create profitable customer relationships (Cunningham, 2002). The sentiment of the customers is important to ensure profitable customer relationships. Therefore, it would be valuable for the customer relationship department to identify customers who have negative sentiment and whom are likely to churn to prevent them from churning and to improve their sentiment.

2.6.4 Customer Support

Literature mentions that the goal of the customer support department is the support business provide to their customers, before and after the sale has been made. Customer support helps customers to have an easy and enjoyable experience with the firm (Salesforce, 2022). The customer service department has several goals. They for instance would like to reduce the response time, reduce the handling time, improve employee skill, improve customer satisfaction, increase customer loyalty, promote self-service and increase efficiency, humanize customer experience (Thomas, 2022).

2.6.5 External Affairs

According to literature, the goal of external Affairs is to build and maintain a relationship with influential partners. These can be specific individuals and organizations (Government Communication Service, 2022). The sentiment of the partners is therefore of utmost important for the external Affairs department.

2.6.6 Human Resource Management

Literature mentions that the goal of human resource management used to be focused on obtaining the right people at the right place and at the right time. Nowadays, this goal is still important but new HRM goals have been introduced as well. Like creating a clear corporate culture, developing happy employees, enhance employee productivity , retaining employees, engaging employees and implementing the best global management practises (HRM Handbook, 2022). Measuring employee sentiment can therefore, be valuable for the HRM department.

2.6.7 Marketing

According to literature, the marketing department is also an important departments as marketing expands your audience and generates your audience into leads (Bitley, 2020). Indeed (2021) mentions that there are 10 different specialisations within marketing and every specialization can have their own subgoals. The specializations are digital marketing, content marketing, social media marketing, visual marketing, search engine marketing, influencer marketing, product marketing, research marketing and email marketing (Indeed, 2021). This means that the marketing department has various goals depending on the specialisation. Goals could for instance be increasing the amount of leads, launching a successful event, establishing a clear brand et cetera.

According to the marketing intelligence analyst, it is important that the marketing department can evaluate the performance of their marketing campaigns, adds and events. Did customers buy more or buy less due to the marketing activities? Did the marketing campaigns, adds, events create positive sentiment? The goal of the marketing department is to create a strong brand image and to attract new customers.

2.6.8 Purchase department

The purchase department should according to literature try to lower the cost, reduce risk and ensure the security of supply, manage relationships, improve product quality, pursue product innovation, utilize technology (BDC, 2022). The department should additionally improve and evaluate the product portfolio. Are customers still happy with the product offer? It is important to evaluate if products and services create positive or negative sentiment. In this way, the purchase department knows which products the department should add or delete from their product or service portfolio.

2.6.9 Sales department

According to literature, the goal of main goal of the sales department is to increase revenue. Other important sales goals are; quarterly revenue numbers, weekly sales opportunities closed, seasonal targets; the insurance company has to enrol 10% more customers than last year during the OEP (Open Enrollment Period) (Bitley, 2020). The more specific the goal the better. Therefore, it is beneficial if the sales department can measure the sales per product, per service, per agent , returning/new customers (Bitley, 2020.

To conclude. the goals mentioned in the interviews align with the goals literature mentions. The interviews provide a few additional goals next to the goals mentioned in the literature. The interview states that creating happy customers is part of the business intelligence department but the literature states that this is part of customer support department. Nevertheless, several department can have the same goal. The interview also proposes another goal for the marketing department namely to evaluate their own performance by investigating how well campaigns and events were conducted based on customer sentiment.

Step 6: Define which metrics can be obtained from sentiment analysis

WHAT: This step defines which metrics can be obtained from sentiment analysis by analyzing its stakeholders. WHY: By analyzing company stakeholders, companies can determine from whom they can measure the sentiment. Determining sentiment analysis metrics is important in order to explore sentiment analysis applications via the systematic approach. HOW: companies can determine their stakeholders. By analyzing the stakeholders companies can developed sentiment analysis metrics. The below paragraphs state how company X developed its sentiment analysis metrics. Table 3 describes the metrics (KPIs) mentioned in literature. Table 4, describes the metrics (KPIs) which are developed by interviews and utilizing the systematic approach (figure 4).

Literature

Companies can measure the sentiment of their customers, employees, shareholders and other stakeholders in several ways. The input for the sentiment analysis can either internal data or external data (Ventiv Technology, 2022). Customer support creates internal data from various channels for instance phone call transcripts, WhatsApp records or email records. Companies can also utilize external data from for instance social media. Therefore, companies first need to decide what they would like to measure and how they can measure it; with internal or external data (Ventiv Technology, 2022). Companies can develop a social media scraper which obtains all social media messages related to a specific company or brand. This is an external method to gather data. Note; when companies utilize this method the sentiment of all individuals within the target market will be obtained, so the sentiment from customers but also from individuals who talk about the company but are not a customer. When companies utilize internal data like customer contact data, they know that the sentiment they acquire is the sentiment of their customers, not of the market.

Bianchi (2021), Fairly (2022) and Roldós (2020) mention in their papers that sentiment analysis can provide 7 KPIs for businesses. These KPIs are valuable as they monitor the sentiment of the market, participants of events, customers and employees. Table 3 presents the 7 KPIs for businesses.

Row #	Measuring sentiment of	KPI	Input	Literature
1	Market	Sentiment of the market about the company	External	Bianchi (2021)
2	Market	Sentiment of the market about the competitors in the market	External	Bianchi (2021)
3	Participants	Sentiment of participants of events the company organizes	External	Fairly (2022)
4	Customers	Sentiment of all customers	Internal	Bianchi (2021)
5	Customers	Sentiment per customer	Internal	Roldós (2020)
6	Employees	Sentiment of all Employees	Internal	Roldós (2020)
7	Employees	Sentiment per employee	Internal	Roldós (2020)

Table 3: Sentiment analysis KPIs derived from literature

2.7.1 Sentiment of the market KPI

This first KPI that literature identified is the sentiment of the market about the company (Bianchi, 2021). This KPI represents the average sentiment of the Dutch population about a company. When BERT is used this means that for instance the score could be 4. This means that the Dutch population thinks moderately positive of a company. The sentiment can be measured by external data like for instance Dutch social media posts, therefore the sentiment is developed by social media users and this means that the representation is not that accurate as senior people (65+) use social media less than the younger generations. Next to this, the KPI represents the Dutch population but this can only be partly achieved when programming a scraper. The scraper can for instance take social media posts which are written in Dutch and whereof the user is located in the Netherlands. The scraper cannot identify if the user has a Dutch nationality (Techopedia, 2012). So, this KPI is not 100% accurate as the input for the sentiment analysis is not 100% accurately representing the Dutch population.

The second KPI in table 3 is the sentiment of the market about the competitors (Bianchi, 2021). The same method was used as with KPI number 1 but this time the web scraper searched for posts about competitors. Therefore the sentiment of the market of several competitors can be compared with the sentiment of the company. This is a valuable evaluation tool to compare sentiment scores with competitors. Figure 6 displays a possible visualization of this KPI. It displays the sentiment from 18 January 2022 until 17 February 2022 (the data is fictional and utilized for visualization purposes).

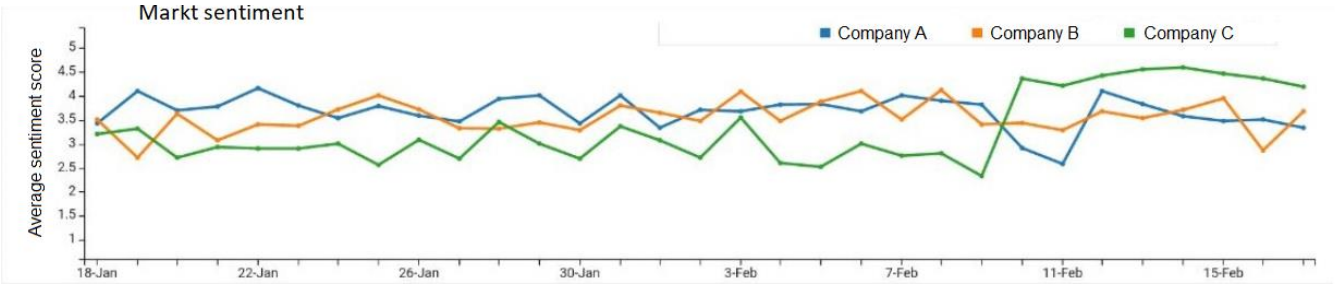

Figure 6: Visualization of market sentiment KPI

2.7.2 Sentiment of Participants KPI

The third KPI “sentiment of participants of events the company organizes” in table 3 measures the sentiment of participants of a specific event or the sentiment of people whom viewed a specific company add (Fairly, 2022). This KPI utilizes external data like for instance web scraper. This web scraper searches for instance social media posts in relation to specific events or campaigns of the company. When a company for instance organizes a run. This event was created by a company and via a sentiment analysis in combination with a social media scraper the sentiment of participants of this run can be obtained. In this way, marketeers can measure if the event (the run) was a success or not. Figure 7 displays a possible visualization of this KPI.

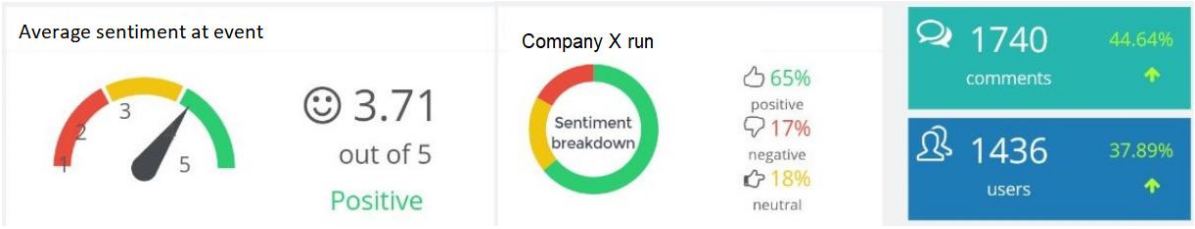

Figure 7: Visualization of event sentiment KPI

2.7.3 Sentiment of Customers

The sentiment of the customer is widely studied as it provides insight into customer satisfaction (Bianchi, 2021). Companies can obtain the average sentiment of all their customers (row 4, table 3) by using sentiment analysis. This sentiment can additionally be filtered by various filters like a topic filter (i.e. car insurances, property insurances), an intent filter (applying for an insurance, changing customer information, cancelling an insurance, claiming a refund) or a customer service employee (i.e. Henk Jansen, Daniek Willemsen). This KPI can give a lot of insight. It gives the average sentiment of all customers but it also provides insight into which business processes generate negative sentiment and which generate positive sentiment. For example the filter combination “applying an insurance” and “car insurances” generates more negative sentiment than the filter combination “applying for an insurance” and “property insurance”. What is the reason for this difference? The performance of customer service employees can also be measured by the sentiment of all customers KPI. Which customer service employee generates lots of negative or lots of positive sentiment? Figure 8 displays a possible visualization of this KPI.

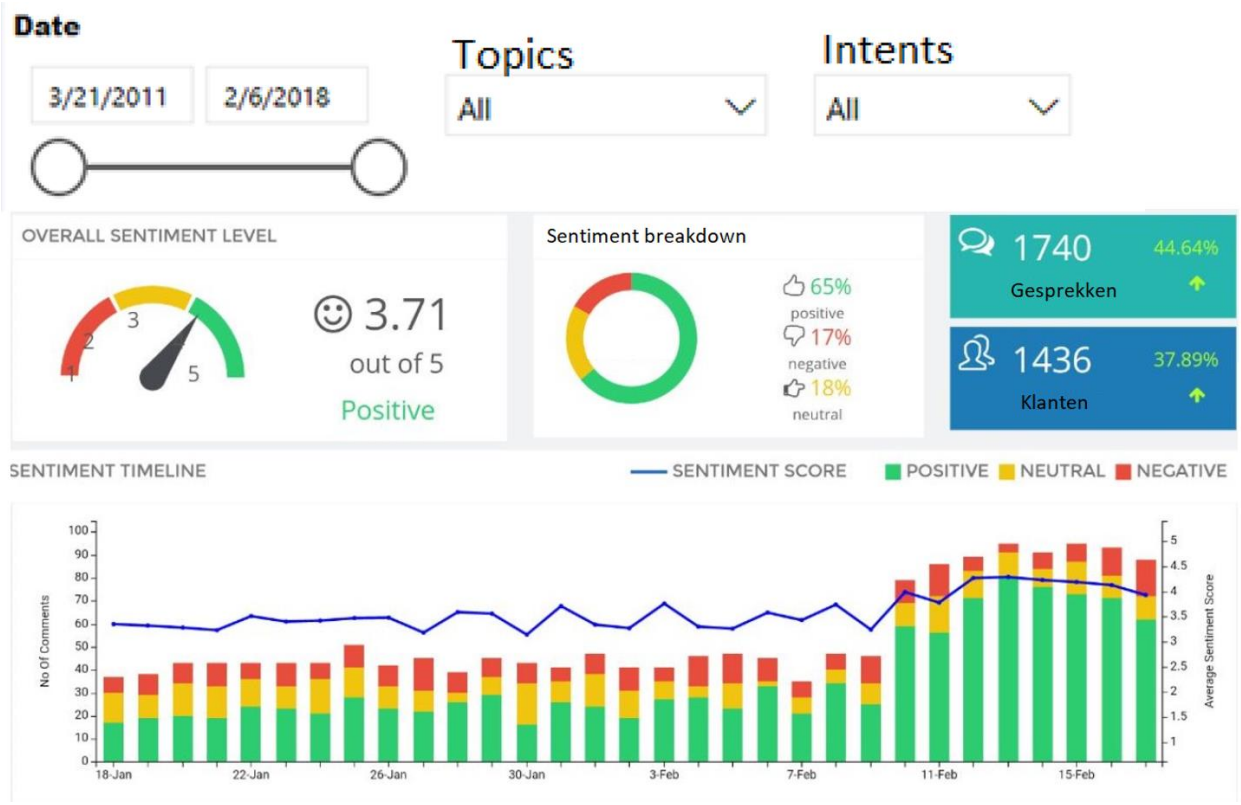

Figure 8: Visualization of customer sentiment KPI

The fifth KPI in table 3 is the sentiment per customer. The sentiment analysis with customer contact data as input can be utilized to add a sentiment KPI in every customer dashboard. Customer support employees can then use this insight to see if a customer that they are in contact with has a positive or negative sentiment towards the company.

2.7.4 Sentiment of Employees

Next to customer related KPIs derived from internal data. An employee-centric KPI can also provide valuable information. The average sentiment of the employees (row 6, table 3) gives insight into the employee satisfaction (Roldós, 2020). The HR department can utilize this KPI to evaluate their own performance. Additionally, the sentiment per employee can be measured (row 7, table 3). This gives insight into the sentiment of every single employee in the company. The input for this KPI is internal data which can be derived from employee meetings, employee emails et cetera.

Table 4 describes the KPIs mentioned in literature. These KPIs are the sentiment of the market about the company, the sentiment of the market about competitors, the sentiment of participants of events the company organizes, the sentiment of all customers (average sentiment of customers, the sentiment per customer, the sentiment of all employees and the sentiment per employee. Column 2 in table 3, shows the target group of the KPI. The target group is the group wherefrom the sentiment will be measured. The fourth column “input” displays if this sentiment will be gathered by internal or external data. The last column describes the source that mentions this KPI.

Case study

Next to the literature, this research describes other KPIs. These KPIs are developed by interviews and by utilizing the systematic approach. Table 4, mentions these KPIs. Table 4 establishes in column 2 the target group; of whom will the sentiment be measured? The third column states the newly developed KPIs. The column "input" describes if the KPI can be developed by utilizing external or internal data and the last column describes if the KPI was developed by an interview or by critical thinking.

Row #	Measuring sentiment of	KPI	Input	Interview
1	Participants	Sentiment of participants of events the competitor organizes	External	Yes
2	Customers	Sentiment per contact moment	Internal	Yes
3	Customers	Sentiment within contact moment	Internal	Yes
4	Employees	Sentiment per contact moment (with HR)	Internal	Yes
5	Employees	Sentiment within contact moment (with HR)	Internal	Yes
6	Shareholders	Sentiment of all shareholders	Internal	No
7	Shareholders	Sentiment per shareholder	Internal	No
8	Shareholders	Sentiment per contact moment (shareholders meeting)	Internal	No
9	Shareholders	Sentiment within contact moment (shareholders meeting)	Internal	No
10	Partners	Sentiment of all partners	Internal	Yes
11	Partners	Sentiment per partner	Internal	Yes
12	Partners	Sentiment per contact moment	Internal	Yes
13	Partners	Sentiment within contact moment	Internal	Yes
14	Suppliers	Sentiment of all suppliers	Internal	No
15	Suppliers	Sentiment per supplier	Internal	No
16	Suppliers	Sentiment per contact moment	Internal	No
17	Suppliers	Sentiment within contact moment	Internal	No

Table 4: Sentiment analysis KPIs developed by interviews and the systematic approach

The first row in table 4 describes the sentiment of participants of events the competitor organizes. This KPI measures the same as the KPI in table 4 row 3 "Sentiment of participants of events the company organizes" but then the sentiment of events the competitor organizes. This can be done to evaluate the success of events compared to events the competitor organizes.

Table 4, row 2 displays the sentiment per contact moment of the customer. The literature mentioned earlier that the sentiment per customer can be obtained. This is valuable for customer support when they talk to a customer. The KPI in table 4 row 2 displays the sentiment per contact moment. If the customer for instance has contact with company X via WhatsApp and via phone call then the sentiment will be measured for both contact moments. This provides customer service employees with insight. It shows the sentiment of the last contact moment of the customer.

The sentiment of the customer can be further utilized by providing the sentiment within contact moments (row 3, table 4). This KPI was established by doing interviews at company X. Contact moment can be split into several parts, for instance, the beginning, the middle and the end of the conversation. A sentiment score can be obtained per section. This gives insight into the development of the sentiment within a contact moment. A sentiment can for instance go up or down during a conversation. This can be visualized in a dashboard. How this can be valuable will be discussed in the application section. Figure 9 displays a possible visualization of a customer centric KPI dashboard developed by using the KPI of the “sentiment per customer” and combining this with the KPIs gathered by interviews and the systematic approach namely the “sentiment per contact moment” and “sentiment within contact moment” KPIs. This dashboard provides an overview of the sentiment of specific customers.

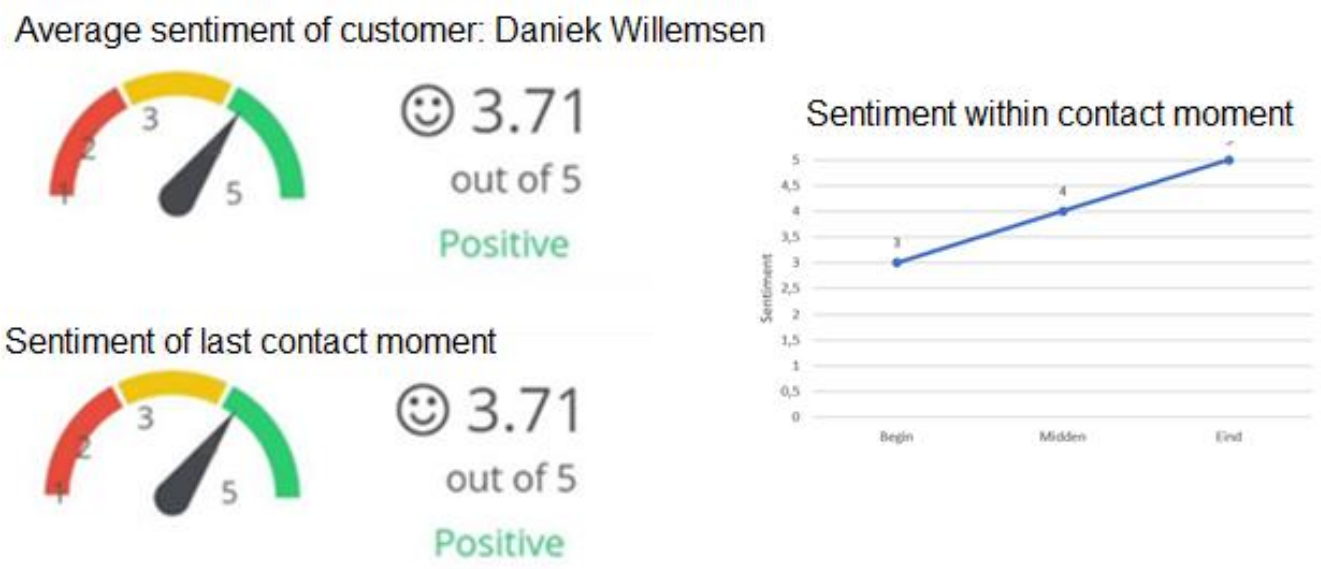

Figure 9: Visualization of sentiment per customer, per contact moment and within contact moment KPI

KPIs can also be developed for customers but also for other target groups. Internal data contains employee data, partner data, shareholder data or supplier data. Therefore the visualization of figure 10 can be applied for not only customers but also other target groups like employees, partners, shareholders and suppliers. In table 4, from row 4 onwards, the KPIs derived from internal data for employees, partners, shareholders and suppliers are visualized in the same format as defined in figure 10. The supplier and the shareholders KPIs are derived from logic thinking. These KPIs were established by first brainstorming about internal data. Which internal data is suitable for sentiment analysis and which target groups can be established. A target group can be established when there is enough data of a data group. This internal data can be data like shareholder meeting recordings.

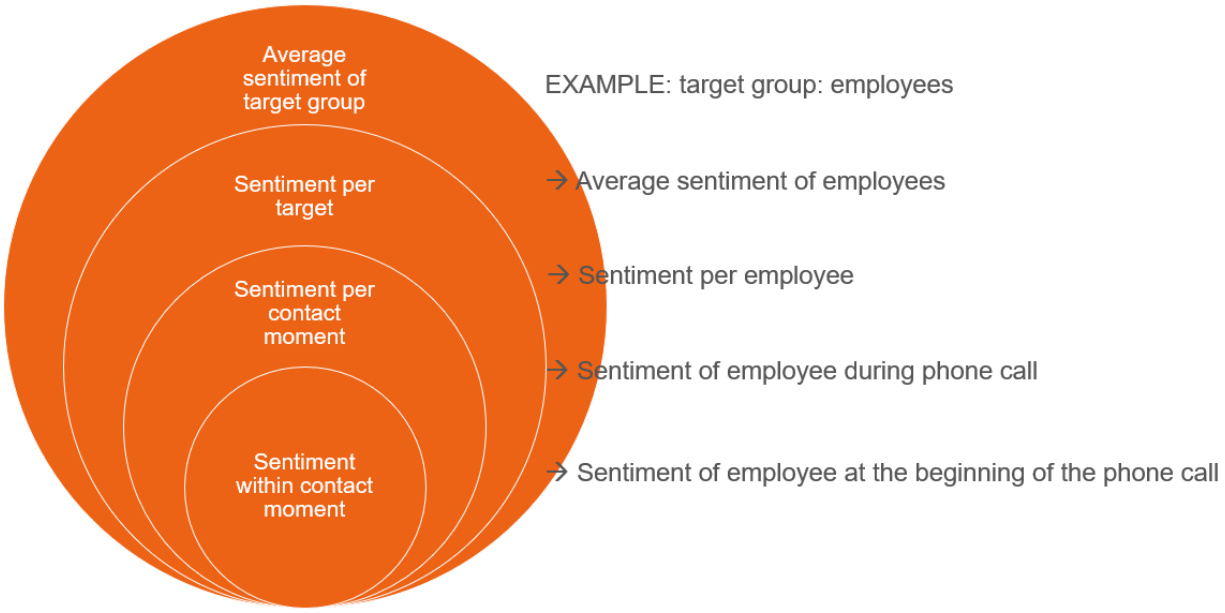

Figure 10: Visualization of the relationship between sentiment analysis KPIs developed by internal data

The interviews align with the KPIs proposed by the literature. The interviews additionally propose more debt to the KPIs. When the sentiment can be accurately measured per contact moment and within a contact moment then this offers more opportunities to examine the sentiment more in-depth. Additionally, the interview proposed more possibilities of obtaining the sentiment from different target groups. Sentiment can namely not only be obtained from the market, customers, participants and employees but also from shareholders, partners and suppliers. This offers more possibilities for generating specific applications which can help businesses.

Step 7: Develop an overview of sentiment analysis applications

WHAT: This chapter provides an overview of sentiment analysis applications. WHY: A complete overview of sentiment analysis applications is important as it enables companies to decide which applications they would like to implement. HOW: By examining literature and by utilizing the systematic approach, companies can develop an overview of sentiment analysis applications applicable for the different departments in their company. The departments which are proposed are the Board of Directors, Business Intelligence, Customer Relationship Management, Customer Support, External Affairs, Human Resource Management, Marketing, Product/Product department, Sales department. In the paragraphs below, an overview will be given of the sentiment analysis applications generated in literature, by interviews and by the systematic approach. Every sub-chapter will explain the applications per division. Table 5 shows all applications which were developed in this research.

Measuring sentiment of	Department	KPI	Application	Data source	Input	Literature	Interview	Systematic approach
Shareholder	Board of directors	Sentiment per shareholder	Shareholder churn prediction tool	Shareholder contact data	Internal			x

Market	Board of directors	Sentiment of the market	Investor prediction tool	web scraper	external	x		
Shareholder	Board of directors	Sentiment per shareholder	Shareholder decision-making tool	Shareholder contact data	Internal			x
Customers	Business Intelligence	Sentiment of the customer (several filters)	Prioritization tool	Customer contact data	Internal		x	
Customers	Customer relationship management	Sentiment per customer	CRM tool	Customer contact data	Internal			x
Customers	Customer relationship management	Sentiment of the customer (several filters)	Partner insight tool	Customer contact data	Internal			x
Customers	Customer support	Sentiment per contact moment & Sentiment within contact moment	Customer service performance tool	Customer contact data	Internal	x	x	
Customers	Customer support	Sentiment per ticket	Prioritization customer tickets tool	Customer contact data	Internal	x		
Customers	Customer support	Sentiment per contact moment & Sentiment within contact moment	Ladder of emotions tool	Customer contact data	Internal		x	
Customers	Customer support	Sentiment of the customer (several filters)	Communication channel tool	Customer contact data	Internal		x	

Customers	External Affairs	Sentiment of the customer (several filters)	Partner sentiment tool	Customer contact data	Internal		x		
Partner	External Affairs	Sentiment per partner	Partner churn prediction tool	Partner contact data	Internal			x	
Partner	External Affairs	Sentiment per partner	Partner decision-making tool	Partner contact data	Internal			x	
Customers	External Affairs	Sentiment of the market	Partner evaluation tool	web scraper	external	x			
Employees	HR department	Sentiment of the employees (several filters)	HR target tool	Employee contact data	Internal	x	x		
Employees	HR department	Sentiment of the employees (several filters)	HR employee assessment tool	Employee contact data	Internal	x	x		
Employees	HR department	Sentiment of the labour market	HR Labour market tool	web scraper	external	x			
Employees	HR department	Sentiment per employee	Employee churn prediction tool	Employee contact data	Internal			x	
Employees	HR department	Sentiment per employee	HR ladder of emotions tool	Employee contact data	Internal		x	x	
Market	HR department	Sentiment of the employees (several filters)	Employee gift tool	Employee contact web scraper	Internal and/or external	x		x	
Participants	Marketing department	Sentiment of the market	Marketing Campaign/Event evaluation tool	web scraper	external	x	x		
Participants	Marketing department	Sentiment of the market	Competitor Campaign/Event evaluation tool	web scraper	external			x	

Customers	Purchase department	Sentiment of the customer (several filters)	Product/service evaluations tool	Customer contact data	Internal	x		x	
Suppliers	Purchase department	Sentiment per supplier	Supplier churn prediction tool	Supplier contact data	Internal				x
Suppliers	Purchase department	Sentiment per supplier	Supplier decision-making tool	Supplier contact data	Internal				x
Market	Purchase department	Sentiment of the market	Purchase tool	web scraper	external	x			
Customers	Sales department	Sentiment per customer	Sales tool	Customer contact data	Internal			x	x
Customers	Sales department	Sentiment of the market	Customer churn prediction tool	web scraper	external	x			

Table 5: Sentiment analysis applications for businesses

Board of Directors

Figure 11 displays all KPIs (gathered in literature, the case study and by the systematic approach) linked to value-generating applications for the board of directors.

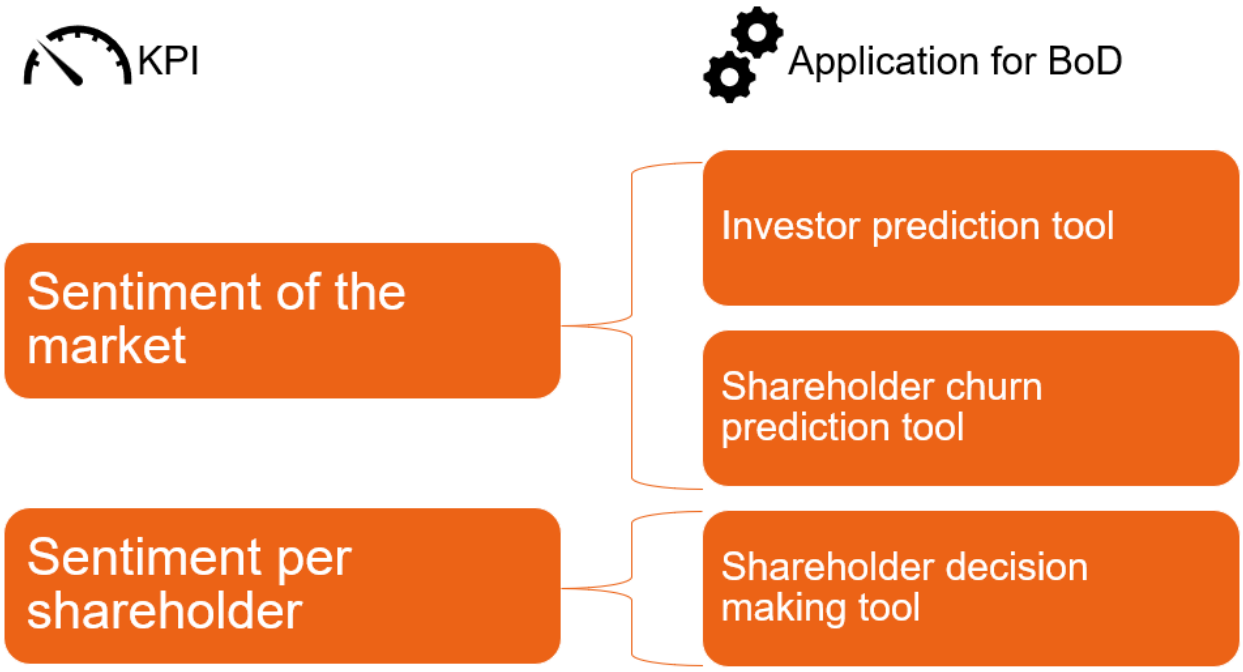

Figure 11: value-generating applications of sentiment analysis for the Board of Directors

Literature mentions several sentiment analysis tools for businesses which the Board of Directors can utilize. Bianchi (2021) mentions for instance that sentiment analysis can also be utilized in the stock market. The investor prediction tool for instance can be utilized by the Board of Directors. The investor prediction tool (Figure 11) utilizes external data via for instance a web scraper to predict if a stock of a company goes up or down based on sentiment. A web scraper obtain all messages on for instance social media platforms which include your company name. This can be used as input for sentiment analysis. A market KPI can be developed on how positive or negative the market sentiment is and this has an influence on investors (Bianchi, 2021). Thus, the investor prediction tool is a valuable tool for the BoD to examine if a company is still appealing to investors. Figure 11 shows next to the investor churn prediction tool 2 more sentiment analysis applications which are valuable for the board of directors namely the shareholder churn prediction tool and the shareholder decision-making tool. These 2 tools are developed utilizing the systematic approach.

The shareholder churn prediction tool utilizes internal data (from for instance shareholder surveys or audio records of shareholder meetings) to predict how many shareholders will sell their shares. This tool was established by the systematic approach. The Board of Directors goal is to protect the interest of the shareholders. Shareholders with negative sentiment are more likely to churn. A model can be developed which predicts how many shareholders sell their shares based on their sentiment. This is a valuable tool for the BoD in order to examine if they protect the interest of the shareholders well (whereof one of the interests is having a successful company). A paper of Murlidhar (2022) mentions that a customer churn prediction tool can be developed based on sentiment analysis. When customer churn predictions are possible for sentiment analysis then shareholder churn predictions are also possible for sentiment analysis. The input is only different. The input for customer churn predictions is customer contact data. The input for shareholder churn predictions is for instance shareholder surveys or audio records of shareholder meetings.

The last application for the BoD is the shareholder decision-making tool. This tool helps to decide what managerial actions cause positive or negative shareholder sentiment. Internal shareholder data can be utilized to develop a sentiment per shareholder KPI. If during a contact moment like a shareholder meeting came up that the company would for instance want to outsource the marketing department. Then the sentiment analysis can help if the sentiment of the shareholders is negative or positive towards this managerial action. The shift in sentiment can help to determine if the decision to outsource the marketing department will be executed or if they determine not to outsource the marketing department anymore.

Business Intelligence

Figure 12 displays the KPIs linked to value-generating applications for the Business Intelligence department (BI).

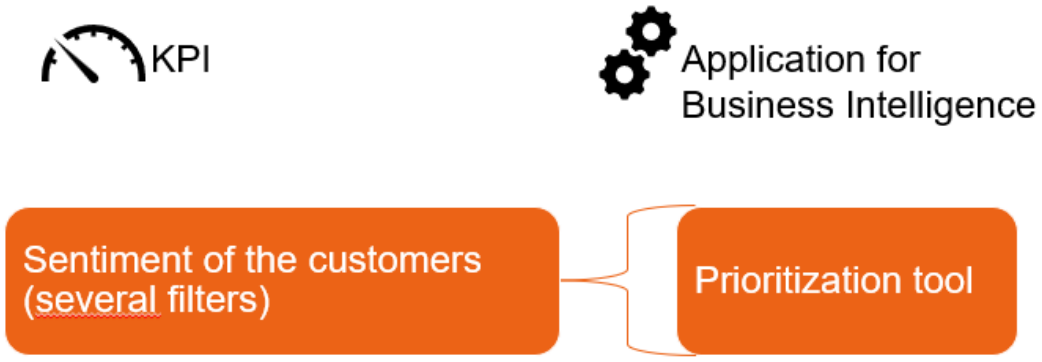

Figure 12: value-generating applications of sentiment analysis for Business Intelligence linked to the corresponding KPI

Literature mentions several sentiment analysis tools for businesses that Business Intelligence can utilize. Bianchi (2021) mentions the benefits of filters within customer sentiment scores. Companies could for instance measure the average sentiment of their customers by using all customer contact data as input but the company could for instance also filter this average sentiment of the customers by contact channel. In this way, the company can evaluate if the sentiment is on average better via the contact channel WhatsApp than for instance email. Other filters can for instance also be applied, like product filters and customer age filters.

The insights about the prioritization tool were gathered by executing interviews with the customer service vision, strategy and innovations manager and the marketing intelligence specialist at company X. The prioritization tool is an interesting tool for the business intelligence department as the prioritization tool offers lots of opportunities to explore business processes which lead to negative sentiment. The sentiment of the customers is developed via a sentiment analysis utilizing internal data (customer contact data). Various filters can be developed like topic filters (car insurance, life insurance), intent filters (applying for an insurance, terminating an insurance, applying for a claim), employee filters (Peter de Vries, Angela Geerdink), period filters (from 1. august until 3. august, from 1. January to 31. December), communication channels (WhatsApp, Email, Facebook, Chatbot) et cetera. This can be utilized by BI to examine which topics, intents and communication channels are generating positive sentiment and which generate negative sentiment. When a communication channel for instance creates lots of negative sentiment then the communication channel should be examined and compared with the other communication channels. Why does it create so much negative customer sentiment compared to the other communication channels? This KPI which displays customer sentiment provides company X with the option to examine what exactly creates negative sentiment. The prioritization tool can then prioritize intents, communication channels and employees who perform badly (creating negative sentiment). BI will then examine why certain filter options generate negative sentiment and how they can improve these negative sentiment scores. By utilizing the prioritization tool, the filter combinations with the worst sentiment score (most negative sentiment score) will be prioritized as urgent matters. These options will be examined first in order to improve the sentiment of the customers.

Customer Relationship Management

Figure 13 displays the KPIs linked to value-generating applications for Customer Relationship Management (CRM).

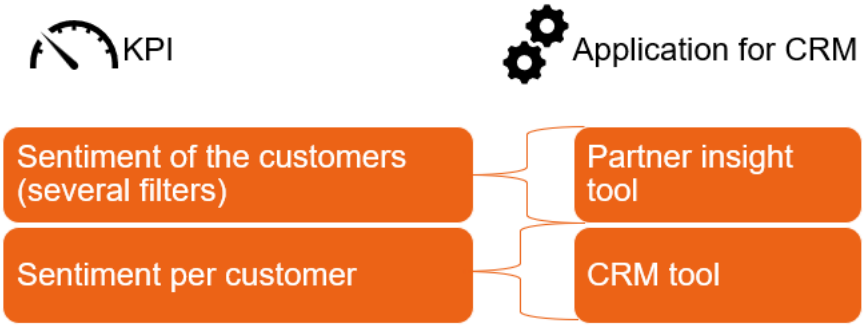

Figure 13: Value-generating applications of sentiment analysis for Customer Relationship Management linked to the corresponding KPI

It can be valuable to customers to provide them with insight intot the performance of partners. The partner insight tool provides the customers with a dashboard where they can easily compare service providers based on the

sentiment scores. This helps customers to choose service providers which help them. This tool can additionally be used for the customer support department. They can for instance recommend to customers which car repair companies are good (create positive sentiment) near their home.

The paper by Murlidhar (2020) mentions that customer churn prediction can be developed by utilizing sentiment analysis. When companies can identify which customers are likely to churn then companies can react to prevent these customers from churning. This is called the CRM tool. When a customer churn prediction dashboard will be developed, CRM can utilize this dashboard to identify which customers are likely to churn. The CRM department can call these customers and ask for their feedback. They examine why the customer has developed negative sentiment and if it is possible to improve the negative sentiment into positive sentiment by talking to the customer. Puzzo (2020) mentions that two of the worst ways to handle angry customers (negative sentiment) are to ignore the customer's concerns and to not ask them for feedback. By talking to the customers about their concerns the CRM department might improve their sentiments.

Customer Support

Figure 14 displays the KPIs linked to value-generating applications for the Customer Support department (CS).

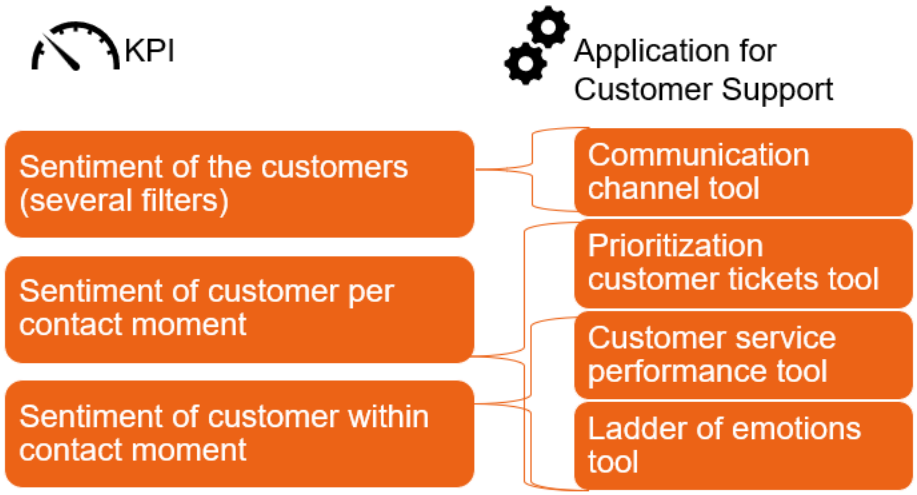

Figure 14: value-generating applications of sentiment analysis for Customer Support linked to the corresponding KPI

Literature mentions several sentiment analysis tools for businesses which Customer Support can utilize. According to Roldós (2020) and IrisAgent (2022), sentiment analysis can also be used as a ranking tool for customer support. This is called the prioritization customer tickets tool. Customer support tickets are labelled based on their urgency. Tickets labelled with negative sentiment will have priority over tickets which are less urgent (have neutral sentiment). It is important to respond fast to a customer with negative sentiment. Huang et al. (2020) namely mention in their study that the customers whose complaints will be handled within 5 minutes, spend more on future purchases.

Biglow (2017) mentions that it is valuable to evaluate customer support employees not only based on peer reviews but also on the review of the customer. Sentiment analysis provides an option to evaluate customer support employees based on their performance. Therefore the customer service performance tool can be created. It helps customer service supervisors to analyze the performance of their customer service employees. Supervisors can examine which customer service employees perform well in turning conversations from positive to negative

sentiment. This means that the KPI of sentiment within the contact moment will be analyzed in bulk per customer support employee. How many times did a customer support employee turn a conversation which started with negative customer sentiment into a conversation which ended with positive customer sentiment? In this way, supervisors can compare customer support employees. Customer support employees can also be deployed based on their strengths. Some customer support employees perform well in turning negative customer sentiment into positive customer sentiment. Other customer support employees are better at maintaining positive customer sentiment throughout a conversation. Supervisors can also check on customer support employees which perform badly; they turn a positive customer sentiment into a negative customer sentiment throughout the conversation.

The interviews within the case study also provide 2 new sentiment analysis applications valuable to the customer support department. During the interview with the customer service vision, strategy & innovation manager, the manager mentions that there is a lot to gain when customer support tickets are prioritized based on their customer sentiment. The order in which tickets will be handled first can be determined based on time and ticket sentiment score. Next to this, he explains that a tool would help to assess the performance between different communication channels. The communication channel tool fits with the sentiment of the customer's KPI. This KPI can be filtered on the communication channels. In this way, the customer support department can compare the performance (sentiment score) between communication channels.

The CRM manager (team leader of a business intelligence unit) explains during the interview that the ladder of emotions also needs to be utilized when dealing with customers. She proposes a tool: the ladder of emotion tool. The customer service department can utilize the ladder of emotions tool to better fit the sentiment of the customer support employee to the sentiment of the customer. This tool helps the customer service employees to better predict customer sentiment and to better fit their own sentiment to the conversation. A customer service employee can for instance, before he enters the call, see the average sentiment of the customer and the sentiment of the customer from the last contact moment the customer had with the company. A customer service employee should act corresponding to the sentiment. If the sentiment of the customer was negative the last time, the customer support employee should not start the conversation extremely happy, they should adapt their sentiment to the sentiment of the customer according. The customer support employee already knows that the last contact moment created negative sentiment. Therefore, they can respond to this sentiment.

External Affairs

Figure 15 displays the KPIs linked to value-generating applications for the External Affairs department (EA).

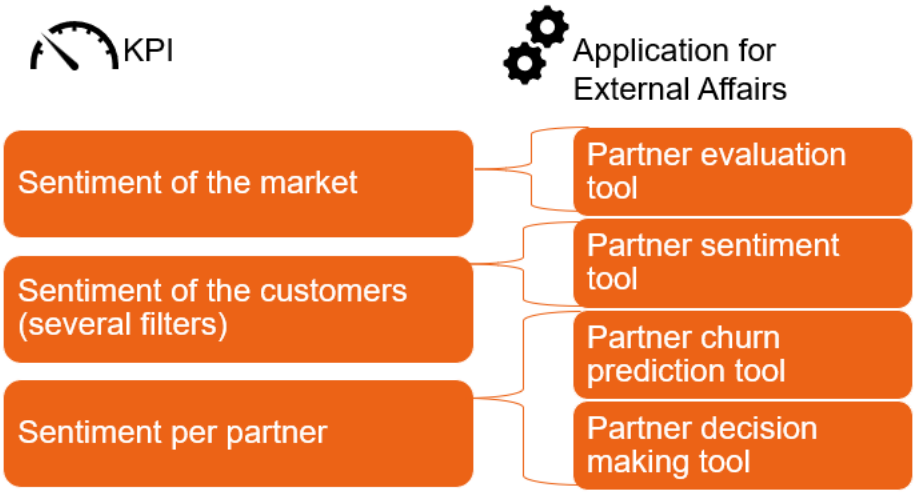

Figure 15: value-generating applications of sentiment analysis for External Affairs linked to the corresponding KPI

Literature provides a sentiment analysis application valuable to the external Affairs department namely the partner evaluation tool. The external Affairs department would like to know which future partners perform well (generate positive sentiment) before they sign a contract with this partner. This can be examined by utilizing a partner evaluation tool. Fang and Zhan (2015) mention in their paper that sentiment analysis can be utilized to rate products and services based on sentiment. A web scraper needs to be developed to obtain external data about future partners. By developing a customer sentiment per partner, companies can examine beforehand which partners provide good service (generate positive sentiment) and which partners do not (generate negative sentiment).

The strategy and innovations manager mentions during the interview that it would also be beneficial for external Affairs to know which current partners perform well (generate positive sentiment). In this way, the contract of the bad-performing partners can be terminated. External Affairs can also talk to the partner about why they generate so much negative sentiment. Therefore, a partner sentiment tool would be nice. External Affairs can check the sentiment of the customer per partner and examine if some partners perform badly.

The partner decision-making tool is similar to the shareholder decision-making tool. This tool helps to decide what managerial actions cause positive or negative partner sentiment. Internal partner data can be utilized to develop a sentiment per partner KPI. If during a contact moment like a meeting with a partner came up that the company would for instance want to change the packaging. Then the sentiment analysis can help if the sentiment of the partners is negative or positive towards this managerial action. The shift in sentiment can help to determine if the decision to change the packaging will be executed or if they determine not to change the packaging as the sentiment of most partners will then shift to negative sentiment.

The partner churn prediction tool is similar to the customer churn prediction tool of Murlidhar (2022). Sentiment analysis can predict if a partner will churn based on partner contact data (i.e. audio records of meetings with the partner, emails and WhatsApp messages). In this scenario partner churn means that the partner will terminate the contract. It is beneficial for external Affairs to know if a partner would like to terminate the contract in the future. In this way, they can already search for new partners which offer the same services.

Human Resource Management

Figure 16 displays the KPIs linked to value-generating applications for the Human Resource Management (HRM).

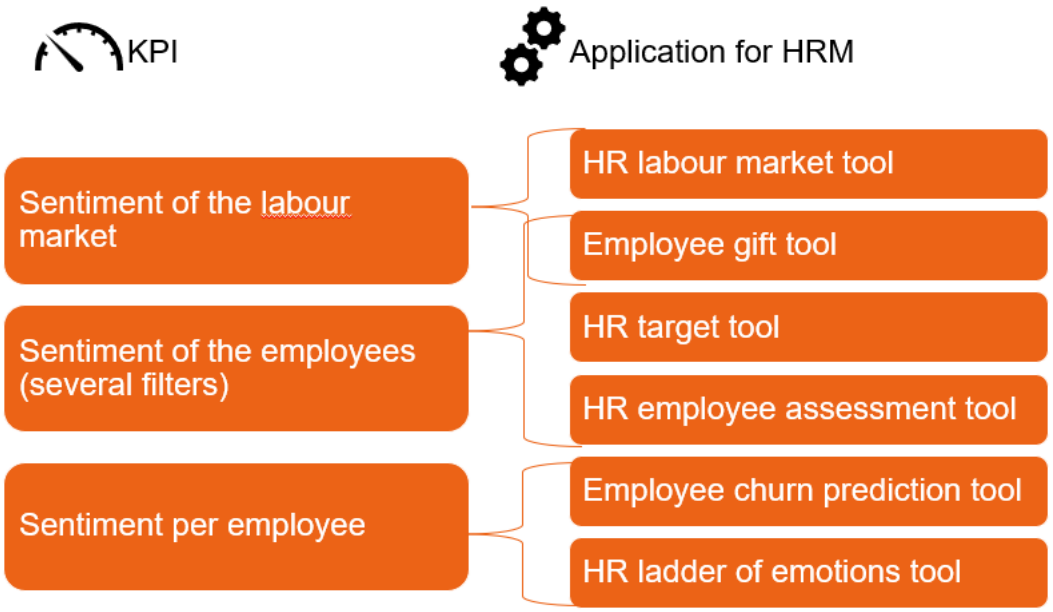

Figure 16: value-generating applications of sentiment analysis for Human Resource Department linked to the corresponding KPI

There are 3 sentiment analysis applications proposed in literature which can generate value for the HR department. The HR labour market tool helps HR to give insight in the sentiment of your employees versus the sentiment of your competitors. This provides valuable information about the company's position on the labour market. How attractive is the company as an employer? Zheng et al. (2022) mention in their paper the usefulness for companies to explore their position in the labour market via sentiment analysis. The HR labour market tool provides information on how easy or hard it is for the company to employ the best candidates for a job based on the company's reputation in the labour market.

The HR department would like to measure the sentiment of the employees to evaluate employee satisfaction scores as high employee satisfaction scores retain employees in companies (Farmiloe, 2022)(Maurer, 2021). The HR target tool is a way to extract this valuable information from the sentiment of the employees. With the HR target tool, they can examine if the employee sentiment increases or decreases. This helps to examine if additional employee benefits improve the sentiment of the employee. A benefit filter could for instance filter on "free fitness membership". The sentiment of the employees with and without this benefit can be compared to examine if the benefit improves the sentiment of the employee.

Farmiloe (2022) and Maurer (2021) describe that sentiment analysis can be utilized to obtain the sentiment of employees. This can be filtered per HR employee to evaluate if he or she performs well. Did he or she increase the sentiment of employees? The customer service performance tool measures the performance of customer service employees but the HR employee performance tool measures the performance of HR employees. In this way, the performances of HR employees can be measured and compared. When HR employees perform badly this should be examined and their contract may need to be terminated. Some HR employees are good at maintaining positive employee sentiment other HR employees are good at improving employee sentiment. The HR employees can be employed based on their strengths.

As earlier mentioned, the CRM manager (team leader of a business intelligence unit) explains that the ladder of emotions can be a powerful tool to fit the sentiment of the customer support employee to the sentiment of the

customer. The HR ladder of emotions tool can be utilized by the HR department to utilize the same method for the employees. The tool helps HR employees to better predict employee sentiment and to better fit their sentiment to the conversation. An HR employee can for instance, before he enters the meeting, see the average sentiment of the employee and the sentiment of the employee from the last contact moment the employee had with HR. An HR employee should act corresponding to the sentiment. If the sentiment of the employee was negative the last time, the HR employee should not start the conversation extremely happy, they should adapt their sentiment to the sentiment of the employee according. The HR employee already knows that the last contact moment created negative sentiment, Therefore, they can respond to this sentiment.

The HR department would like to know which gifts and benefits are popular for employees. Fang and Zhan (2015) mention in their paper that sentiment analysis can be utilized to rate products based on sentiment. Thus, it is possible to rank employee gifts and employee benefits based on customer sentiment. The employee gift tool thus provides valuable insight into which gifts and benefits are most popular. This helps to effectively enhance employee sentiment.

Similar to the customer churn prediction tool, the employee churn prediction tool measures how many employees are likely to terminate their contracts in the future. Murlidhar (2020) mentions in his paper that customer churn can be predicted based on customer sentiment analysis. Thus employee churn can be predicted based on employee sentiment analysis.

Marketing

Figure 17 displays the KPIs linked to value-generating applications for the Marketing department.

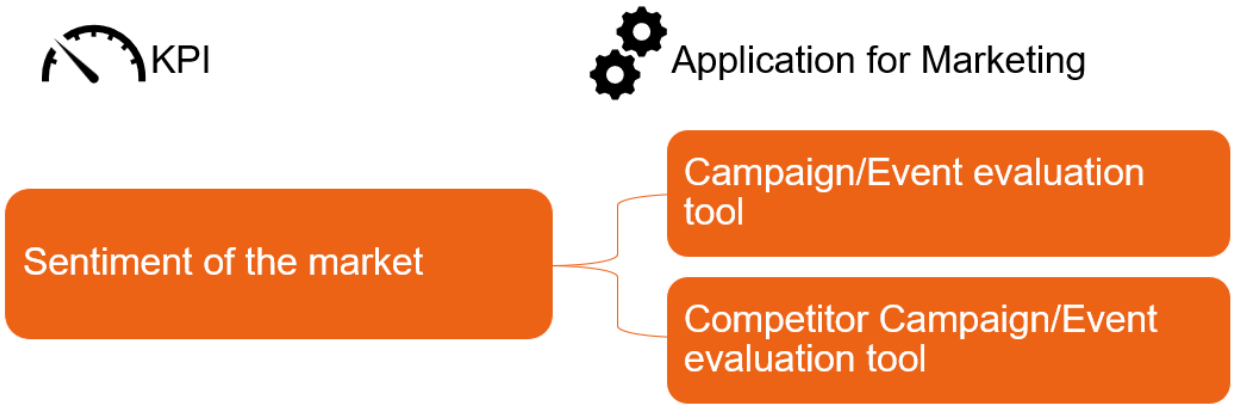

Figure 17: value-generating applications of sentiment analysis for Marketing linked to the corresponding KPI

Literature provides a new sentiment analysis tool which generates value for the marketing department. Sentiment analysis can be utilized to examine how well marketing, PR and sales campaigns are doing. Events can as well be assessed based on their sentiment score. The sentiment score can be acquired by using a social media crawler (Fairly, 2022). This helps the marketing department to measure the sentiment of the customers who participated in company events, who watch ads and who read company content. An article by Llewellyn explains the importance of measuring the performance of events and campaigns (2022). The marketing campaign/event evaluation tool can be valuable to evaluate the performance of the events and campaigns. An ad can for instance create lots of negative sentiment. When this will be measured, the marketing department can react by deleting the ad as soon as possible.

The ad which generated negative sentiment can be studied. Why did this ad generate negative sentiment? The marketing department can react accordingly with a new ad.

marketing campaign/event evaluation tool mentioned in the literature can also be utilized to analyse marketing campaigns and events of competitors. The marketing department can respond to negative ads of the competitors with counter ads which generate positive sentiment. For instance, Axe released around 2011 their campaign with the "Axe effect". These campaigns created some angry sentiment as it can be displayed as toxic masculinity. Around 2017, Axe changed direction with its ads. Instead of promoting the macho culture the brand now stimulates to rethink stereotypes (Ruiz, 2021). When companies evaluate the campaigns of their competitors they can react to this. A competitor of Axe could have for instance released a rethink stereotypes ad to increase customer sentiment after the toxic masculinity ad of Axe. In this way, the competitor can positively differentiate itself from Axe.

Purchase department

Figure 18 displays the KPIs linked to value-generating applications for the Purchase department.

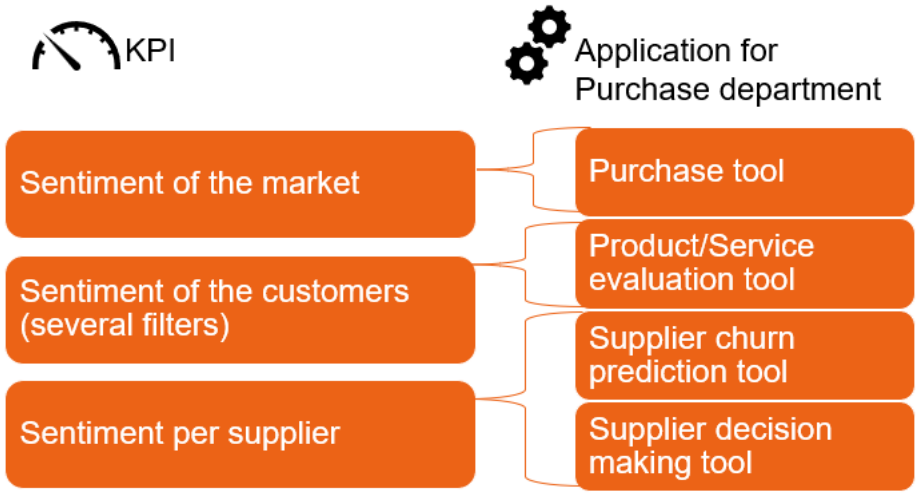

Figure 18: value-generating applications of sentiment analysis for the purchase department linked to the corresponding KPI

Literature proposes 2 sentiment analysis applications which can be valuable for the purchase department. Fang and Zhan (2015) mention in their paper that sentiment analysis can be utilized to rate products based on sentiment. The sentiment of the market can be utilized as a purchase tool for the purchase department. They can obtain sentiment scores per product by utilizing a web scraper. In this way, the purchase department can select the products which generate the most positive sentiment scores and add them to their product portfolio. The current product portfolio can also be evaluated by sentiment scores of their own customers. By utilizing internal data (customer contact data) instead of external data (i.e. a web scraper), companies have more knowledge about the sentiment of their current product portfolio. This evaluation helps to determine which products generate negative sentiment and should be deleted from the current product portfolio. This tool is called the product/service evaluation tool.

According to Fairly (2022), there are already various applications of sentiment analysis in business. It can for instance be used as a purchase tool or a product/service evaluation tool. Sentiment analysis can for instance be used as a purchase tool for the purchase department. Potential new products can be examined by executing a sentiment analysis. A scraper can for instance scrape a review website or social media in order to obtain the

sentiment of customers regarding products. When there is a highly positive sentiment over a certain product then purchasers could decide to add the product to their collection (Fairly, 2022).

The supplier decision-making tool is a tool developed by utilizing interviews. This tool is similar to the shareholder decision-making tool and the partner decision-making tool which were brought to attention by the customer service vision, strategy & innovation manager. The tool helps to predict the sentiment of the supplier about certain topics. This helps the purchase department to make decisions.

The purchase department can utilize this supplier churn prediction tool to predict whether suppliers are likely to terminate the sales contract. This tool is similar to the customer churn prediction tool, which is also mentioned in the paper of Murlidhar (2022). When the purchase department knows that the supplier is likely to terminate the contract then the purchase department can already start looking for substitutes.

Sales department

Figure 19 displays the KPIs linked to value-generating applications for the sales department.

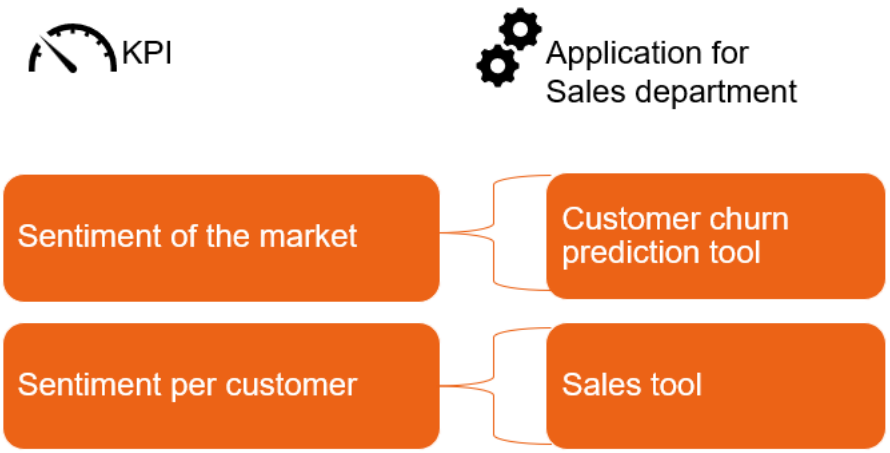

Figure 19: value-generating applications of sentiment analysis for the sales department linked to the corresponding KPI

The customer churn prediction tool can be linked to the customer sentiment KPI. Murlidhar (2020) mentions in his paper that customer churn can be predicted based on customer sentiment analysis. The sales department can utilize this tool to predict customer churn. The customer churn prediction tool helps to predict churn based on the average sentiment of the customers. If the average sentiment of all customers at a company declines then it is highly likely that more customers will churn. Thus the customer sentiment KPI helps to predict churn. A customer churn prediction will help the sales department to determine how many customers are likely to churn.

The sales department would like a tool so they can identify which customers they should and should not contact. Angry and displeased customers (negative sentiment) can feel a lack of empathy when a salesperson calls them to sell something, when the customer still has unresolved negative sentiment concerning a case the CRM department should first contact them (Puzzo, 2020). Therefore a sales tool is handy. A filter can for instance be applied to the sales emails. If a customer has negative sentiment then do not send sales emails to customers. This prevents that the customer worsens their sentiment.

This chapter provided an overview of the sentiment analysis applications per department which were mentioned in literature, which were mentioned in the interviews and which were developed by utilizing the systematic approach.

To conclude, sentiment analysis can be used as an evaluation tool by various departments. By giving a sentiment score to text input the sentiment of customers, employees, shareholders, partners and much more can be measured (Fairly, 2022)(Roldós, 2020). In this way, a company knows if they are doing well by comparing the customer sentiment scores of 3 months ago with the customer sentiment scores of today. Via a social media scraper the company can also evaluate how they are propositioning themselvesFF in the market. The sentiment score of competitors can be acquired by a social media scraper. In this way, the sentiment scores of a certain company can be compared with the sentiment scores of another company. This can of course, also be done for specific products. Which products can be linked to positive sentiment and which products can be linked to negative sentiment? In this way, companies can decide on which products they should delete from their product portfolio and which products they should add to their product portfolio (Fairly, 2022).

Step 8: Prioritize the sentiment analysis applications based on business value

WHAT: Step 8 measures the business value per application. WHY: It is important to measure how much value every sentiment analysis application generates in order to determine if developing a sentiment analysis model is worth the investment. By determining the business value of implementing sentiment analysis in the business, the company can decide if it should or should not invest in sentiment analysis by analyzing the amount of business value the applications generate. HOW: The following paragraphs, show how company X measures the business value of the sentiment analysis applications. Company X determined the business value per application via a survey. Figure 20 until 29 show the results of the survey. The employees were able to rank the possible applications based on how valuable they are to the firm. They could rank the applications from 1 (not valuable) to 7 (extremely valuable). Figure 20 shows that the prioritization application is the most valuable application with an average score of 6,67. The sales tool is the second most valuable application according to the survey with a score of 6,34.

All applications proposed in this research show that they are valuable for business as none of the applications scores low (all applications score at least a 3 on business value on the Likert scale). When the business value of applications will be compared with applications proposed in literature and applications derived from interviews and the systematic approach then it shows that the applications which are derived from interviews and the systematic approach provide more business value. The application mentioned in literature with the highest business value score is the customer churn prediction application with a score of 6,05 The second highest-scoring application proposed in literature is the customer service performance tool. This shows that there are many new sentiment analysis applications proposed in this research which can provide significant value for business. As the highest scoring applications based on business value are the prioritization tool which is mentioned in an interview and the second highest scoring application is the sales tool which is derived from interviews and the systematic approach.

Figure 20: Sentiment analysis applications ranked per business value

Board of Directors

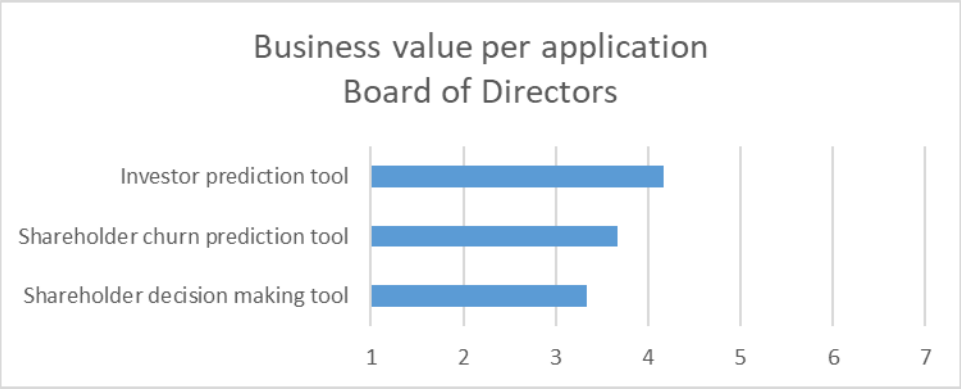

Figure 21: Sentiment analysis applications ranked per business value for the board of directors

When assessing the applications applicable to the Board of Directors, the most valuable application is the investor prediction tool mentioned in literature. The other 2 applications are less valuable but still valuable for businesses. The other 2 applications are derived from the systematic approach.

Business Intelligence

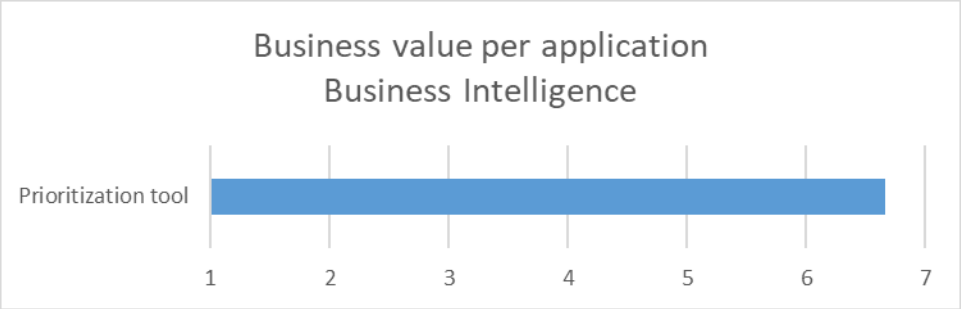

Figure 22: Sentiment analysis applications ranked per business value for business intelligence

This application is the most valuable application for businesses. It scores high on the Likert scale and the application is derived from an interview.

Customer Relationship Management

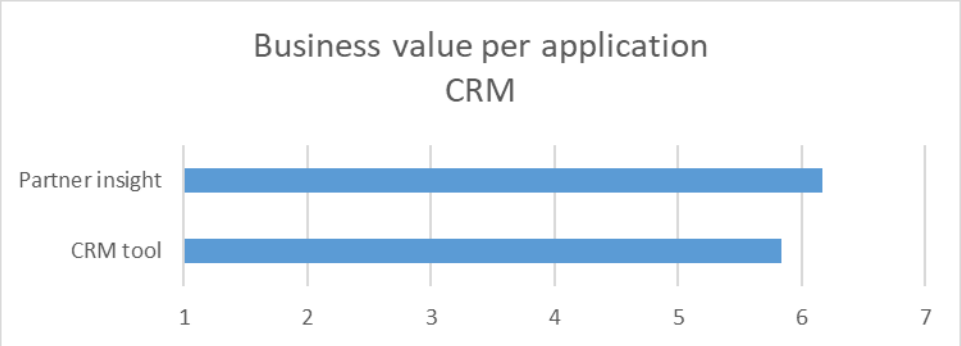

Figure 23: Sentiment analysis applications ranked per business value for customer relationship management

The partner insight tool is the most valuable business application for the CRM department. This tool was derived from the systematic approach. The CRM tool was also obtained from the systematic approach and scored high on the Likert scale as well.

Customer support

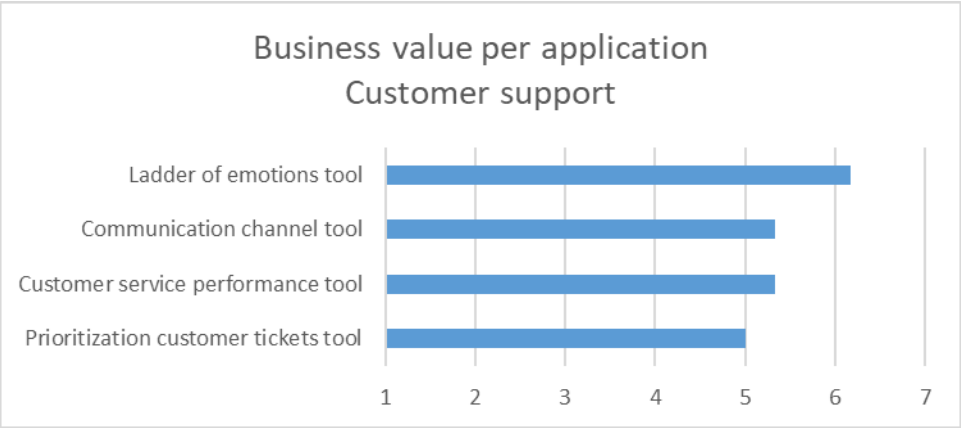

Figure 24: Sentiment analysis applications ranked per business value for customer support

The most valuable applications for customer support were the applications derived from interviews namely the ladder of emotions tool and the communication channel tool. The customer service performance tool and the prioritization customer tickets tool are valuable applications as well and these are mentioned in literature. This research, therefore, developed more valuable applications than the literature mentioned for this department.

External Affairs

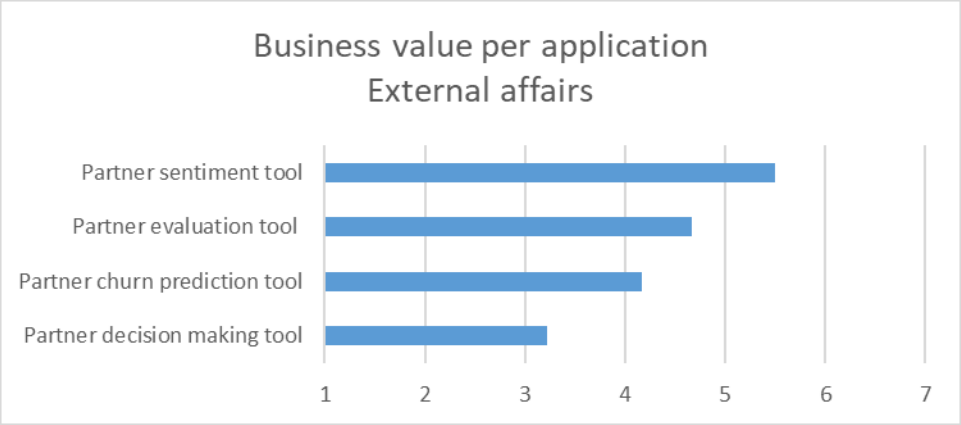

Figure 25: Sentiment analysis applications ranked per business value for external Affairs

The partner evaluation tool was mentioned in literature, but the partner sentiment tool derived from an interview provides more business value. Still, all 4 applications are valuable to the external Affairs department as all 4 applications score above 3.

Human Resource Management

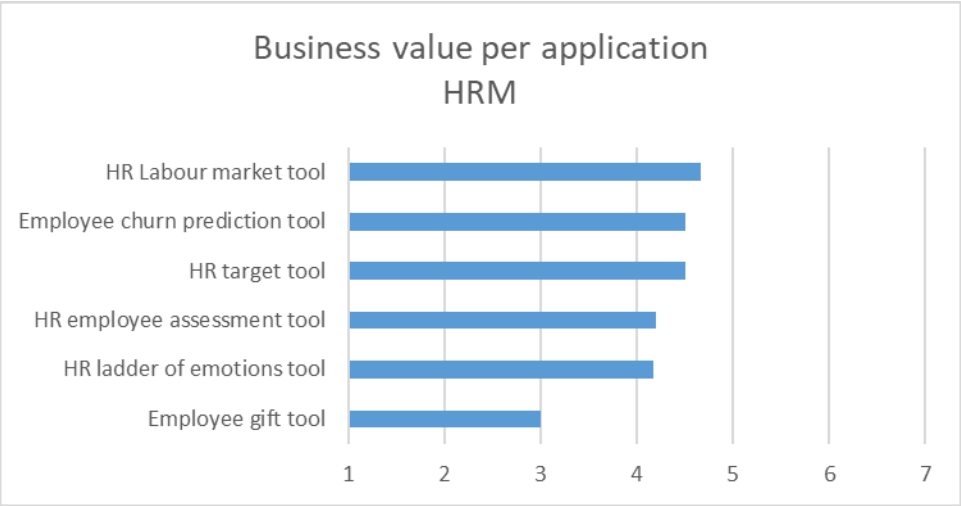

Figure 26: Sentiment analysis applications ranked per business value for human resource management

The most valuable application for the HR department was derived in literature and is the HR labour market tool. Nevertheless, 5 out of 6 applications score between 4 and 5 points on the Likert scale, therefore the business value is approximately the same. The only application which scored lower on the Likert scale is the Employee gift tool.

Marketing

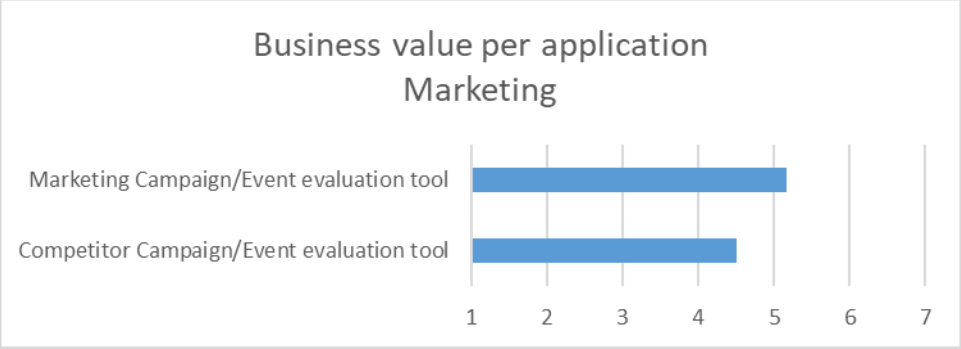

Figure 27: Sentiment analysis applications ranked per business value for marketing

The application of the marketing campaign/event evaluation tool provides a higher business value than the competitor campaign/event evaluation tool. This is expected as it is more important to measure the performance of the marketing campaigns of your own company than the performance of marketing campaigns of competitors. The marketing campaign/event evaluation tool was mentioned in literature and the competitor campaign/event evaluation tool was derived from logical thinking.

Purchase department

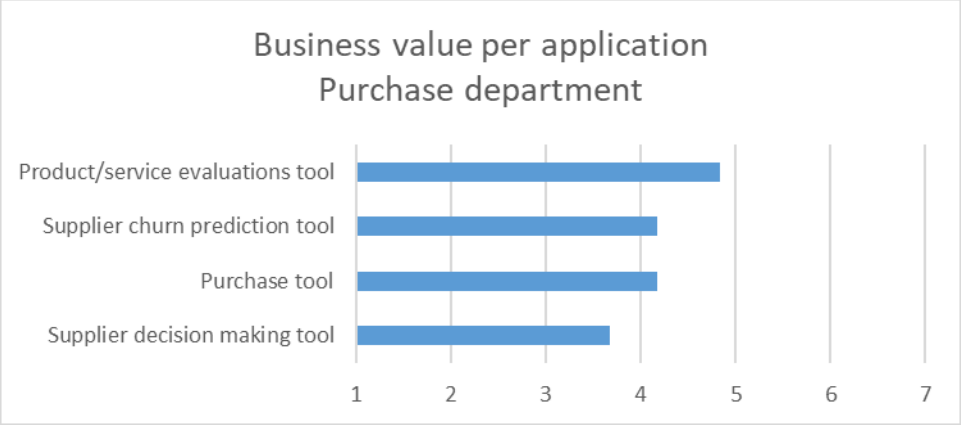

Figure 28: Sentiment analysis applications ranked per business value for purchase department

The application which has the highest business value for the purchase department is the product/service evaluation tool (mentioned in literature) although the supplier churn prediction tool (derived from the systematic approach) and the purchase tool (mentioned in literature) score relatively the same. All 3 applications have a score between 4 and 5. The supplier decision-making tool (derived from the systematic approach) scores lower but the application is still valuable to the purchase department.

Sales department

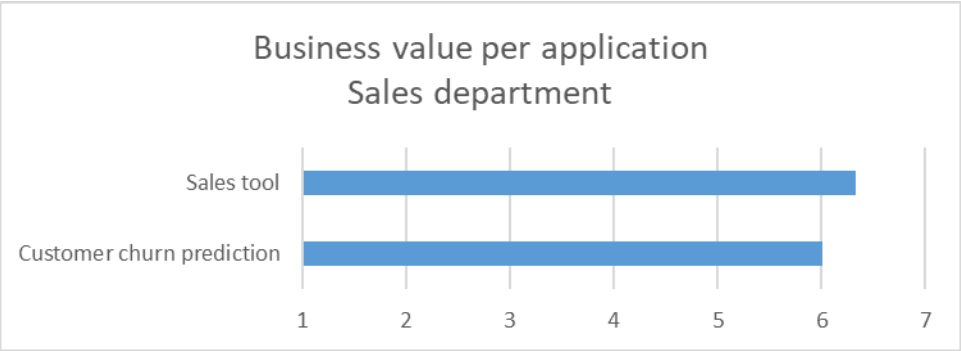

Figure 29: Sentiment analysis applications ranked per business value for sales department

The sales tool (derived from logical thinking) provides more business value to the sales department than the customer churn prediction tool which was mentioned in literature. Still, both applications score very high in comparison to all business applications mentioned in this research as both applications score above 6.

To conclude, this research has offered several departments within company X with multiple new sentiment analysis applications which provide significant business value. Therefore, company X should invest in sentiment analysis as it provides more than 28 value-generating applications. The survey shows that all applications show a score of higher than 3 which means that the applications create value for the departments. The systematic approach to explore new sentiment analysis applications works well as several newly developed applications are more valuable than the applications mentioned in literature. This is the case for the applications mentioned in the following departments: Business Intelligence, CRM, Customer support and sales department. When companies analyze the

business value of sentiment analysis applications they can utilize this analysis to decide if they should or should not invest in sentiment analysis. Do the cost, time and effort outweigh the benefits of sentiment analysis? If the answer is yes, then a company should not utilize sentiment analysis. If the answer is no, then this research recommends the company to implement sentiment analysis.

5. Discussion

This research shows that sentiment analysis applications can provide value for businesses. The applications mentioned in literature do provide business value according to the survey but the literature also misses lots of other sentiment analysis applications which can provide value for businesses. Next to this, literature is focused on perfect execution of sentiment analysis models but in reality data and sentiment analysis models have limitations. Attention should be paid to where the sentiment might not be obtained accurately.

Theoretical Implications

This research proposes a new method of systematically exploring new sentiment analysis applications for businesses. The systematical approach of obtaining new sentiment analysis applications works well as the survey shows that the newly developed sentiment analysis applications (generate in some departments) more business value then sentiment analysis applications already mentioned in literature.

Practical Implications

This research contributes to existing practice by providing a clear guideline for business on how to obtain accurate sentiment analysis scores by utilizing sentiment analysis (step 1 to 4). Next to this, this research explains how a systematic approach helps businesses to explore new sentiment analysis applications. Next to this, the guideline helps businesses to decide if they should or should not invest in sentiment analysis by measuring the business value for the sentiment analysis applications.

Limitations of sentiment analysis

The previous chapters explained how sentiment can best be obtained and utilized in order to improve business performance. Unfortunately, sentiment analysis has some limitations which should be taken into account before businesses should utilize sentiment analysis.

Sentiment analysis has various limitations. The model should for instance be fine-tuned in order to obtain valuable and accurate sentiment scores. Some datasets are not suitable for finetuning sentiment analysis models. The fine-tuned model than might not exceed the 80% threshold (Richards, 2022) of accuracy in order to outperform human analysts. Next to the accuracy of the model, the computing time should also be taken into account. If the model runs for instance 300 rows in 3 days then the model is not useful as humans can then outperform the sentiment analysis model; they will be faster in predicting sentiment scores.

There are other limitations next to the accuracy and computing time. Sarcasm is for instance a big threat to an accurate sentiment analysis model. If the input has large texts of sarcasm then the model does not predict the sentiment accurately. In the results, I discussed earlier, this limitation can be mitigated by applying a sarcasm model before utilizing the dataset as input for the sentiment analysis model. In this way, sarcastic input can be filtered and the overall accuracy score of the model will increase.

Data security and data privacy are important topics to consider while utilizing sentiment analysis. Companies in the Netherlands can receive big fines when they do not comply with data security and data privacy legislation. Firms can for instance be fined up to 20 million euros or 4% of their yearly revenue when they do not comply with the “Algemene verordening gegevensbescherming” (Ministerie van Justitie en Veiligheid, 2020). Therefore it is important to choose the right sentiment analysis model which ensures data privacy and data security. Next to a safe

sentiment analysis model, companies should be aware of the fact that they cannot use data from people (employees, customers or other stakeholders) without that they know that the data will be utilized for business intelligence purposes. The target group of the sentiment analysis (i.e. consumers, employees, shareholders et cetera) first need to allow companies before companies can utilize this data.

The last limitation of sentiment analysis is that sentiment can be incorrectly linked to other concepts. BERT for instance predicts the sentiment on a scale from 1 to 5, where 1 is negative sentiment and 5 is positive sentiment. Negative sentiment consists of a whole range of emotions like anger and sadness. Positive sentiment has a whole different range like gratitude and happiness. In this way, it is still hard to measure the voice of the customer as company X does not know which emotions are connected to positive or negative sentiment scores. Therefore, this research also recommends to further elaborate sentiment analysis and to utilize it for categorizing emotions into categories like for instance sadness, anger, disappointment, disbelief, love, happiness, gratitude, irritation and so on. Company X should first define which emotions they want to focus on while categorizing emotions. After this, they can elaborate the sentiment analysis model in these multiple categories.

Limitations of the guideline

The guideline proposed in this research does have some limitations. The guideline might not work well for small companies without lots of budget for innovations. As the implementation of sentiment analysis costs time and money. Next to this, the company needs enough data to implement sentiment analysis and therefore this guideline might not be useful to companies which do not have lots of in-house data. The guideline could have added a section on how smaller companies could obtain data by for instance buying data from other companies. The company also needs expertise to implement sentiment analysis well. N to this, this research discusses how companies can implement sentiment analysis by utilizing pre-trained models. There are also other ways of implementing sentiment analysis like creating a sentiment analysis model yourself or by outsourcing sentiment analysis. Next to this, new pre-trained sentiment analysis models are shared every day. Therefore, the current selection of Dutch pre-trained sentiment analysis models will be outdated fast. This could also be added to a guideline, as it provides information to a company on which strategy of implementation they should take. This research only discusses ways of implementing sentiment analysis by utilizing pre-trained sentiment analysis models. Lastly, this research measures the business value by utilizing a survey. The true business value of applications can only be measured after the implementation of the applications as the business value of the applications might be lower. It could for instance be that an employee which should use the application does not use the application because he does not know how the application works. It can also be that employees do not utilize an application because they don't have the time or if they simply prefer to not use an application. The systematic approach of obtaining new sentiment analysis does also have some limitations. Companies might struggle with developing new applications even when they can analyze the goals and the metrics. Sometimes it is hard to connect goals and metrics and it does need some part of creative and out-of-the-box thinking. The order of the steps is also maybe not correct. It might be more beneficial to start with step 5 to 8 and end with step 1 to 4. In this way, companies can first determine if they should implement sentiment analysis. If the answer is yes, then they can examine how they should implement it.

Gap between theory and practice

Lastly, this research would like to mention that there could be a gap between theory and practice. In theory, the accuracy scores could be quite high, while in practice the sentiment could not have been measured accurately. This gap could for instance be created by sarcasm. The proposed KPIs and tools can cause threats if companies are led by KPIs which are measured incorrectly.

Future research

Future researchers could examine how easy the actual implementation of sentiment analysis models and applications is in business. Next to this, future researchers could examine new sentiment analysis models and methods. Next to business value, the applications could be ordered based on several considerations. For businesses, it is interesting if next to the business value an application can be implemented based on budget, time, the skill of personnel and much more. Lastly, future researchers could examine if a company can best outsource sentiment analysis or develop a sentiment analysis model in-house. If companies decide to develop a sentiment analysis model in-house they could make use of pre-trained models. Future research could recommend if a company should make use of pre-trained models, if they should create their own model or if they should outsource the development of the model.

6. Conclusion

This research answers the research question “How can companies best obtain and utilize sentiment via a sentiment analysis in order to improve business performance”. It examines how companies can best obtain and utilize sentiment in a business setting by utilizing sentiment analysis. Sentiment analysis is a valuable automated sentiment extraction method and there are various pre-trained models which companies can utilize. There are various guidelines which help companies to implement sentiment analysis but none of them helps companies to answer if and how they should implement sentiment analysis in order to gain business value. Therefore, this research presents a guideline of steps which helps companies to select the best pre-trained sentiment analysis model fitting to their organization. The guideline helps companies to explore sentiment analysis metrics and applications and links them to business value. Lastly, the guideline helps companies to determine whether they should or should not invest in sentiment analysis based on the business value sentiment analysis applications generate in their company.

This guideline proposes to first determine what the purpose of their sentiment analysis model is. What do they want to measure (sentiment of the customers, employees, shareholders, partners, suppliers, other stakeholders)? When the company knows the purpose of their sentiment analysis, it can select a suitable dataset as input for the sentiment analysis. If the data set is developed by utilizing NLP techniques (like audio records transcription software) then companies should first establish how accurate the data set is. If the dataset has an accuracy above 70% then the dataset is suitable as input for the sentiment analysis model. The amount of sarcasm needs to be investigated as well. If the dataset has too much sarcasm then the dataset is also not suitable as input for the model. This can be examined via a sarcasm detection model.

The dataset first needs to be cleaned before it can be utilized in the sentiment analysis model. NaN values, need to be deleted. The dataset also needs to be adapted to the suitable input. Some sentiment analysis models are trained on data which does not include capital letters. Others do not recognize special characters or want the input to be in a certain dtype object. Sentiment analysis models also have a maximum amount of characters per row that they can process. Stop words can also be deleted in order to fasten the computing time. Companies can also decide that for, for instance, customer support audio transcripts they want to filter only the words that the customer said. In this case, the company first needs to delete the text which was said by the customer support employee. It is handy if companies have a column with the original data and a column with the input data if the data needs to be cleaned thoroughly. Companies should also decide on how the output of the model should look like. Would they like a scale from 1 to 5 or a scale from minus 1 to plus 1?

Lastly, when companies chose a fitting sentiment analysis model, they should fine-tune the model when it is machine-learning-based. This research recommends this step to improve the accuracy of the machine-learning model. This research recommends companies to at least have an accuracy of 80% in order to obtain value from it. When a company fine-tunes the model, it should think about what positive sentiment and what negative sentiment is. As this decides how strict the sentiment is on what is positive and what is negative.

This research found two sentiment analysis models which were suitable for Dutch sentiment analysis. BERT and Pattern.nl. In order to determine which model fits best to a specific company, the company needs to think about 8 considerations. The 8 considerations are the explainability of the model, complexity of the model, size of the dataset, dimensionality of the data, training time and cost, inference time and performance of the model. It is important to balance the computing time, costs and accuracy of the model in order to develop a valuable sentiment analysis model.

Sentiment analysis can develop various metrics. It can measure the sentiment of customers, employees, shareholders, partners, suppliers and other stakeholders. It can utilize internal data like customer contact data, employee contact data, business meeting transcripts et cetera and it can utilize external data like data obtained by using a web scraper on for instance social media (Facebook, TikTok, Instagram, LinkedIn), comparative websites (Trustpilot, Booking.com) and much more websites. It can measure the sentiment of individuals but also of specific target groups using filters. These KPIs should be linked to applications in order to provide business value. The applications gathered via literature, interviews and the systematic approach are ranked based on business value. A survey was conducted at company X which shows the most valuable applications.

The most valuable applications in this research are the prioritization tool and the sales tool. These tools are quick to implement and do not require a budget. The prioritization tool adds business value by ordering which business processes should be optimized first by ordering them by sentiment score. The business processes with the most negative score will be optimized first. The sales tool helps the sales department to target customers based on sentiment. In this way, they know which customers are more prone to up-sell and cross-sell strategies based on their sentiment. The 4 applications which create the most business value are all obtained via interviews or the systematic approach. This shows that these newly developed sentiment analysis applications do create value and in these cases even more value than the sentiment analysis applications mentioned in literature.

Concluding, this research proposes a guideline which helps companies to decide if and how they can implement sentiment analysis. By doing this, the research fills the knowledge gap where companies do not know how and if they should implement sentiment analysis. The guideline recommends companies to first determine what the purpose is for the sentiment analysis model. Next companies should select and clean data properly. Additionally, they should determine which sentiment analysis model fits to their needs based on the 9 considerations proposed in this research. This research developed also a new methodology to explore new sentiment analysis applications for businesses. The new methodology of the systematic approach helps companies to determine metrics from sentiment analysis by analyzing its stakeholders. Metrics like market KPIs and customer KPIs. These can be linked to business goals and objectives in order to obtain value-generating applications for the business. The systematic approach resulted in various new sentiment analysis applications for company X and the survey showed that the new applications proposed in this research do provide business value. The new applications named the prioritization tool and the sales tool generated the most business value. Overall, 28 business applications generated value for Company X and therefore, the guideline recommends company X to implement sentiment analysis. This guideline can be used by other companies as well in order to obtain business value via sentiment analysis models.

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8. Appendix

Interview data scientist
How do you select a suitable dataset for sentiment analysis models?
How do you clean data before you utilize it for sentiment analysis models?
What sentiment analysis models do you know for the Dutch language?
How do you decide upon a sentiment analysis model?
What KPIs can be developed from sentiment analysis?
Wherefor could sentiment analysis be valuable?

Interview customer service vision, strategy & innovation manager
From whom would you like to measure the sentiment?
What KPIs can be developed from sentiment analysis?
What sentiment applications do you know?
Wherefor could sentiment analysis be valuable?

Interview marketing intelligence analyst
From whom would you like to measure the sentiment?
What KPIs can be developed from sentiment analysis?
What sentiment applications do you know?
Wherefor could sentiment analysis be valuable?

Interview team leader business intelligence unit
From whom would you like to measure the sentiment?
What KPIs can be developed from sentiment analysis?
What sentiment applications do you know?
Wherefor could sentiment analysis be valuable?

Table 1: Interview questions

Toegevoegde waarde onderzoek

Doel van het onderzoek
Dit onderzoek wordt geleid door Laura Haarhuis. Het doel van dit onderzoek is kwantitatieve data verkrijgen over de toegevoegde waarde van nieuwe toepassingen. De toepassingen worden op dit moment nog niet door [redacted] geïmplementeerd.

Onderzoeks-details

Hoe gaan we te werk?
U neemt deel aan een onderzoek waarbij we informatie zullen vergaren door:
- U een vragenlijst voor te leggen welke u schriftelijk kunt invullen

Uitsluitend ten behoeve van het onderzoek zullen de verzamelde onderzoeksgegevens worden gedeeld met [redacted] Resultaten van het onderzoek zullen gepubliceerd worden in mijn thesis. De thesis is geanonimiseerd: in de masterthesis wordt [redacted] benoemt als "Company X".

Vertrouwelijkheid van gegevens

Wij doen er alles aan uw privacy zo goed mogelijk te beschermen. Er wordt op geen enkele wijze vertrouwelijke informatie of persoonsgegevens van of over u naar buiten gebracht, waardoor iemand u zal kunnen herkennen.
Voordat onze onderzoeksgegevens naar buiten gebracht worden, worden uw gegevens zoveel mogelijk geanonimiseerd, tenzij u in ons toestemmingsformulier expliciet toestemming heeft gegeven voor het vermelden van uw naam, bijvoorbeeld bij een quote.

In een publicatie zullen anonieme gegevens of pseudoniemen worden gebruikt. De audio-opnamen, formulieren en andere documenten die in het kader van deze studie worden gemaakt of verzameld, worden opgeslagen op een beveiligde locatie bij de Universiteit Twente en op de beveiligde (versleutelde) gegevensdragers van de onderzoekers.

De onderzoeksgegevens worden bewaard voor een periode van 10 jaar. Uiterlijk na het verstrijken van deze termijn zullen de gegevens worden verwijderd of worden geanonimiseerd zodat ze niet meer te herleiden zijn tot een persoon.

De onderzoeksgegevens worden indien nodig (bijvoorbeeld voor een controle op wetenschappelijke integriteit) en alleen in anonieme vorm ter beschikking gesteld aan personen buiten de onderzoeksgroep.

Vrijwilligheid & Vragen

Vrijwilligheid
Deelname aan dit onderzoek is geheel vrijwillig. U kunt als deelnemer uw medewerking aan het onderzoek te allen tijde stoppen, of weigeren dat uw gegevens voor het onderzoek mogen worden gebruikt, zonder opgaaf van redenen. Het stopzetten van deelname heeft geen nadelige gevolgen voor u of de eventueel reeds ontvangen vergoeding.

Als u tijdens het onderzoek besluit om uw medewerking te staken, zullen de gegevens die u reeds hebt verstrekt tot het moment van intrekking van de toestemming in het onderzoek gebruikt worden.
Wilt u stoppen met het onderzoek, of heeft u vragen en/of klachten? Neem dan contact op met de onderzoeksleider:

Laura Haarhuis
[redacted]

Tot slot heeft u het recht een verzoek tot inzage, wijziging, verwijdering of aanpassing van uw gegevens. Contacteer hiervoor de onderzoeksleider.

1. **Door dit onderstaande checkboxen aan te vinken erken ik het volgende:** *

- [ ] Ik ben voldoende geïnformeerd over het onderzoek. Ik heb bovenstaande informatie gelezen en heb daarna de mogelijkheid gehad vragen te kunnen stellen. Deze vragen zijn voldoende beantwoord.
- [ ] Ik neem vrijwillig deel aan dit onderzoek. Er is geen expliciete of impliciete dwang voor mij om aan dit onderzoek deel te nemen. Het is mij duidelijk dat ik deelname aan het onderzoek op elk moment, zonder opgaaf van reden, kan beëindigen. Ik hoef een vraag niet te beantwoorden als ik dat niet wil.

Toegevoegde waarde van toepassingen

De onderstaande vragen worden gesteld om informatie te vergaren over de business value van toepassingen. Geef een score van 1 tot 7 voor de toepassingen hieronder. 1 = niet waardevol, 7= extreem waardevol.

Indien de toepassing niet duidelijk uitgelegd wordt, mag je de vraag overslaan.

Business Intelligence (Sectie 1/9)

In deze sectie word je gevraagd om de toepassingen voor Business Intelligence te beoordelen op toegevoegde waarde. Hoe waardevol is de toepassing voor Business Intelligence? Er is 1 toepassing geformuleerd die van toegevoegde waarde kan zijn voor Business Intelligence.

2. De **prioriterings-tool** prioriteert producten, diensten, communicatie kanalen en stappen in de klantreis op basis van sentiment score van klanten. Hoe positief, neutraal of negatief ervaart de klant bepaalde producten, diensten, communicatie kanalen en stappen in de klantreis? Dit geeft waardevolle inzichten voor Business Intelligence.

   Voorbeeld: Het sentiment van de klant (positief, neutraal, negatief) meten per dienst. Business Intelligence kan met de prioriterings-tool diensten prioriteren op basis van hoe negatief het sentiment van de klant is. De dienst die het meest negatieve sentiment genereert bij klanten staat bovenaan de evaluatie lijst. Dit houdt in dat Business Intelligence gaat kijken waarom deze dienst zoveel negatief sentiment genereert. De prioriterings-tool helpt Business Intelligence te identificeren welke diensten het eerst geoptimaliseerd moeten worden om het negatieve sentiment van de klant om te buigen naar een positief sentiment.

   (1 = niet waardevol, 7 = zeer waardevol)

   1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

Klantrelatie Management (Sectie 2/9)

In deze sectie word je gevraagd om de toepassingen voor de Customer Relationship Management (CRM) afdeling te beoordelen op toegevoegde waarde. Hoe waardevol zijn de toepassingen voor klantrelatie management? Er zijn 2 toepassingen geformuleerd die van toegevoegde waarde kan zijn voor CRM.

3. De **klantrelatie tool** helpt de klant churn te voorspellen op basis van het sentiment van de klant gedurende de klantrelatie. Als het gemiddelde sentiment van de klant daalt, is de kans groter dat deze klant zijn relatie beëindigd (churn). Hier zouden vervolgens acties op genomen kunnen worden, om de klant te behouden.

   (1 = niet waardevol, 7 = zeer waardevol)

   1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

4. De **partner-tool** voorziet de klanten van een dashboard waar ze gemakkelijk dienstverleners kunnen vergelijken. Denk daarbij aan een autogarage om een schade te repareren. De klant ziet in het dashboard hoe positief, neutraal of negatief andere klanten zijn over een dienstverlener op basis van de sentiment score van andere klanten. Dit zou een extra service kunnen zijn voor de klant.

   (1 = niet waardevol, 7 = zeer waardevol)

   1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

Klantenservice (3/9)

In deze sectie word je gevraagd om de toepassingen voor de klantenservice afdeling te beoordelen op toegevoegde waarde. Hoe waardevol zijn de toepassingen voor de klantenservice? Er zijn 4 toepassingen geformuleerd die van toegevoegde waarde kunnen zijn voor de klantenservice.

5. De **klantenservice prioriterings-tool** (e-mails, WhatsApp berichten, chatberichten) is een tool die klantenservice tickets prioriteert op basis van sentiment en wachttijd. Klantenservice tickets worden geprioriteerd op basis van hun urgentie: klanten met een negatief sentiment (boos, verdrietig) zullen sneller geholpen worden.

   (1 = niet waardevol, 7 = zeer waardevol)

   1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

6. De **klantenservice evaluatie tool** helpt supervisors van de klantenservice bij het analyseren van prestaties van hun medewerkers.

   (1 = niet waardevol, 7 = zeer waardevol)

   1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

7. De **klantenservice kanaal tool** is een hulpmiddel waarbij het klantsentiment per communicatiekanaal kan worden gefilterd. Op deze manier kan de klantenservice de prestaties (sentimentscores) tussen communicatiekanalen vergelijken.

   Voorbeeld:
   Chatbot genereert een negatief sentiment bij klanten
   Email genereert een neutraal sentiment bij klanten
   Telefonie genereert een positief sentiment bij klanten

   Hierbij kan de klantenservice onderzoeken waarom de chatbot meer negatief klant sentiment genereert. Ze kunnen dan proberen om de chatbots zo optimaliseren zodat ze een beter klantsentiment genereren.

   (1 = niet waardevol, 7 = zeer waardevol)

   1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

8. De klantenservice kan gebruik maken van de **emotieladder tool** om het sentiment van de klantenservice medewerker beter af te stemmen op het sentiment van de klant. In het klantsentiment dashboard kunnen klantenservice medewerkers zien wat het gemiddelde sentiment van een klant is (positief, neutraal, negatief). De klantenservice medewerker kan inspelen op dit sentiment.

   Voorbeeld:
   De klantenservicemedewerker kan voordat hij een email beantwoordt van de klant bekijken wat het gemiddelde sentiment is van deze klant en wat het sentiment was tijdens het laatste contact moment. Indien het sentiment van de klant tijdens het laatste contactmoment negatief was dan kan de klantenservice medewerker hier rekening mee houden als hij begint met antwoorden op de nieuwe email van de klant.

   (1 = niet waardevol, 7 = zeer waardevol)

   1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

Marketing (Sectie 4/9)

In deze sectie word je gevraagd om de toepassingen voor de marketing afdeling te beoordelen op toegevoegde waarde. Hoe waardevol zijn de toepassingen voor de marketing afdeling? Er zijn 2 toepassingen geformuleerd die van toegevoegde waarde kunnen zijn voor de marketing afdeling.

9. De **marketing evaluatie tool** kan de prestaties van evenementen en campagnes evalueren op basis van het sentiment via Social media berichten. Een advertentie kan bijvoorbeeld veel negatief klant sentiment opwekken. Wanneer dit gemeten wordt, kan de marketingafdeling reageren door de advertentie zo snel mogelijk te verwijderen. De advertentie die een negatief sentiment genereerde kan bestudeerd worden. Waarom heeft deze advertentie negatief sentiment gegenereerd? De marketingafdeling kan hier vervolgens actie op ondernemen.

   (1 = niet waardevol, 7 = zeer waardevol)

   1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

10. De **concurrerende marketing evaluatie tool** evalueert de prestaties van evenementen en marketingcampagnes van de concurrent op basis van het sentiment via Social Media berichten. Op deze manier weet de marketingafdeling welke evenementen en campagnes van de concurrent voor een negatief (of positief) klant sentiment hebben gezorgd. Hierop kan de organisatie reageren.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

Board of Directors/ Management (Sectie 5/9)

In deze sectie word je gevraagd om de toepassingen van het meten van sentiment voor het Board of Directors te beoordelen op toegevoegde waarde: Hoe waardevol is de toepassing voor het Board of Directors en/of Management? Er zijn 3 toepassingen geformuleerd die van toegevoegde waarde kunnen zijn voor het Board of Directors.

11. De **aandeelprijs voorspel-tool** kan voorspellen of de prijs van een aandeel van een bedrijf omhoog of omlaag gaat op basis van het sentiment van de markt.
Het sentiment kan positief sentiment, neutraal sentiment of negatief sentiment zijn. Positief sentiment betekent dat de markt positieve gevoelens heeft met betrekking tot het bedrijf. Het bedrijf zorgt voor blijdschap en waardering. Negatief sentiment is sentiment van de markt zoals boosheid, teleurstelling en verdriet. Neutraal sentiment betekent dat er geen duidelijk negatief of positief gevoel naar voren komt of dat de positieve en negatieve reacties elkaar uitbalanceren.
De markt wordt gedefinieerd als iedereen die een mening kan hebben over een bedrijf. Het gemiddelde sentiment van de markt is dus het gemiddelde sentiment van iedereen die een mening kan hebben over het bedrijf.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

12. 5.2. De **aandeelhouder churn voorspel-tool** voorspelt hoeveel aandeelhouders hun aandelen verkopen op basis van het sentiment van de aandeelhouders.
Het sentiment van de aandeelhouders is het gemiddelde sentiment van alle aandeelhouders en kan positief, neutraal of negatief zijn.

    Het sentiment kan positief sentiment zijn, neutraal sentiment of negatief sentiment. Positief sentiment betekent dat de markt positieve gevoelens heeft met betrekking tot het bedrijf. Het bedrijf zorgt voor blijdschap en waardering. Negatief sentiment is sentiment van de markt zoals boosheid, teleurstelling en verdriet. Neutraal sentiment betekend dat er geen duidelijk negatief of positief naar voren komt of dat de positieve en negatieve reacties elkaar uitbalanceren.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

13. De **aandeelhouders besluitvormings-tool** helpt het management om beslissingen te maken. De aandeelhouders besluitvormings-tool laat zien wat het sentiment is van aandeelhouders per voorgelegde strategische beslissing. Dit helpt het management om inzichtelijk te krijgen in hoeverre aandeelhouders verdeeld zijn over een bepaalde voorgelegde strategische beslissingen. Dit helpt het management in hun besluit om de strategische beslissing door te voeren of niet.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

Externe relaties (Sectie 6/9)

In deze sectie, word je gevraagd om de toepassingen voor de afdeling externe betrekkingen te beoordelen op toegevoegde waarde. Hoe waardevol zijn de toepassingen voor de externe relaties? Er zijn 3 toepassingen geformuleerd die van toegevoegde waarde kan zijn voor de externe relaties.

14. De **partner besluitvormings-tool** helpt externe relaties om beslissingen te maken. De partner besluitvormings-tool laat zien wat het sentiment is van partners per onderwerp tijdens een meeting. Dit helpt externe relaties om inzichtelijk te krijgen in hoeverre partners verdeeld zijn over een bepaalde onderwerpen. Dit helpt externe relaties in hun besluit om wel of niet producten en/of diensten te verwijderen.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

15. Sentiment analyse kan voorspellen of een partner de samenwerking binnenkort gaat beëindigen (op basis van het sentiment van de partner). Het is goed om te weten of een partner in de toekomst het contract wil beëindigen. Op die manier kan de afdeling alvast op zoek naar nieuwe partners die dezelfde diensten aanbieden. Dit heet de **partner churn voorspelling tool**.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

16. Welke potentiële toekomstige partners presteren goed (genereren een positief klantsentiment)? Dit kan waardevol zijn voor bedrijven, voordat ze een contract tekenen met een partner. Dit kan worden onderzocht met behulp van een **partner evaluatie tool**.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

17. Het kan ook nuttig zijn om te weten welke huidige partners goed presteren (een positief sentiment genereren bij klanten). De **partner sentiment tool** kan het sentiment van de klant per partner meten en onderzoeken hoe de partners presteren. Indien een bepaalde partner veel negatief klant sentiment genereert kan de oorzaak achterhaald worden.

    Voorbeeld:
    3 autogarages die in het service portfolio staan in Twente. De klant woont in Twente en heeft schade opgelopen met zijn auto. Hij wil de deuk in zijn auto repareren. De verzekeraar vergoedt de service die autogarages 1, 2 en 3 aanbieden.

    Autogarage 1: positief klant sentiment
    Autogarage 2: positief klant sentiment
    Autogarage 3: negatief klant sentiment

    Autogarage 3 genereert veel negatief klant sentiment daarom kan ervoor gekozen worden het contract met autogarage 3 te beëindigen. De klant wordt dan alleen doorverwezen naar garages die wel positief klant sentiment genereren.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

Human Resource Management (Sectie 7/9)

In deze sectie word je gevraagd om de toepassingen voor de afdeling Human Resource Management te beoordelen op toegevoegde waarde. Hoe waardevol zijn de toepassingen voor Human Resource Management? Er zijn 6 toepassingen geformuleerd die van toegevoegde waarde kunnen zijn voor de Human Resource Management.

18. De **arbeidsmarkt tool** helpt HR om inzicht te krijgen in het sentiment van hun eigen werknemers over hun eigen bedrijf versus het sentiment van de werknemers van de concurrent over de concurrent.

    Voorbeeld:
    Sentiment van Achmea medewerkers over Achmea
    Versus
    Sentiment van Menzis medewerkers over Menzis

    Op deze manier kan HR erachter komen hoe aantrekkelijk het bedrijf voor werknemers in vergelijking met hun concurrenten.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

19. Het is mogelijk om werknemer geschenken en andere werknemer benefits te beoordelen op sentiment. Welke werknemer benefit genereert het meest positieve sentiment bij werknemers? De **relatiegeschenken tool** geeft inzicht in hoeverre geschenken het sentiment van werknemers verbeterd. Dit helpt om het sentiment onder medewerkers effectief te verhogen.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

20. De HR-afdeling zou het sentiment van de werknemers kunnen meten om de werknemerstevredenheid te kunnen evalueren. De **HR target tool** geeft inzicht in het werknemerssentiment. Stijgt of daalt het sentiment van werknemers? Dit helpt om te onderzoeken of secundaire arbeidsvoorwaarden, salarissen, nieuwe werkplekken, nieuwe afdelingsdivisies daadwerkelijk het sentiment van de werknemer verbeteren.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○

21. De **HR-werknemerprestatietool** meet de prestaties van HR-werknemers. Hierbij wordt het sentiment van medewerkers gemeten tijdens gesprekken met HR. De HR-werknemersprestatietool meet of een HR werknemer het sentiment van andere werknemers verbeterd door middel van gesprekken met werknemers.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

22. De **werknemers churn voorspellingstool** meet hoeveel werknemers in de toekomst waarschijnlijk hun contract zullen opzeggen. HR krijgt hierdoor meer inzicht in welke medewerkers waarschijnlijk hun arbeidscontract zullen beëindigen.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

23. De **HR emotieladder tool** kan een hulpmiddel zijn voor HR om het sentiment van de HR-medewerker af te stemmen op het sentiment van de medewerker. De HR-medewerker ziet het gemiddelde sentiment van de werknemer en het sentiment van de werknemer tijdens het laatste gesprek met HR. Op basis hiervan kan de HR-medewerker zijn of haar toon en gedrag aanpassen passend bij dit sentiment.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

Inkoop afdeling (Sectie 8/9)

In deze sectie word je gevraagd om de toepassingen voor de inkoop afdeling te beoordelen op toegevoegde waarde. Hoe waardevol zijn de toepassingen voor de inkoop afdeling? Er zijn 4 toepassingen geformuleerd die van toegevoegde waarde kunnen zijn voor de inkoop afdeling.

24. De **inkoop afdeling** kan de inkooptool gebruiken om te identificeren welke producten en/of diensten positief klant sentiment en welke negatief klant sentiment opwekken. Voordat de inkoopafdeling nieuwe producten/diensten inkoopt kan het sentiment van deze producten/diensten gemeten worden om erachter te komen of ze een goede toevoeging zijn aan het product/service portfolio op basis van het klant sentiment wat ze genereren.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

25. Het huidige productportfolio kan ook worden geëvalueerd aan de hand van klant sentiment. Deze evaluatie helpt om te bepalen welke producten een negatief sentiment genereren uit het huidige product portfolio. Indien producten (of diensten) zorgen voor sterk negatief sentiment dan moeten ze wellicht geschrapt worden uit het assortiment. Deze tool wordt de **product/service evaluatie tool** genoemd.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

26. De inkoopafdeling kan deze tool gebruiken om te voorspellen of leveranciers het verkoopcontract binnenkort zullen beëindigen. Wanneer de inkoopafdeling weet dat de leverancier waarschijnlijk het contract zal beëindigen, kan de inkoopafdeling al beginnen met het zoeken naar vervangers. Dit heet de **leverancier churn voorspellingstool**.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

27. De **leveranciers beslissings tool** voorspelt het sentiment van de leveranciers over bepaalde onderwerpen. Dit helpt de inkoopafdeling bij het nemen van beslissingen. Indien de inkoopafdeling besluit dat de leveringstermijn niet langer mag zijn dan 24 uur, dan kan dit gevolgen hebben op het sentiment van leveranciers. Negatief sentiment van veel leveranciers kan ervoor zorgen dat de leveranciers geen producten meer aan een bedrijf wil verkopen.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7
    ○ ○ ○ ○ ○ ○ ○

Verkoop afdeling (Sectie 9/9)

In deze sectie word je gevraagd om de toepassing voor de verkoopafdeling te beoordelen op toegevoegde waarde. Hoe waardevol zijn de toepassingen voor de verkoop afdeling? Er is één toepassing geformuleerd die van toegevoegde waarde kan zijn voor de verkoop afdeling.

28. Met de **sales tool** kan gestuurd worden op contact dat waarde toevoegt. Bijvoorbeeld als een klant een negatief sentiment heeft ontwikkeld gedurende de relatie, dan is het beter om goed naar de klant te luisteren in plaats van te benaderen met andere/nieuwe producten of diensten. Met de sales tool worden klanten met een negatief sentiment uitgesloten van up- of cross-sell benaderingen.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7

29. De **customer churn voorspellings-tool** helpt de sales afdeling in te schatten hoeveel klanten in de toekomst het contract beëindigen.

    (1 = niet waardevol, 7 = zeer waardevol)

    1 2 3 4 5 6 7

30. Weet jij nog andere interessante sentiment analyse toepassingen?

    Voer uw antwoord in

Bedankt!

Ik hoop dat de enquête jullie heeft geïnspireerd en dat het nieuwe en interessante inzichten heeft gegenereerd! Bedankt voor het invullen van deze enquête!

Figure 30: Survey at company X