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The Influence of Sentiment Analysis in Digital Marketing

A Qualitative Study for Evaluating Success Dimensions of Sentiment Analysis and its Role in Digital Marketing

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ABSTRACT:

This thesis explores the efficacy of sentiment analysis within digital marketing, examining its role and success through qualitative methodologies, including semi-structured interviews with industry professionals. As digital marketing evolves, understanding consumer sentiment becomes crucial for tailoring strategies that resonate with target audiences. Our study delves into the application of Natural Language Processing (NLP) techniques to analyze large datasets, focusing on sentiment analysis' capability to discern and categorize consumer emotions from digital interactions. Results indicate that sentiment analysis significantly enhances decision-making processes, enabling businesses to adjust their strategies based on real-time consumer feedback. Challenges such as data volume and the complexity of human language are discussed, highlighting the need for advanced analytical tools. The research contributes to the field by confirming the integral role of sentiment analysis in modern digital marketing, suggesting that its strategic use can provide businesses with a competitive edge in understanding and responding to consumer behavior effectively.

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Table of Contents

Figures

Tables

1 Introduction

In the following chapter, we will introduce our research topic with a background and why the chosen topic is of interest. This chapter also describes the purpose of our study and concludes with a section where we describe our limitations.

1.1 Background

There is no doubt that the technological, transformative force that is digitalization, has been present in our current information age, and will continue to maintain its presence in the future (Tihinen & Kääriäinen, 2016). In a business context, the characterization of the term digitalization seems to be businesses and their endeavors to obtain the ideal mix of technologies for their commercial prospects. On the other hand, Caputo et al. (2021) defines the word as a broader sociotechnical process of integrating digital technologies into the daily social life of people. In addition, Brennen and Kreiss (2014) refers to digitalization as organizations, industries, countries, etc, either adopting or expanding digital or computer technology usage. Certainly, the small difference, yet at the same time complementary descriptions of the word, includes aspects of technologies and their digitality, while underlining the implementation of these in various areas of life. Simultaneously, an important acknowledgement from these authors is the difference between ***digitalization*** and ***digitization*** - while the former has been defined previously, the latter describes the process of converting analogue data into a digital format. It is an important distinction, as digitalization involves integrated digital technologies into, for example, all areas of a business and therefore changing how business processes work.

Digitalization has an impact on our day-to-day existence, not least the businesses' digital marketing. It has been clear that these processes have to adapt to gain competitive advantage according to Shpak et al. (2020). Bala and Verma (2018) agrees, mentioning that the shift towards digitalization has dramatically affected marketing strategies, with a handful of digital marketing tactics becoming crucial such as content creation and the power of social media. As consumers increasingly rely on digital platforms for product information and purchases, it is certain that digital marketing is key to unlock advantages in the competitive landscape. The awareness of consumer behavior on these digital platforms is a further important aspect to consider as it opens up opportunities to tailor the businesses' strategies more effectively. Bala and Verma (2018) essentially say that digital marketing is a fundamental element of the modern marketing strategies that businesses need to incorporate to keep up with the rapidly changing digital landscape. Technological advancements continue to shape this landscape, with artificial intelligence being an important component to adapt, as well as big data which will be explored further below.

Resembling the takeaway from Shpak et al. (2020) together with Bala and Verma (2018), Miklosik and Evans (2020) elaborates on technological advancements and their role in the marketing industry. Central to their article is the role of big data in marketing. To elaborate on the term big data - it is simply larger, more complex data sets, particularly from recently discovered data sources (Tiao, 2024). The sheer volume of these data sets exceeds the capacity of conventional data processing software. To analyze these large datasets, machine learning has been increasingly integrated into marketing strategies to generate meaningful insights. The adoption of big data technologies in turn enables organizations to become more data-driven, which entitles them to make decisions based on substantial analytical evidence rather than intuition. True to Tiao's (2024) statement, organizations face challenges in managing the sheer volume and diversity of data (Miklosik & Evans, 2020). Business issues that are not normally solvable can be tackled with the help of these enormous amounts of data, and that is where machine learning comes in. It is revolutionizing marketing by enabling detailed consumer insights, which enhances decision-making and strategic planning.

1.2 Subject of Interest

The current digital landscape is formed from digitalization. With the rise of the Internet as the source of universal information, people use this technology to express views and opinions. Consequently, there is a wealth of customer-generated content that is available (Wankhade et al. 2022). While the Internet is at the forefront of this new age, it is also evident that changing traditional marketing approaches to adopt new strategies is a necessity to stay connected with businesses' audiences (Poorani & Vidhiya, 2021). This is where the authors Shpak et al, (2020) and Bala and Verma (2018) chime in and agree by observing that the digital transformation significantly affects the realm of digital marketing. Businesses have to adapt their digital marketing strategies, and notes that understanding consumer behavior on, for example, digital platforms allows businesses to better tailor their strategies. Digital marketing is a vital component of modern marketing strategies, necessary for keeping up with the rapidly evolving digital landscape. What's more, big data and machine learning are significant trends in the current marketing landscape, providing businesses with the tools to analyze large data sets and gain detailed consumer insights, which in turn enhance decision making and strategic planning (Poorani & Vidhiya, 2021). However, there are still challenges in digital marketing in the current day. Not only does technology continue to advance forward, but businesses must adapt to them to maintain a competitive edge.

In recent years, sentiment analysis has become progressively popular among researchers as well as business, governments and other organizations as the era of big data is present, driven by the vast increase in social media use (Shayaa et al. 2018). This natural language processing (NLP) task overlaps with the broader field of machine learning, where machine learning is often used as a tool with frameworks and techniques for NLP. Sentiment analysis works in the way that it analyzes vast amounts of textual data to identify people's attitudes, thoughts, judgements and emotions. Its main objective is to determine whether the mood of the writer is positive, negative neutral (Wankhade et al. 2022). To further develop Wankhade et al.'s (2022) observations, Shayaa et al. (2018) mentions that sentiment analysis is a NLP task that can be used for determining people's opinions to gain meaningful information about product development, customer service, and what is more central in this thesis, marketing. As earlier stated, Poorani & Vidhiya (2021) mentions the advancements of technology that are relevant to the marketing landscape, and sentiment analysis is one of them. With the role of big data in marketing as noted from Miklosik and Evans (2020) and Tiao (2024), there is value in using machine learning to analyze big data effectively and to use the gained insights for improved decision making and strategic planning. The subject of interest here is the question of how successful sentiment analysis is for businesses that are utilizing it for analyzing big data and what role it has in digital marketing. This question poses aspects of effectiveness and measurements, as well as how vast volumes of diverse data can be managed (Poorani & Vidhiya, 2021). With the help of sentiment analysis, it is possible to understand public sentiment and, based on this understanding, make data-driven decisions in digital marketing, to gain a competitive advantage (Wankhade et al. 2022).

1.3 Research Question

In conclusion, there are two aspects that are of interest in which two research questions have been formulated:

1. *How successful is sentiment analysis for businesses, and their users, that utilize it?*
2. *What role does it have in a digital marketing context?*

1.4 Purpose

This thesis aims to uncover how the usage of sentiment analysis can contribute to digital marketing and evaluate how successful it is as it stands. The qualitative studies that have been conducted focuses on identifying and evaluating the various ways businesses have integrated and applied this technology internally for their own and externally for their customers' digital marketing strategies, to further discover the insights and potential benefits obtained from the practice of sentiment analysis. Additionally, this thesis will investigate the type of data that is used in sentiment analysis and what specific challenges arise when using big data. Lastly, personal, individual perspectives and judgements of the application of the technology are studied.

1.5 Delimitations

To evaluate sentiment analysis and its application, the study is limited to focus solely on businesses that have already integrated an NLP tool into their services targeted at external customers for their digital marketing or for internal use. Additionally, this is a study that has been conducted with anonymous individuals R1, R2, R3, and R4, all from different organizations but with similar roles. This is to capture their own insights and perspectives from a similar industry field with the evaluation of sentiment analysis and its role for digital marketing. This scope provides transparency, sets valid expectations and helps guide future research directions.

In order for the study to be relevant to the scientific field of information systems, we therefore avoid detailed descriptions of the technology behind sentiment analysis, as this is a study area for a scientific field such as computer science.

2 Literature review & Theoretical Framework

In this chapter, we begin with an overview of digital marketing and big data before heading into the overview of sentiment analysis and its challenges and application in digital marketing. Thereafter, we conclude the chapter by describing the theoretical framework and the motivation behind its usage for this study.

2.1 Digital Marketing

Marketing, as a standalone concept, refers to using offline media and traditional tools to reach an audience by promoting a product or service. With the rising popularity of television since the 1950s, advertisers have been able to reach a large audience in the comfort of their homes, unlike earlier methods such as newspaper advertisements, billboards, or radio. These approaches remained the marketing standard until the early 2000s, when digitalization and the growth of the internet and social media began to evolve rapidly. Along with this came the term Digital Marketing, which brought marketing to novel modern electronic devices, typically phones, computers or tablets. Developing a reliable marketing strategy today includes a more complex and competitive buying environment than before. Chaffey & Ellis-Chadwick (2022) define digital marketing as “the use of digital media, technology and data to reach and interact with audiences using different digital devices and platforms, combined with traditional media, to achieve marketing objectives”. The goal is to acquire new customers and maintain a strong and healthy relationship to already existing customers. Digital marketing can be everything from a video, image or text on a social media platform to search engine and email marketing. Traditional marketing is often dominated by so called “push media” - where enterprises send out (push out) targeted material to their audience and potential customers. The consumers are passive recipients and the information being broadcasted is primarily unidirectional. “Pull media”, on the other hand, is more common when working on digital platforms and focuses on pulling in a consumer base and directing them to the enterprise’s official webpage or social media. It convinces the customer to seek out information about the product or service on their own, through e.g search engines or product reviews (Chaffey & Ellis-Chadwick 2022). However, marketers have less control over who receives their marketing in pull media, which can be a weakness unless the marketing is wisely tailored depending on the desired kind of audience it should reach. This is where sentiment analysis tools play a part.

There are three types of different strategies on how businesses choose to do their marketing: Paid, owned and earned media (Chaffey & Ellis-Chadwick 2022). Paid media means that the content has been paid to be promoted, commonly seen as videos before a YouTube clip, pop-ups on a website or perhaps a sponsored image in a social media feed. Owned and earned media are on the other hand free, where owned media is the company’s own presence on different platforms such as their official webpage or their Facebook and Instagram account. Earned media is when a third party is speaking of the company, product or service without any intentional involvement from the seller. Chaffey & Ellis-Chadwick (2022) offer several examples of earned media, including publishers, bloggers and influencers.

In addition to paid, owned and earned media, there are also six specific digital media channels that businesses use to market their products: Search engine marketing, Social media marketing, Display advertising, Digital PR, Digital partnerships and Digital messaging (Chaffey & Ellis-Chadwick 2022). Chaffey & Ellis-Chadwick suggest that paid, owned and earned media can be considered as different options available within these media channels, and that a combination of them all gives a total of 18 digital communication techniques for a business to exploit. Social media marketing plays a rather big part in digital marketing, but to take advantage of the marketing benefits that social media has to offer, it is important to participate in and understand customer conversations. Chaffey & Ellis-Chadwick recommends five activities in which social media plays a role in supporting marketing goals. The first one specifically highlights the importance of marketers listening to the audience and understanding their customer characteristics and behavior. It creates loyal customers and by learning more about how consumers perceive a product, it is easier to improve and develop the product further according to customer demands. Although it is a challenge to keep the attention and interest of audiences today, long-term engagement is arguably more important than a short term interaction (Chaffey & Ellis-Chadwick 2022). Furthermore, it generates a good image of the company to show involvement with the consumer base.

2.2 Big Data and Big Data Analytics

Big Data is a concept that has evolved significantly since its origin, resulting in multiple definitions and interpretations over time. Manyika et al. (2011) refers to big data as “datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze” (p. 1) whereas Gantz and Reinsel (2011) instead put emphasis on the attributes of big data. They describe it as “a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data” (p. 6). Boyd and Crawford (2012) define big data as a “cultural, technological, and scholarly phenomenon” (p. 663) that rests on the interplay of technology, analysis and methodology. Both Zikopoulos and Eaton (2011) and Waller and Fawcett (2013) are in accord regarding the observation that it is a collection of large data sets for which traditional management tools cannot be used effectively. Additionally, it is of importance to understand the different structures that big data can be sorted into; Structured data, Semi-structured data and Unstructured data. Structured data is often stored in a predefined location in the same type of format, such as information in a database or spreadsheets. It is usually easy to work with by using database management tools. Unstructured data, on the other hand, includes textual, verbal and visual media and is stored in its native format (Vijayarani & Sharmila 2016). This is typically found in multimedia such as emails, social media, web pages or other similar sources.

Despite the various definitions, there is a consensus that exists among researchers where the phenomenon can be described with the help of special types of characteristics. Zikopoulos and Eaton (2011) present three primary characteristics known as “The 3 Vs”: (1) Volume, the scale and size of data being generated; (2) Velocity, the speed at which data is generated, collected and processed; and (3) Variety, the different types and formats of data. These characteristics have also been endorsed by multiple organizations, such as Oracle and Gartner. Two more Vs have emerged over the past years: (4) Value, which represents the business value of insights extracted from big data; and (5) Veracity, which is the quality and truth of data (Vijayarani & Sharmila 2016). These two have contributed to the expansion of the framework even further from the original 3Vs, becoming 5V.

Where big Data focuses on storing, managing and processing data, Big Data Analytics (BDA) is rather about extracting meaningful insights from said data to support the decision-making processes. Analyzing great amounts of data allows companies to observe and predict patterns, as well as identify previously unknown correlations and gain valuable insights that can influence the processes either positively or negatively (Alwan & Ku-Mahamud 2020). Big data holds significant relevance and importance across multiple fields, such as the government, science, healthcare, banking, manufacturing and transportation, and they can all benefit from analyzing it properly. The business industry has also recognized the value of BDA and is applying it within customer analysis, product and service innovation, market forecasting, supply chain and performance management, risk management and fraud detection, to mention just a few examples (Chong & Shi 2015).

It is also important to be aware of the challenges of extracting and analyzing Big data. Alwan & Ku-Mahamud (2020) mentions that “the main issue of data analytics found with BD [big data] is related with the volume of the data" (p. 7). Both Sharef et al. (2016) and Tiao (2024) second this issue when it comes to extracting especially semi-structured and unstructured data, often encountered in social media. This is mainly because of the large amounts of continuously generated data in real-time which, at the time of collection, may have an unknown or unclear value. It makes it hard to analyze promptly and accurately, and the diverse formats and styles in which the data is generated can complicate the analysis even further, making the quality and accuracy of the data (read Veracity) ever more uncertain, leading to less valid and less trustworthy analysis results (Sharef et al. 2016). According to Goodwin at the International Data Corporation (2019) approximately 80-90% of the future IT organization’s data will be unstructured data, which is estimated to grow to 7.5ZB by 2025. Therefore, it can be a crucial step to integrate BDA within businesses to better handle the large amounts of data that is constantly being generated.

Moreover, the relevance of Big data analytics in the Natural Language Processing (NLP) field will be further discussed in the following paragraphs on sentiment analysis, which is a specific type of application of NLP.

2.3 Sentiment Analysis

2.3.1 Sentiment Analysis of Big Data

As the overview of big data has been established, there is a need to delve deeper into what sentiment analysis is and its relevance to big data. This NLP task is encompassed by the broader field of text analytics, which has undergone a high rate of development parallel to the colossal amount of data that has emerged over the years (Shayaa et al. 2018). The opportunity to gain an understanding of the unstructured data is paramount, and as a result text analytics has been an important approach in that regard. In addition to being expressed by NLP, sentiment analysis also consists of data mining and machine learning techniques. Its main use is to identify and extract subjective information from large datasets, in essence unstructured, textual data. This process primarily focuses on determining sentiments - positive, negative or neutral - expressed within texts. These sentiments are everywhere, not least the abundant opinions, views and attitudes towards products found, for example, in reviews. Alongside sentiment analysis is opinion mining which is similar in the terms of the usage of natural language processing techniques. Opinion mining is described as assessing "people's opinion on a product, person, event, organization, or topic from a user or group of user perspectives" (Shayaa et al. 2018). While sentiment analysis and opinion mining are sometimes considered to be two distinct terms, both Taboada (2016) and Medhat et al. (2014) mention that opinion mining and sentiment analysis are interchangeable terms in the research field. It is noteworthy to mention that the definition of sentiment analysis is to find and evaluate the sentiment expressed in a text to some researchers, whereas opinion mining gathers and examines people's opinions about an object. This is evident in the description of the two by Shayaa et al. (2018). However, many sources including Taboada (2016), Medhat et al. (2014), Wolff (2020) as well as Clark (n.d.) suggest that the terms are used interchangeably, and therefore a decision to use sentiment analysis as the primary term has been determined for this thesis.

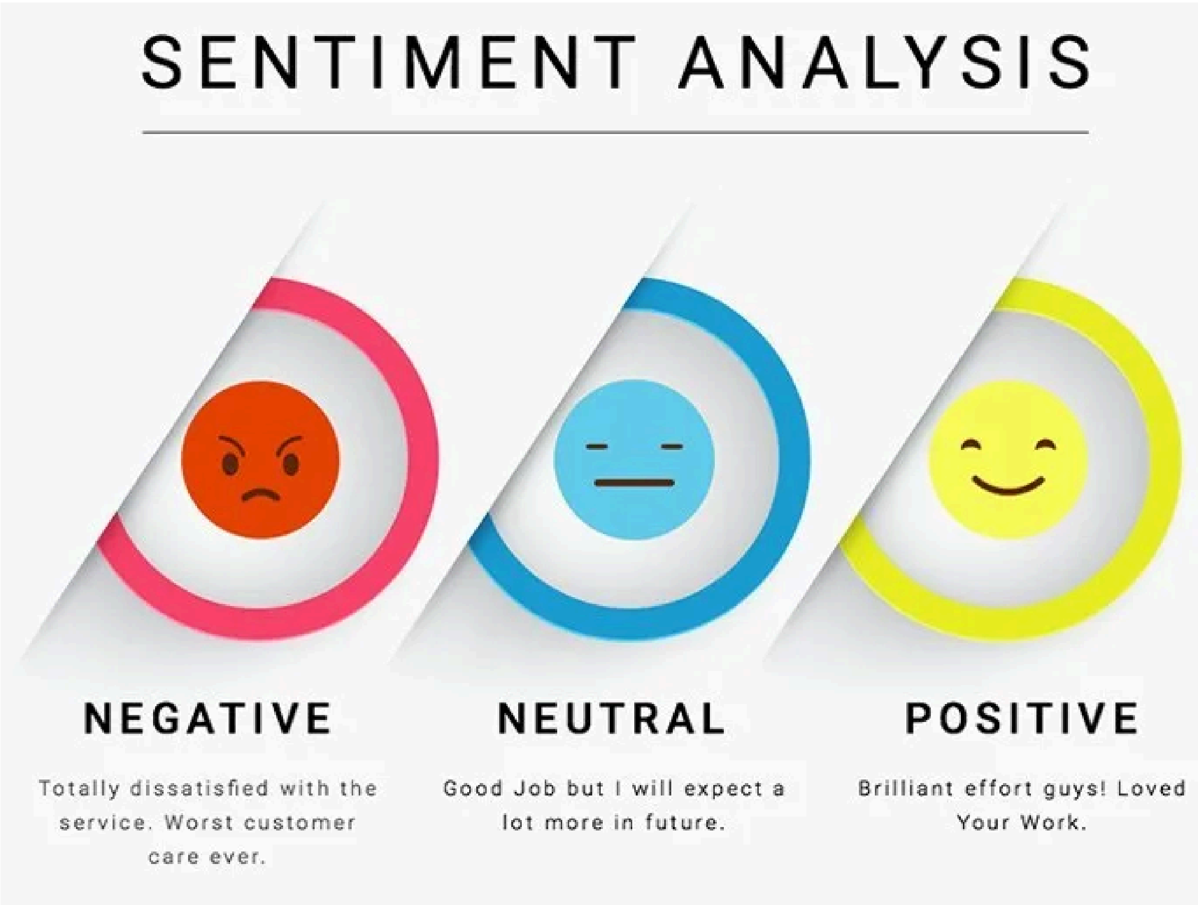

Figure 2.1: Classification of emotions from sentiment analysis (Dixit, P. 2020)

2.3.2 Challenges in Sentiment Analysis of Big Data

There are several challenges that are currently prevalent when it comes to the field. While big data is an important element for businesses to understand their customers' opinions and apply sentiment analysis to better their marketing, Shayaa et al. (2018) acknowledges that sentiment analysis alone is not enough to understand the customers' view. For example, there needs to be an integration with other data sources such as competitors' information and economic indicators. Furthermore, there is a complexity in evaluating the rate of sentiment influence on social media based on follower count and sentiment polarity. Lastly, the increase of social bots poses a problem as well. They can be used by businesses to manipulate the general opinion. Additionally, key takeaways from Wankhade et al. (2022) regarding challenges in sentiment analysis are multiple. The unstructured data may contain sarcasm, ambiguity and irony, which the NLP process has a difficult time to interpret. The human language poses an adversity in the complexity for the machines, not always conveying straightforwardness and being precise in the context, tone and cultural nuance. The same can be said about cultural specificity of humor, as the experience varies widely across cultures. Sentiments might likewise be influenced by social reasons that do not necessarily reflect true personal feelings. As an example, there might be a positive review or other textual data from a customer to conform to social norms or to define their identity, which is not an accurate representation for their actual opinion.

2.3.3 Application in Digital Marketing

> *Sentiment, or how people feel, runs the world. Social media has given a voice to the previously unspoken, and with it the ability for companies to monitor how people feel about their brand. No longer is it just large businesses with a marketing team that can access this valuable information – small businesses can too* (Wisneski, 2023).

Shayaa et al. (2018) explains that the application of sentiment analysis has been applied in many areas such as healthcare, the financial sector, sports, politics, hospitality and tourism, and consumer behavior. This is also in line with Wankhade et al. (2022) that also mentions that with the rise of the internet and social media, sentiment analysis's relevance and application has greatly increased. As per the quote above, Wisneski (2023) agrees with the underlying meaning of what Wankhade et al. (2022) is saying about the rise of social media. The authors also underline the influence sentiment analysis has on market research and enhancing customer relationship management. Particularly in public opinion monitoring, businesses can keep track of the sentiments in real-time; Wisneski (2023) notes that the aspect of real-time is a powerful use case in acting accordingly to fix e.g. negative brand mentions or negative reviews. Analyzing competitors' strengths and weaknesses are also made by understanding customer perceptions and market conditions (Taherdoost & Madanchian, 2023). Furthermore, with the help of sentiment analysis informed decisions can be made due to the fact that the technology assesses the public opinion and therefore they can adjust their products or services. In essence, it has quite the impact on decision making (Dash et al. 2022). By harnessing the vast amounts of unstructured data available and having an understanding of the public sentiment, new marketing strategies can be developed accordingly, as well as adapting current strategies. Something that Markham et al. (2015) stresses on, is that analytics is a tool, not a solution itself. The success in deriving value from it depends on using it thoughtfully and targeting areas where it can be most effective. “A key misunderstanding about big data is that the analysis makes the decision: the analysis only provides information to support the decision making” (Markham et al. 2015, p. 35).

2.4 Evaluating Information Systems Success

2.4.1 Dimensions of the D&M IS Success Model

There is a comprehensive framework for evaluating information system's (IS) success called the D&M model, initially proposed 1992 by DeLone and McLean (Petter et al. 2008). In the IS research field, the D&M model has been proven and is widely used for measuring the success of information systems within organizations and individuals, with a holistic approach. There are extensive studies on the exploration of its applicability in various settings, including the likes of e-commerce and enterprise systems, testing the model's robustness. The D&M model has had a role in advancing the understanding of the overall effectiveness of information systems for both organizations and individuals. The core dimensions of the model have been revisited by the original proposers and today includes six interrelated dimensions of success, which Petter et al. (2008) breaks down into the following points:

1. **System Quality:** Measures the desired characteristics of an IS, such as system usability, reliability, functionality and performance.
2. **Information Quality:** Assesses the quality of the output provided by the IS, focusing on relevance, accuracy, timeliness and comprehensibility of the information produced.
3. **Service Quality:** An addition to the D&M model when the original proposers revisited their model. This dimension evaluates the quality of the support that system users receive from the IS department and IT support staff in the organization. It includes responsiveness, empathy and competence of the support staff.
4. **System Use:** Refers to the extent to which an IS is utilized in the organization. The dimension considers both the depth and breadth of system use. This dimension has the amount of use, nature of use and purpose of use as examples for its focal points.
5. **User Satisfaction:** Measures the users' satisfaction with the IS, including their overall experience and fulfillment of expectations.
6. **Net Benefits:** Lastly, this dimension reflects the impact of the IS on the organization or individuals, assessing how the system contributes to productivity improvements, improved decision-making and other outcome-based benefits. This variable replaced the previous dimensions individual impact and organizational impact of the past D&M model.

2.4.2 Interrelationships within the D&M Model

An important factor of the D&M Model is the suggested interrelationships among the six dimensions (Petter et al. 2008). This indicates that improvements in one area can enhance or influence the performance in others. The first three mentioned dimensions in the numbered list all directly influence user satisfaction and system use, while the two latter are predictors of net benefits (see Figure 2.2). To clarify, as seen within Figure 2.2, the construct "system use" is not seen and is instead replaced by "intention to use" and "use". DeLone and McLean argued in their updated model that the dimension had to be clarified further, explaining that in a process sense, "use" predates "user satisfaction", while in a casual sense a positive experience with "use" will result in better "user satisfaction". In addition, increased "user satisfaction" will then lead to a higher "intention to use", which will successively affect "use" (Petter et al. 2008). For this thesis, "system use" will be used that encompasses "intention to use" and "use". Lastly, certain "net benefits" are expected to arise as a result of "system use" and "user satisfaction". It is generally anticipated that the "net benefits" are positive if the IS or service is to be continued. Thus, this dimension will further positively influence and reinforce "use" and "user satisfaction". This part of the model works as a feedback loop, and is still valid even if the "net benefits" are negative. In cases as such, the lack of positive benefits may lead to reduced usage and potentially to the discontinuation of the system, as an example.

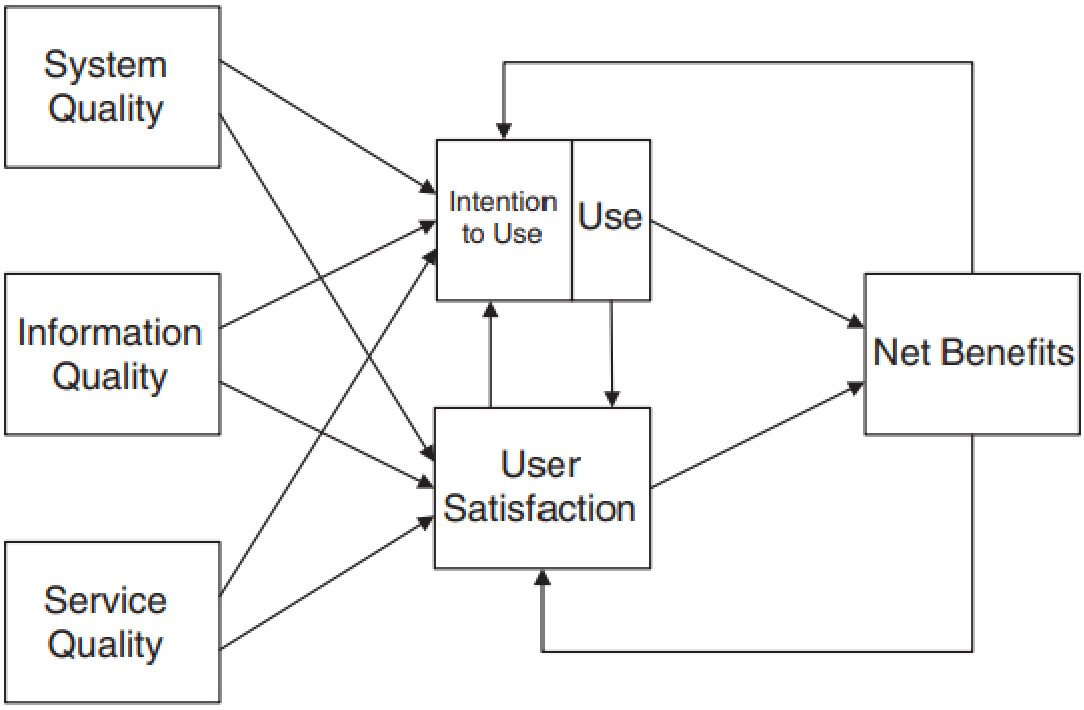

Figure 2.2: The D&M Model (Petter et al. 2018, p. 238)

2.5 Motivation for Theoretical Framework

The framework that is provided by DeLone and McLean aligns with the research question presented in this thesis. First of all, the connection between sentiment analysis to IS is based on the fact that it is used within Information Communication Technology (ICT)-based methods (Charalabidis et al. 2015). In other words, sentiment analysis techniques are integrated into ICT systems. Charalabidis (2015) further mentions that sentiment analysis helps ICT systems align with objectives of IS. As sentiment analysis is embedded in the broader goals of IS through its involvement in ICT systems, the D&M model is made relevant for evaluating sentiment analysis tools and systems.

Secondly, the D&M model provides a comprehensive framework. By using it, insights around the different dimensions can be gathered to answer the research question in hand. Each of the dimensions can be adapted to assess aspects of sentiment analysis systems: (1) technical performance of the sentiment analysis system to evaluate system quality; (2) relevance, accuracy and usefulness of the insights provided by sentiment analysis to evaluate information quality; (3) the quality of support services, including customer support, documentation, and training to evaluate service quality; (4) how extensively the sentiment analysis tool is used and how well its functionalities are utilized to evaluate system use; (5)

the tool's result, ease of use, and features to evaluate user satisfaction; and (6) the overall impact of the sentiment analysis system on business outcomes, such as improved decision making to evaluate net benefits. The net benefits for this thesis will mostly be in the context of digital marketing. Thus, the net benefits in this case revolves around e.g. customer relationship, brand monitoring, and overall informed decision making for marketing strategies. However, this does not mean avoiding other benefits apart from digital marketing that sentiment analysis brings.

Thirdly, the proven track record of the D&M Model, mentioned by Petter et al. (2008), means reliability and its stance in establishment is beneficial for arguing its use as a theoretical framework due to its credibility. The D&M Model has been used for both quantitative and qualitative studies, not only demonstrating the strength of its track record, but also versatility and the depth in analyzing IS success through different methodological lenses. Examples of previous studies conducted with the D&M Model as a theoretical framework include "Evaluating the D&M IS Success Model in the Context of Accounting Information System and Sustainable Decision Making" by Lutfi et al. (2022), where they assessed the impact of all the dimensions of AIS (Accounting Information System) usage, which ultimately influenced the quality and sustainability of decision-making. This was a quantitative study using a self-administered questionnaire with 101 decision-makers familiar with AIS usage. To give an example of a qualitative study, Rahman and Ekaputri (2021) aimed to analyze how well Jurnal, a web based accounting application, supports the financial activities of a medical device sales company called PT. Afham Karya Nusantara. Their research design was of a qualitative one, where they employed observations, literature review and most notably interviews. There were cases of studies that were both quantitative and qualitative that operated with the D&M Model, namely ones from Bossen et al. (2013) and Roky and Meriouh (2015). The former's objective was to evaluate a newly implemented EHR (electronic health record) in the "shake-down" phase immediately following its deployment. It utilized a mixed-methods case study approach based on the D&M Model, adapting it to fit the healthcare context. The evaluation included questionnaires, semi-structured interviews, follow-up focus group interviews, ethnographic observations and performance data analysis. The latter evaluated the success of an information system called XPPS used in the automotive industry. This demonstrates the theoretical framework's applicability for versatile settings, where the study conducted by Roky and Meriouh (2015) went beyond traditional business IT environments into more specialized industrial settings. The methodological approach they utilized was a mixed-methods case study, where they first performed an exploratory qualitative study at SEBN MA, an auto parts manufacturer in Morocco, to then later introduce the quantitative method of administering surveys.

For these reasons above, a decision to use the D&M Model as a theoretical framework has been made to answer the research question. Its application on the methodology is presented in Appendix 1 & 2.

3 Methodology

In this chapter, we describe how the empirical data was collected and the motivation for the choice of methods made during the course of the thesis, as well as the selection of respondents. It includes a description of semi-structured interviews as our primary method of data collection, and our analytical approaches. We also evaluate the study's quality and ethical considerations.

3.1 Strategy for Literature Searching

The literature review follows a qualitative approach which borrows several different themes and arguments to construct one all-inclusive theme. It demonstrates a new approach that we have not found in prior studies, enhancing the knowledge and offering fresh insights within the research field. Including a literature review serves great purpose as it educates the reader on the topic and contributes to identifying weaknesses and shortcomings in prior research. It gives the reader a background of relevant information, as well as updated, new findings regarding the topics that are discussed (Denney & Tewksbury 2013). In the following paragraph we will explain our methods in detail, and how we found the literature needed to support our thesis. We looked up extant literature which provides various insights in sentiment analysis' potential role in product development, specifically tailoring it to digital marketing. According to Denney & Tweksbury (2013) academic journal articles are one of the most appropriate sources. Therefore, a primary usage of Google Scholar and Lund University Library search (LUBsearch) was exercised to find relevant research. In order to guarantee credibility and trustworthiness of the sources, we restricted Google Scholar to Review articles and "literature review" was added as a keyword in LUBsearch. Through these both means, we reached journal articles and conference papers from top journals and conferences, with the majority being published in ResearchGate and ScienceDirect.

The English keywords stated below were either searched individually or in a combination of multiple keywords in the same search field.

- Big Data
- Big Data Analytics
- Digital Marketing
- Sentiment Analysis
- Text Analytics
- ISSM
- D&M Model

To eliminate unnecessary articles and choose relevant sources we would initiate the process by reading the title of the source. We would click on the ones we deemed of importance and continue by reading the abstract and occasionally conclusions. This would then be followed up by a quick overview of the article and lastly a thorough reading should it meet our requirements fully. We did not particularly filter the searches after sources published after a specific year, but made an effort to try to include information only from recent years if possible.

3.2 Method of Data Collection

Research studies are typically constructed based on two methods of collecting data; Quantitative and Qualitative. Quantitative studies are used for identifying whether a statistical relationship exists between variables or not, and how strong or common such a relationship is (Denney & Tewksbury 2013). Though “Broadening horizons: Integrating quantitative and qualitative research” is an old article, Verhoef & Casebeer already stated in 1997 that quantitative research is applicable for establishing cause-and-effect relationships and determining opinions, attitudes and practices of a larger scale of people. It generates reliable and generalizable data and Hammarberg et al. (2016) continues to support this by stating that quantitative methods are appropriate when factual data (variables and numerical form) are required to answer the research question. In most cases it involves the collection of data about a circumstance using standardized measures and statistical analysis, and essentially emphasizes on ***how*** the studies were conducted and in terms of what method was of use in prior similar works. This type of research tends to be deductive, relying on surveys to test specific hypotheses (Verhoef & Casebeer 1997). Qualitative studies, on the other hand, regard a more subjective point of view to understand how individuals perceive and observe certain situations. Denney & Tewksbury (2013) describe this type of study as a way of understanding how the social world functions and how the participants in that setting interact with that world. Experience, perspectives and standpoints from the participants are often not suitable to be counted or measured. Instead of numerical factual data, qualitative research collects and interprets narrative data, such as textual, verbal or visual (Hammarberg et al. 2016). Instead of trying to clarify phenomena in an experimental setting with loads of participants, qualitative methods focus on a natural environment, emphasizing on the participant’s personal experience and views.

Taking this knowledge into account, we have therefore decided to conduct a qualitative method of gathering data for our study, as we are interested in the personal insights and opinions of the company’s sentiment analysis development process. Quantitative research can be dismissed as “over-simplifying individual experience in the cause of generalization, requiring guesswork to understand the meaning of aggregate data” (Hammarberg et al. 2016, p. 498), which is an outcome we seek to avoid. A quantitative study would not benefit the study enough as we want to look at the business process at a closer scale and not get an overview of the situation. We want smaller samples with rich and detailed data, based on the participant and not the researcher’s interpretation.

3.2.1 Semi-Structured Interview

There are several different qualitative methods that can be used for collecting data, such as case studies, narrative research approaches, discourse analysis, and many more, that all rely on the informant’s experience. According to Denney & Tewksbury (2013) ethnography (observation and participant observation) and interviews are two of the most common approaches. Interviews are, just like big data, divided into three categories: Structured, semi-structured and unstructured. It essentially revolves around the researcher's level of engagement in an open or dynamic conversation with the interviewee. Structured interviews use exactly the same, pre-established questions for each participant, never going off script and not asking or mentioning anything else than what's been decided beforehand (Oates 2006). Semi-structured and unstructured interviews instead allow the researcher to go off script and initiate conversation. The purpose is, as opposed to structured interviews, to 'discover' information rather than to 'check'. Unstructured interviews are the opposite of structured interviews, where the researcher has less influence over the direction of the interview. The participant is introduced with a topic and then allowed to speak freely about personal experiences, beliefs or behavior. Semi-structured interviews are a mix of the two and will be prepared with a set list of themes and questions that should be asked, but can be moderately changed depending on where the conversation in the interview leads to. The participant might bring up a point or issue that has not been considered in the preparation, which calls for improvised questions regarding that new topic.

Semi-structured interviews have been chosen for this particular study as we are interested in certain themes, but still want the informant to bring up new possible points of view that we might not have considered. We want to discover and learn what role sentiment analysis takes within businesses and the user's personal insights of applying it. Therefore we have to lead the interview to the right topics, yet still let the interviewee speak freely about their experiences.

3.2.2 Email Interview

Another qualitative method that can be used are email interviews. Email interviews have become more prevalent as digital communication tools develop, offering new opportunities and challenges for qualitative researchers (Burns, 2010). With this growing acceptance as a legitimate qualitative research method, there is the opportunity to use it. However, just having email interviews is often not enough. There is more weight in complementing it with other methods to have an enriched data collection process and therefore it should be implemented in conjunction with other methods, alongside with consideration for the limitations as will be presented below.

There are several advantages and disadvantages to using this approach for qualitative purposes (Burns, 2010). To start off with the advantages, having email interviews means next to zero costs, high convenience as well as the space for iterative follow-up capabilities. The iterative nature of email interviews gives the opportunity to ask follow-up questions over time to help clarify responses and dive deeper into topics. Furthermore, they can be conducted anytime without requiring travel or preparation and there is a reduced labor of transcription work following an email interview as the responses are already in text. Burns (2010) also provides a framework based on two criteria: participants' professional writing skills and their computer proficiency which can be used to see relative advantages and disadvantages. If the interviewee in question is comfortable with typing and using computers it will result in a more effective email interview. On the other hand, the interviewee may be discouraged in participating if less confident in their typing or spelling abilities. It is also hard to gauge the participant's emotions or intentions with the absence of non-verbal cues since pressing "send" does not convey nuances. The iterative process of the follow-up questions also brings about delays and a lack of spontaneity.

What is important when constructing an email interview questionnaire is to be clear. It is essential to carefully consider how questions are presented to participants, as email interactions can differ significantly from face-to-face interviews. The presentation is also evident in the aspects of ethical considerations - emails are prone to misinterpretation which consequently requires careful consideration of ethical guidelines. When sending out emails there has to be an understanding that one cannot fully decide the intended audience (Burns, 2010).

3.3 Selection of Companies

The process for selecting companies was inherently driven by the research objective. We were interested in developers and users of sentiment analysis in the business, and therefore we started searching for companies that were in relation to this. This type of selection is also known as Purposive Sampling, the Homogenous type (Etikan et al. 2015). Purposive sampling is a technique frequently used in qualitative research where researchers intentionally choose participants with a particular type of attribute, experience or knowledge in relation to the research question. Furthermore, homogenous sampling is a subcategory of purposive sampling which focuses on candidates that share similar traits and characteristics (Etikan et al. 2015). The common factor in our case, and a crucial criteria, was that companies who were users needed to have already implemented some form of sentiment analysis, whilst developers needed to have launched the service and not be in development. We focused on creators with a fairly well established product or users with a larger user base, increasing the likelihood of more data to collect and analyze for the sentiment analysis tool. Initially we limited the search to Sweden-based companies only, but realized the response times were not in our favor and decided to contact companies worldwide instead.

The Google search engine was used for identifying sentiment analysis developers or users, whereas the search for actual employees took place primarily on the social media platform LinkedIn, as well as on the official company websites. We also contacted people of interest from our own private networks. The majority of the companies that were contacted were developers of sentiment analysis and not users.

A standard text format was sent out to any person we deemed fulfilled the criteria that were required. This was usually sent out via email, but also via support tickets on websites. In very few cases we would call the company’s official phone number in an attempt to reach the person we wanted to interview. The pre-written text included an introduction of us as researchers and students, a brief explanation of sentiment analysis and digital marketing, our interest in interviewing one of their employees and reassuring them that participation is voluntary and private details will be marked as confidential.

3.3.1 Respondents

An estimation of 50 people and companies were contacted in total, where 7 replied and four were interested in being interviewed. The respondents were all data scientists or data analysis with various years of experience in their current position. Among the respondents, two were from Europe, one from North America, and one from Africa. The majority, as stated previously, worked at a company that were developers of a sentiment analysis tool and provided it as a product in their kit, along with several other services. After the respondents had replied, stating that they are interested in helping with our study, we would exchange a few emails, deciding date and time, prior to sending out a meeting request via Zoom. The first meeting was meant to briefly inform the respondent about the interview contents and structure, as well as inform them about confidentiality, anonymity and that we will be recording the interview. If the respondent had time, we would conduct the interview immediately after the introduction meeting, otherwise we would decide on a new date and time to hold the actual interview.

One of the interviews was conducted with a respondent via mail (see Appendix 4). The respondent did unfortunately not have any time slots available that were long enough to hold an interview, therefore we collectively decided to cast a mail interview. We mailed them the questions according to the interview guide - slightly modified to ease the understanding for the respondent, and the respondent simply sent it back.

Table 3.1: List of Respondents

Respondents	Role	Interview length	Time and date	Appendix
R1	Senior data scientist	49:06 minutes	23-04-2024	Appendix 3
R2	Senior data analyst	--:-- (Email interview)	03-05-2024 (Received questionnaire)	Appendix 4
R3	Chief data scientist	53:03 minutes	06-05-2024	Appendix 5
R4	Data analyst	23:01 minutes	08-05-2024	Appendix 6

3.4 Interviews

To prepare for the interviews, having the literature review as the background was crucial to have a guiding structure. The interview guides (see appendix 1 & 2) were constructed on the back of the literature review. In this thesis, there are two interview guides. One is more relevant and used for the research question and the other one had its purpose for a redacted research question. There is a purpose for keeping the old interview guide, as the interview conducted with this guide provided value for the research. It still stands in this thesis to provide clarity, the same goes for the first interview. Nonetheless, the goal of the interviews is to examine how successful sentiment analysis is in itself, as well as what kind of role it has for their internal and / or customers' digital marketing. Therefore, the D&M model was the chosen method to investigate this thesis research question. Per the interview guides, the columns "Context / Theme" and "Dimension of IS Success Model (The D&M Model)" were adopted in the guides to act as a foundation and lead the interviews into the correct path, as well as staying on topic and ensure that all relevant questions were answered. Essentially, the interview guides were significant tools in achieving the purpose of the study and ensuring that all relevant information was collected.

The conducted semi-structured interviews were held on Zoom and lasted between approximately 20 - 50 minutes. All interviews were held in English, for consistency through the thesis and universal accessibility. Discussions and reminders about ethical considerations transpired ahead of the interview, such as confidentiality and permission to record. Before asking the main questions, the respondents were briefly asked to describe their role and organization they work in. These first types of questions were labeled as background information, before heading towards the main questions to cover the relevant topics. Lastly, the interviewee was asked if they had any other information that might be relevant to our study, and we thanked them for the insights and the impact of their perspectives on our study. As the interviews on Zoom were of the semi-structured kind, our interview guides provided structured questions but at the same time were open to discussion and follow-up questions and clarification. Deviations from the script occurred as per this interview approach, but the conversation remained focused while it was at the same time, flexible enough for deeper data gathering. In terms of the email interview, the same discussions about ethical considerations were in place before sending out the questionnaire. The structure of the questionnaire was mostly the same as the semi-structured interviews, with the exception of deviations from the script because of the nature of the method. This means that the respondent answered directly to each given question, without the interviewers being able to instantly delve deeper and ask follow-up questions. Further, there was an effort in presenting the questions in the questionnaire to be clear and precise in what the question really entails. For example, we tried to exemplify our questions with the use of "e.g.".

The interview questions were ordered in the way that the interviewee first had to answer questions about necessary information that would be relevant before delving into the application of sentiment analysis. The first two "Context / Theme" questions were acting as this imperative material, connecting our literature review about digital marketing along with big data and the analytics of it. The aspect of sentiment analysis was later introduced in the third "Context / Theme" while the fourth and last "Context / Theme" delved deeper into the D&M model. We had about 1 to 4 questions per dimension that were seen as relevant. Initially, it was structured in a way where the different dimensions and their questions came in a chronological order, however after revising it became clear that it was better to have a logical, sequential order on our questions, regardless of what dimension they belonged to. Using the D&M model as a foundational theoretical framework we made sure the interviewee answered questions for all dimensions, consequently bringing up sentiment analysis in all relevant aspects. This approach captured the width of the application of the NLP task in their business.

3.5 Data Analysis

3.5.1 Recording and Transcribing

The semi-structured interviews we held were recorded, making sure we remained focused on the questions and answers. This means we didn't have to bring attention in writing down valuable insights and data and instead put our full attention on the interviewee. The recording and audio file was later saved in Google Drive shared between the authors, to ensure safety and accessibility. The audio file was later transcribed with Whisper, an automatic speech recognition system from OpenAI (OpenAI, 2022). Whisper has several models that vary in size, designed to suit different needs. Whisper model medium was utilized on our end, due to the capabilities of our hardware. The transcription from Whisper was then manually corrected and verified with the usage of the audio file. These corrections were everything from errors from Whisper to removal of repetitions and filler words. The modifications were done without impacting the meaning of content. For the email interview, the answers provided by the respondent were directly put into the transcription.

3.5.2 Deductive Approach

The way the interview guide provided a useful structure for organizing the transcriptions for the data analysis. The majority of the main questions that were asked to answer our question were categorized by the different dimensions of the IS Success Model, more specifically the D&M Model. Therefore, the deductive approach could be used to classify the transcription as per Oates (2006). Her work in the research of IS and computing explains that deductive approach as basing the transcription's classification on the theories that are being presented in the literature review. Table 3.2 below shows the different dimensions of the D&M Model functioning as categorization with different colors, used to highlight parts of the interviewee's answers related to a specific dimension.

Table 3.2: Categorization colors of transcription

Color	Categorization
(red)	System quality
(orange)	Information quality
(yellow)	Service quality
(green)	System Use (Intention to use / Use)
(blue)	User satisfaction
(purple)	Net benefits
(pink)	Future implications

Oates (2006) also puts importance in not staring blindly at the present categories. There can be new themes in the transcribed data that can have relevance for the research. The interviews conducted also presented comments on future implications of sentiment analysis, and therefore were also highlighted as categorization with a specific color presented in Table 3.2. The full transcriptions can be found in the appendixes (see Appendix 3-5).

3.6 Reliability and Validity

The empirical data collected from the conducted interviews is limited, which should be taken into consideration when reading through several subchapters of this thesis. Marshall et al. (2013) states that a multiple case study, such as ours, typically requires a greater number of interviews than we've conducted. This limitation could therefore affect the generalizability of the conclusions and discussion, suggesting that the results should be seen as ***indicative*** rather than ***definitive***. The results might have taken a different shape if more interviews were conducted in a broader scale of the world, or if we had exclusively targeted a specific sector of digital marketing. There is no guarantee that similar results would show, should future researchers attempt to recreate this study. Despite this, the study still retains a reliable structure, with a well thought out interview guide, created with the support of the D&M model to align with the research objective. Two of the interviews may be seen as short or insufficient as one is roughly 20 minutes (Appendix 6) and the other is an email interview (Appendix 4). However, they could instead be seen as two interviews that strengthen the statements of Respondent 1 and Respondent 3, who give answers that are more detailed and in depth, which could directly be connected to the literature review. Furthermore, the questions in the interview guide are meant to cover a broad range of insights from organizations that specialize in sentiment analysis development and Digital Marketing. They have been formulated to keep a neutral tone, ensuring that they are not leading, which forces the participant to give an expected answer. Questions that require a "yes" or "no"-answer have been avoided and were only asked as follow up questions, as they do not bring any significant insights and can limit the depth and detail of the response. The data analysis application is designed to analyze various possible kinds of answers and would be applicable to any other interview, assuming additional interviews were conducted.

3.7 Ethical Considerations

It is of significant importance to ensure a study is aligned with the ethical requirements when conducting interviews. Oates (2006) demonstrates five main rights: right not to participate, right to withdraw, right to give informed consent, right to anonymity and right to confidentiality, which should always be considered and presented to the participant before collecting the data. These main points laid as a base to a concise consent form that was offered, which respondents could sign to help ensure their sense of security. The form included a brief summary about the study's objective and research purpose, what type of study that's been selected and an estimated duration of the (semi-structured) interview. It stated the contact details of the researchers, whether there are risks or benefits for any of the persons involved and how the data they provide will be used in this study. One passage of text specifically clarifies that the participant has the right to withdraw from the study at any time without consequence, and all data collected from them will be eliminated should they choose to do so. Lastly, the form addresses that participating is voluntary and confidential, and that signing the form confirms that the respondent has read and understood the conditions. Certain levels of confidentiality had already been established before the interviews, including the assurance that the data will only be used for the purpose of the study and would not be disclosed elsewhere. Additionally, participants were informed that any wish to exclude a specific statement would be removed without any questioning. The voluntary aspect of participation was mentioned on multiple occasions, including when we sent out the interview requests, when we booked the interview and during the actual interview.

3.7.1 Anonymity

The identities and personal details about the respondents and their organizations have been marked as [COMPANY] and [NAME] in Appendix 2 - 5. We have also added [CUSTOMER] as some of the respondents mention their customers by name. This is to ensure that the data collected, in terms of insights and opinions, stays anonymous and can not be traced back to the person nor company that the person works for (Oates, 2006). It encourages the interviewee to openly express their opinion without suffering any consequence such as discrimination, social stigma, or professional repercussions. We have also restrained from mentioning gender and age as it is unrelated to the study and keeps the thesis to a neutral tone.

4 Results

In this chapter, we present the empirical data we collected through interviews. The sections in this chapter follow the literature review, with the D&M Model being divided up in its different dimensions. Further, the respondents that the research findings are based on are referred to as R1, R2, R3 and R4. This is to ensure confidentiality of the respondents.

4.1 Overview of the Digital Marketing

Both R2 and R3 use the common digital media channels to digitally market themselves. R2 states that they use social media platforms such as Facebook, Instagram, X, as well as Google Ads (R2:6), while R3 suggests that they run banner campaigns and webinars (R3:6). Additionally, both of them mention email marketing and LinkedIn as two shared platforms they use for digital marketing. R4, on the other hand, does not go into detail about which specific platforms are used within their company, but instead suggests that "every company is into digital marketing" and that "traditional marketing is very hard to keep track of" (R4:2). R4 also worked with a customer who used TikTok and several social media platforms just like R2 and R3. R1, a developer and provider of the sentiment analysis tool, says that their customers want to reach an audience that consume platforms such as Twitch, YouTube or TikTok.

When asked about what type of customers they reach, and to what extent, R2 states that:

> It varies depending on the target audience and specific campaign objectives. However we always aim to maximize our reach by leveraging the capabilities of each digital marketing platform, and optimizing our campaigns for maximum visibility and engagement (R2:8).

R3 answers this question by saying that they are "very horizontal", meaning that they meet the needs of a wide range of customers from different industries, and not only one niche industry. R3 explains it like this:

> The reach has always been, you know, not massive. We were sort of a smallish business, a five to 10 million in revenue year kind of business, sort of by the end there. So we played in a lot of different industries, but never specialized into one. We went into two packs. We did a whole bunch of hospitality. That was another major area for us and then COVID hit and then we had to pivot again. So it's been a little bit of everything under the sun, not never sort of the major player. We're always a little bit niche, a little boutique, but for people who had hard problems, we were usually the ones that ended up finding sooner or later (R3:8).

4.2 Overview of the Big Data

R1 mentions that their customers use the tool to primarily analyze live streaming services, meaning that examples of data they analyze could be e.g comments and chat logs on those platforms. They work with millions and millions, in some cases even billions of rows, when collecting real time data (R1:14). These vast amounts of data is something that R3 also recognizes, who says that they run about a billion documents a month, and that "it was even more earlier on" (R3:12). When it comes to the type of data, R3 further mentions that their customers analyze [support]-emails, news articles, web chats, call transcripts, support channel transcripts of audio files and surveys, even though surveys are of a smaller data set. Both R2 and R4 give examples of collecting data from social media, however R2 additionally adds that they analyze information regarding their own digital marketing activities, which is anything from age, sex and location demographics to website tracking statistics (R4:8 & R2:10).

R4 mostly works with textual data (R4:10) and R2 with both structured formats such as spreadsheets, databases or APIs and unstructured data, which includes social media posts, customer reviews and text feedback (R2:12). R1 explains their collected data as:

> … statistics connected to a period in time. And whatever data that's connected to that specific point in time (R1:22).

99% of the data that R3's tool supports is unstructured data, but they are also able to handle structured formats. It is primarily text and when it comes to audio they typically process transcriptions. In some cases they analyze images through image recognition, this is usually regarding reviews (R3:16). R3 further believes that video analytics will become more common in the future, but pinpoints that the cost benefit is not there yet.

When it comes to challenges in big data, R1, R2 and R3 all collectively agree that volume is the biggest issue of collecting and analyzing datasets. It requires proper equipment and creates demands on the technology which needs to be enabled (R1:24). R2 seconds this by adding that it calls for advanced storage systems (R2:14), and R3 states that "you need to be robust" against dealing with such large scales of data. Part of a secure sentiment analysis tool is to prepare for potential failures and build code that can manage unexpectedly higher data volumes than initially calculated (R3:21). Apart from volume being an issue in Big data, there's also mentions of auto-scaling (R3:21), analyzing real-time data (R2:14) and the problem of trying to analyze it for the first time (R4:12). R1 highlights a key component, which is essentially collecting and storing data faster than it is being generated. This can ease the process of handling large quantities of datasets.

4.3 Overview of the Application of Sentiment Analysis

The respondents were asked to give an overview of their sentiment analysis tool and how it typically is applied on the collected data. Regarding how to connect the content between words and make sense of the data, R1 explains that:

> … models within, or approaches within sentiment analysis, can help us to aggregate that and summarize it in a sense that can be used to just have a quick look at it and then understand how it really landed with the audience (R1:28).

R3, too, elaborates on a "clause-based sentiment model" They provide two versions of the tool, tailored to different use cases. One which revolves around quality that uses an English BERT for English sentiments, and a multilingual sentiment BERT for any other language. Additionally, their tool looks for overlaps between specific tags or entities mentioned in the text and their associated sentiments, providing scores for various aspects such as entities, companies, and products. The emphasis is on analyzing sentiment based on these entities and tags rather than solely on the overall document sentiment. Their tool aims to operate natively in various languages, avoiding the need for translation services, and is capable of accurately identifying sentiment in different languages (R3:27). R4 refers to the models as "blueprints" for running sentiment analysis through various data. The process includes handling a large volume of complaints, potentially hundreds or thousands, which can be time-consuming to manually read and score. To address this, the approach involves preparing and cleaning the data, then manually reading the first and last few lines of each complaint to gauge sentiment. Their tool is used to automatically score the sentiment of words or phrases within the text, with positive phrases being assigned a "green" score and negative phrases a "red" score. This scoring system helps to categorize the overall sentiment of the text as positive or negative (R4:14). Similarly, R2 applies:

> Natural Language Processing (NLP) algorithms to categorize text data into positive, negative or neutral sentiments. We mostly analyze from social media platforms to sum up sentiments and how customers perceive, not only during, but before and after a campaign as well (R2:16).

None of the respondents utilized or provided sentiment analysis alone. The tool can be used in combination with e.g. social listening tools, Customer Relationship Management (CRM)-systems, web analytics platforms (R2:18) and coding softwares used for machine learning tasks such as text analysis (R4:16). By scripting and coding in these softwares, they can break down the text and see how well the language processing aligns with the sentiment scores assigned to individual words and sentences. This process allows for scaling up analysis from a small sample to a larger dataset, providing insights into the distribution of sentiments within the data. R4 emphasizes the importance of using sophisticated language processing models for these tasks.

4.4 System Quality

34.4.1 Model Design and Evaluation

R1 evaluates their sentiment analysis in production as quite strong and further explains how they ensure system quality of it:

> The way for us to sort of try to ensure some kind of quality is to use a combination of models where we see that certain models have different strengths and weaknesses. Some of them are more maybe [sic] complex and sometimes maybe too complex. Some of them are actually better at capturing, you know, simple signals in the kind of data. So what we try to do is to use a combination of different models as like a voting mechanism. And then the most dominant sentiment score or sentiment output is the one that we flag the text with, basically (R1:44).

The evaluation of R4's model starts by training it on a sample and seeing if the accuracy and quality of the output is plausible before scaling it for broader application (R4:24). Something that R4 notes is the degree of user-friendliness when building and validating the model "... it's only difficult at the first, but once you build a model that you can see that it's quality analysis … it's not that complex" (R4:24). If the understanding of analytics to effectively manage the model is hard, it is essentially better for businesses to outsource it. On the other hand, "if you analyze and you understand the analytics language, it's not complex" (R4:24), noting that familiarity with this field favors the ease of use.

4.4.2 User Engagement and Feedback Integration

To better the sentiment analysis tools, R3 put an emphasis on interviewing customers of their service and trying to put a customer's hat on, to see for example what improvements can be made on intuitiveness, what to expect from it and adjusting data interpretation to better reflect the actual customer base (R3:43). The latter involves re-evaluating data like tag frequency and considering whether certain data should be weighted differently based on its relevance to a significant portion of the customer base. These are various product management and development activities, aimed at enhancing user experience and addressing customer needs of the usage of their sentiment analysis. The discussion also touches on usability configurability of the sentiment analysis tools. R3 further mentions that these activities have been their strength "You know, this was always something we sold ourselves as, you know, highly tunable, highly configurable" (R3:43). When it comes to latency and uptime of sentiment analysis, R3 states that those are "normal IT problems at that point" (R3:43). R3 highlights challenges primarily associated with backend operations and data handling. They mention the need to address specific customer issues by adjusting their system setup.

4.4.3 Quality Assurance and Continuous Improvement

R2 indicates that they thoroughly evaluate and validate the sentiment analysis tools against a number of criteria to make sure they satisfy their unique needs and produce accurate results (R2:24). To address problems such as data quality and noise that might be present in unstructured data, as well as enhance accuracy and reliability of sentiment analysis they continuously aim to keep on improving their methods, models and algorithms.

Simultaneously, R2's reason for optimizing the sentiment analysis capabilities lie in to deliver better business outcomes (R2:38). Additionally, R3 remarks that there is significant focus on quality assurance, including conducting unit tests and interaction tests for the user interface, as well as developing written texts (R3:43). Generally, making better sentiment analysis involves extensive testing, product ideas and interviews with customers – all which are essential for any successful software business. It can be therefore concluded that a thorough approach is needed when evaluating software quality for running a software business given this answer from R3.

4.4.4 Challenges in Data Management and Bias

Text data is currently both easy and hard to work with, this is indicated by R1 as they place the remark that it is simple to store (R1:44). On the other hand, in the angle of utilization, they recognise that:

> ... it's easy to store, of course, you put it somewhere, but then when you want to use it and when you want to pipe it through a sentiment or the NLP model or whatever, then accessing that is sometimes difficult depending on how you decide to store it and process it (R1:71).

Data can also introduce biases (R3:61). R3 draws the comparison between the earlier belief that machines could not be biased because they merely processed data to today's realization that the data itself can introduce biases, which influences everything that follows in the data processing chain. Although R3 notes that data may be the root of the issue, it does not eliminate the responsibility for the outcomes generated by machines. Additionally, R3 points out that these types of systems typically prioritize general or common patterns over minor variations, which can lead to problems. This acknowledgement indicates a shift towards recognizing and addressing the inherent challenges of bias in automated systems.

4.4.5 Challenges in Language and Cultural Nuances

There are limitations in the aspect of reliability of sentiment analysis. For example, sarcasm and irony poses challenges for sentiment analysis to interpret (R1:44). It is a complexity in the sense that the tone of voice is vague as a consequence. Cultural context also plays a role according to R1, as there are cultural ways of expressing (R1:71). R2 and R3 further supports the challenge of sarcasm, irony and cultural nuances (R2:26, R2:34, R3:53 & R3:63). While R2 always tries to aim for reliable output, they bring up an example of "oh great, another launch…" (R2:26) which will be interpreted literally and output as positive, even though it is sarcastic. Added complexities include indirect language, as well as problems with data quality, noise in unstructured text data, bias in sentiment classification algorithms and scalability of these techniques (R2:38). R4 further enhances the language challenge by bringing up slang, noting that especially in Africa, their languages contain a lot of slang, making it harder for the model to distinguish what the customer is trying to say (R4:28). R4 draws a language comparison between the United States of America where English is mandatory, to the continent of Africa:

> … in the States [United States of America] where English is mandatory, here you might find that language might be one of the barriers. How a customer express himself, maybe a mixture between two languages, and the model is unable to pick up.

> What does this language mean? Is it good? Is it bad? And that gives a bit of … not bias, but kind of the capping system … you can see it's kind of those gray areas where you really don't know what to say, ideally. So that's the drawback, especially in Namibia, where you have 14 languages in one country (R4:28).

R3 explains that although individual analyses might be inaccurate, these errors generally average out when analyzing data at scale, like millions of articles (R3:47). They also aim for a symmetrical error function to ensure that random errors cancel each other out, making the overall results more reliable despite some inaccuracies. Some further technical issues lie in trade-offs involved in scaling language models and sentiment analysis tools across diverse languages and industries (R3:53). R3 acknowledges the immense challenge of effectively handling the vast diversity of human languages and industry-specific nuances, describing it as an "unsolvably large problem" (R3:53).

4.5 Information Quality

4.5.1 Challenges in Accurate Sentiment Translation

According to R1, getting accurate evaluations of output quality is not easy (R1:48). The reason being that there is no opportunity for human intervention especially when dealing with different languages. For instance, R1 gives an example of translating content from one language to another (say German to English) before analysis can lead to misalignments and inaccuracies in capturing the true sentiment. Due to the complexities of language and the limitations of current NLP models, manual or human review of sentiment analysis outputs is significant to ensure accuracy and proper representation of the sentiments expressed. "... it's difficult to know the output … without looking at and quality checking the output with the input" (R1:50) is an indicator of that.

4.5.2 Handling Sarcasm and Cultural Nuances

It is indicated by R1 that there may be a lack of accuracy in the output of sentiment analysis when there is a lot of sarcasm and irony involved (R1:44). The NLP task's output may show it as negative, while it was actually positive. R1 essentially coins false positives. It becomes a challenge to find the right balance that can best represent what is being expressed accurately – whether it is positive, negative or other as R1 argues. R3 agrees with the problems of sarcasm, context and cultural nuances for instance wrong use of Japanese honorifics:

> I thought was [sic] interesting was a lot of sentiment in Japanese is sort of indiscernible to outside readers because like a fair amount of, um, conflict is expressed through misuse of honor effects and stuff like that. So if you're mad at your boss, you might call him as if he was your inferior sort of report or something. Well, without knowing your relationship, without knowing who the same bill is too, and like this outside context of how the two of you are related, like the data is not there (R3:47).

4.5.3 Simplification and Loss of Nuance

The limits which R3 points out is that sentiment analysis outputs either binary or numeric value making most of the finer-grained information to disappear (R3:47). Even though these tools make data simple enough to process - for example deciding on polarity in tweets - this simplicity results in their capturing only a fraction of what was intended.

4.5.4 Variability Across Content and Industries

R3 discusses the variability in the quality of sentiment analysis output between different types of content and industries (R3:45). English news content typically has higher quality outputs due to its clarity, whereas tweets tend to lower the overall quality because they often are, said by R3, “just unintelligible” (R3:45). The quality of output also declines in specialized industries that use industry-specific jargon, exemplified by the security industry. Here, terms like “hacks” and “catastrophic” are standard, and not necessarily negative, despite potentially being interpreted negatively outside of the context. “That’s just, those are just terms of art” (R3:45) adds.

4.5.5 Accuracy and Performance Metrics

While the complexities of the output are there, R1 acknowledges that the representation is quite accurate. There will be outliers and the output of sentiment analysis will not exactly be the same as if a human would analyze it, but the sentiment is largely portrayed correctly on an aggregated level (R1:50 & R1:65). R1 essentially says that they:

> … think the output would be quite close on like a total level … it’s not you [sic] can’t guarantee you arrive to one hundred percent accuracy, but you will get the rough sort of consensus of it (R1:50).

For R3, they throw out an 80% accuracy on their output from sentiment analysis (R3:45). This number is usually what you get, and has always been R3’s target number. However, R3’s company have shifted away from using specific accuracy metrics in customer discussions about their sentiment analysis output. R3 further elaborates that they found that citing particular performance percentages was not helpful and often led to unproductive debates with customers. Instead, R3 states that they chose to focus on the broader value propositions of their tools, such as reliability, configurability, high, uptime and cost competitiveness. R3 does add in that they track internal metrics, but does not prioritize them in discussions because achieving a universally acceptable accuracy level, like 80%, is challenging due to inherent human disagreement rates (R3:45).

4.5.6 Practical Insights from Customer Feedback

The output gives an overview of the quality of complaint used by the customers for R4. To clarify R4 gives the explanation:

> You can also determine if your customers are using high level English, very frustrated, using strong grammar that can be used. These are people that took the time to write the complaint. So you are dealing with very, very, very unhappy customers due to the intensity and the scoring, because you are scoring the language, right? Either you are

> scoring it, is it neutral, is it negative, or is it positive? And secondly, also, should one then use languages that are not too strong, then you can see, okay, this is just someone that is giving a slight complaint. But if someone sends you a 500 essay, that is serious business, compared to someone that is giving you three sentences, for sentences. Yes, he is frustrated, but not compared to someone that took the time to write a 30 minute essay (R4:26).

Another thing R4 notes is the advantage with open, free systems compared to surveys which tend to be biased in the structure of questions to gain a good overview of how customers feel (R4:34). Sentiment analysis output shows how extreme the feelings are in free text, compared to surveys. This is because the customers can air out whatever strong or soft words they use.

4.6 Service Quality

4.6.1 Diverse Support Infrastructure

As R1 and their company develop their own sentiment analysis from scratch with the help of, for instance, pre-trained models, they do not receive any kind of support from any other outsourced personnel or department (R1:77). In comparison, R2 receives support from "both from internal data science teams as well as external vendors" (R2:40), while R4 usually receives support from IT (R4:32). When it comes to the end-user, R1's customer might raise concerns about the output of the NLP task to R1's business and in those cases R1 and their team will explain why the output turned out a certain way (R1:48).

R2 mentions that the quality of the support varies depending on the factors responsiveness and resources available from the support team (R2:40). To minimize arising questions, R2 puts a prioritization on proactive type of communication, where they strive to maintain open communication and exchange crucial information among themselves ahead of time. This allows them to troubleshoot issues as needed. R4's support is simple, mentioning that they "help me scrape data off LinkedIn … so that I can compile it into an Excel file or CVM file, and then run it into a software" (R4:32).

From the perspective of R3 - their business has "always got very well, uh, regarded for support" (R3:55) which has contributed significantly to customer retention and satisfaction. R3 mentions that the support service has been characterized by generous availability hours, quick response times and a proactive approach to resolving issues. This is further clearer in that they "have like 99.99, whatever uptime service level agreements with our customers" (R3:21). R3 looks back to their startup days and says this about their fundamental pillar for their high-quality support:

> … the guy who sort of ran that early on was just a people pleaser at heart. And so we were able to, I think he really put his fingerprints on the support, uh, efforts for a long time, even after he was gone (R3:55).

The infrastructure of R3's support includes a support staff for NLP in general (R3:59). Both internal and external users are supported by this staff. Initially, the team dealt more with external clients than internal ones due to the small size of the business. However, as the company grew and became part of a larger organization, R3 expresses that the support staff began to be viewed almost as customers too:

> I almost consider them a customer, you know, as sort of a concept, obviously we're the same team and we're working together and I, you know, interface with them as colleagues, but I also think of them as a customer, our sort of main customer of this product. And so the same sort of learning from them, the same sort of supporting them absolutely applies. And yeah, even from the very early days, you know, I don't know which number, but employee eight or something probably was a support person. Right. It was always a, you know, a part of the team (R3:59).

Moreover, they have support channels to help their customers that are utilizing their sentiment analysis (R3:43). They also have an operation team that make sure that R3's service is always up and running and make sure the response is fast and the lag time down.

4.6.2 Education

R1 highlights teaching end-users about the limitations associated with sentiment analysis and NLP (R1:79). The effort to manage expectations and educate about the system's limitations is an ongoing and essential part of the process and at this stage, R1 have addressed it as much as currently possible. Moreover, R3 acknowledges that there is another limitation in the users' own knowledge – people want to find "unknown unknowns", information they are not even aware that they are missing (R3:51). What it means, according to R3 is that a significant part of this challenge is helping customers recognize how much sense they already have about what will be discovered by the data, especially regarding good or bad things:

> And that was a major challenge was just getting customers to understand how much of experts they already are and how much, you know, the sort of simplistic understanding of the LL- the pre LLM stuff could bring was not really going to move the needle for them (R3:51).

4.7 System Use

4.7.1 R1's Use of Sentiment Analysis

Regarding system use, R1 states that sentiment analysis is not the main focus of their portfolio or any specific product, though it has seen an increase in demand both internally and externally (R1:34 & R1:65). Rather the technology works as an element they provide within their architectural framework and broader portfolio. It is a service that they provide for end users and what they develop (R1:48 & R1:56). The service they provide is open to the global scale, meaning that they work with different languages and different countries (R1:34). Its purpose and nature of use is exemplified for watch manufacturers, where R1's sentiment analysis service helps the service-user (in this case the watch manufacturer) to determine changes in the way they develop their watches. Sentiment analysis exists as a component and is not the focal point of their services. In addition, the utilization of sentiment analysis is rather new to them, stating that they started using it within the last year (R1:38). This new addition of technology is clearly mentioned in that "… we are quite in a somewhat early state in really using this [sentiment analysis] and deliver it and working together with the client and making sense of it" (R1:79). As of right now, sentiment analysis stands for five percent of their business and does not necessarily solely use it to guide the processes (R1:34 & R1:60).

4.7.2 R2's Use of Sentiment Analysis

R2 states that they use sentiment analysis to "mostly analyze from social media platforms to sum up sentiments and how customers perceive, not only during, but before and after a campaign as well" (R2:16). Compared to R1, R2 mentions that they leverage their sentiment analysis "to a significant extent" (R2:20). This is especially true in their brand monitoring, where R2 analyzes online mentions and discussions (R2:30). Identifying emerging trends or issues, as well as gauging customer satisfaction levels, are also major aspects of where they leverage their sentiment analysis.

4.7.3 R3's Use of Sentiment Analysis

For R3's case, sentiment analysis is likely their most important feature:

> I'd say it's the marquee feature … I would say sentiment has been the dominant thing that people have been interested in in [sic] extracting from text. So I would say it's, it's the reason most people come to us (R3:29).

The degree of use is high for R3, as it is one of their centerpieces of their business (R3:33). Why they use sentiment analysis is open-ended according to R3. One of the things they tribute to the usage of sentiment analysis is to monitor social media, especially early on. "... are there problems showing up with my brand that I'm unaware of, right?" R3 clarifies (R3:35). It helps companies maintain control over their public image and messaging, as well as proactively respond to potential crises.

R3 explains that sentiment analysis and social media monitoring is integrated into broader customer experience programs, which a lot of companies have (R3:35). This is to gather real-time feedback on various aspects, R3 mentions an example on the aspect of service in hotel front desk interactions:

> If I know, you know, I've identified the 800 different topics as a hotel, right? So we've got a gigantic tag set for hotel. I know as a hotel, this is where customers interface with, and I could ask them, you know, how was the front desk experience? Were the flowers fresh, right? Did, you know, were the, did you have enough towels? But if I can actually just score and see in reviews online or in feedback we get, just free text field, sort of free, you know, feedback, then I know how to run my business. I can identify whatever they do (R3:35).

The previous net promoter score (NPS) and customer satisfaction metrics are being supplemented or replaced by sentiment analysis due to challenges of traditional survey methods, such as high costs and demographic accessibility (R3:35). More specifically, R3 argues it is "... just like a NPS replacement" (R3:35). NPS and sentiment are highly correlated - if the NPS is high, the sentiments are positive and vice versa. The extent of use of sentiment analysis goes beyond direct customer service enhancement as R3 described before. R3 extends the use to cases in training call center employees and conducting predictive analytics.

4.7.4 R4's Use of Sentiment Analysis

R4 scrapes data online from social media with the help of a software and analyzes it with sentiment analysis (R4:8 & R4:14). R4's purpose of use is identified with "... you can have it for an overview of a company, you can have it for a product … you want to have brand loyalty" (R4:18). When it comes to the degree and manner of use, sentiment analysis is conducted on a regular basis (every three to six months) and particularly after introducing significant changes, like a new product or rebranding. Here is an example from R4 to how to have an overview of engagement from customer:

> Ideally, you launch, what's your favorite product? What do you like? Coffee, for example, coffee. The coffee decides to change its branding, necessarily decides to change its branding. So you want to find out what's the sentiment customers have to the new branding. Then you do a sentiment analysis to say, okay, are the customers reacting so well with a new change? Or are the customers angry with a new change? Ideally, no one will come knock to your company and say, no, I don't like the change. But if you take that Twitter response, or their Instagram comments, and you have them on Excel file, you can then score say look, actually, 40% are angry, 30% are actually happy with a new change. And then the 30% are actually not sure (R4:18).

4.7.5 Complementary Tools

To get a more comprehensive understanding of customer behavior and preferences, R2 utilizes other tools apart from sentiment analysis (R2:18 & R2:36). R2 remarks that "each tool has its strengths and limitations and can't be compared as they complete, rather than compete with each other" (R2:18). Since sentiment analysis, alone, cannot capture the full picture there is an ongoing collaboration between e.g. data analysts and marketers, according to R2 (R2:46). The examples of tools mentioned were social listening tools, CRM-systems, and web analytics platforms. Moreover, R3 agrees in the aspect of sentiment analysis not being enough to capture the whole picture, especially when connected to tags and entities (R3:51). "You're trying to tell them a more nuanced story" R3 words (R3:51). This nuance has been one of the major issues for LLMs, but R3 notes that they have finally begun to start helping:

> I would say nuance has been one of the major challenges that LLMs are finally starting to help with, but it was always like, yeah, okay, right. Especially cause it was like, Oh, it looks like people aren't happy about the long waits, like, yep, yeah, they don't like that. Oh, but you know, um, the, the good customer service that's positive. And like, yep, people are usually glad when they're nice to them. So you're trying to find something more nuanced (R3:51).

4.8 User Satisfaction

4.8.1 R1's User Satisfaction

R1 mentions that the demand for their service of sentiment analysis has increased, both internally and for the end users (R1:65). This indicates that the customers are happy with the tool that is provided to them, and that there is a need for such a service. There are limitations that R1 means are "impossible" to handle at the moment so their satisfaction is not one hundred percent (R1:73). R1 acknowledges that the quality and accuracy of sentiment analysis cannot be fully guaranteed. However, from the perspective of R1, they are positively set on the technology.

4.8.2 R2's User Satisfaction

In comparison, R2 claims they and their team are quite satisfied with sentiment analysis (R2:42). R2 does acknowledge that there are areas of improvement. R2 gives the example of:

> adding even more advanced machine learning techniques, or possibly utilizing larger and more diverse datasets to train the algorithms and expanding data sources to get a comprehensive view of the customer perspective (R2:42).

Furthermore, the quality of the data has an effect on R2's satisfaction level (R2:44). To elaborate, R2 mentions that sentiment analysis "has a hard time analyzing spam, irrelevant comments or slang words" (R2:44). R2 further mentions the importance of improving and continually working on the challenges and optimization of the models to gain more accurate results.

4.8.3 R3's User Satisfaction

When R3 was asked about their satisfaction with the sentiment analysis tools and the information that it provides, they remarked the question as "weird":

> … it's a weird question because I'm providing it. So I'm not, I try not to be though … I shouldn't be satisfied if I'm happy what [sic] we're doing, then, you know, that's a problem. Like then what are we doing here? And then to the extent that stuff gets solved and we're, we're done (R3:61).

R3 continues by saying that in their 15 years in their field, they see a lot of issues, but also a lot of growth (R3:61). R3 is most pleased with the maturity and education that has been improved over the years, and exemplifies this by reflecting on the evolving understanding of biases in machine learning and data processing mentioned previously under the chapter *4.4.4 Challenges in Data Management and Bias*. The appreciative level of R3 is not only reflected by an understanding of biases in data processing, but also the understanding of limitations on sarcasm. They note that "I think the education has been going well", but also note in terms of benefits that "I think the signal is accurate enough to make business decisions off of" which is "awesome" (R3:61). Although R3 is excited over the things mentioned above, they remind that they are not satisfied with sentiment analysis:

> I'm excited about all those sorts of things, but at the same time, every time I put a document in and it gets something wrong, I'm like, uh, right. A little bit of chalk, you know, fingers in the chalkboard there. So I'm not satisfied, but I'm the weird person to be asking that question of (R3:61).

From the customers' end, R3 believes that overall the customers are generally high, provided they understand the system's capabilities and limitations (R3:63). Customers' satisfaction lies particularly in the handling of specific types of data. R3 also brings up that most of their customer losses attributed to businesses closing rather than dissatisfaction. However, R3 acknowledges a general dissatisfaction with the system's tunability - customers desire improvement without investing effort. Once again there are also challenges with nuanced cases. R3 closes by mentioning that their company has an ongoing effort to reduce the number of niche areas where the technology performs poorly (R3:63).

4.8.4 R4's User Satisfaction

R4 says that they are 100% satisfied, but like all the other respondents, believes it is not perfect (R4:34). The overview of customer engagement is a positive aspect, according to R4, mentioning that they can determine if they are "on the bridge of chaos or no" (R4:34). Challenges that affect R4's satisfaction "boils down only to language. For me, it's only language and I think also the receiver of the report" (R4:36). For the latter, R4 explains that there are cases of wasted analysis when the marketing team feels that the sentiment is not aligned with their core and rejects it. For the language part, grammar is one of the biggest challenges to R4. A brief mention of source of data as a challenge is also there, with complaints on different formats that can not be scripted. Especially in Africa, not everyone would want to write how they feel due to education levels. It is a continental challenge, and R4 draws the comparison and adds that big data from Europe and America is always good.

4.9 Net Benefits

4.9.1 Automation and Productivity

With sentiment analysis comes the automation of analysis of text data (R1:50). This means that R1 and their business do not have to manually go through text and sort out the sentiments. R1 put it in an example of the productivity benefits of sentiment analysis:

> We are able to analyze, … let's just take a number like we can analyze 100 messages per second, or we can analyze a two hour long video in two minutes. But for you, … you need to watch the whole video for two hours. You need to maybe, you know, scribble, I mean, transcribe everything manually and then you need to redo it again. So it would take you six hours to arrive to an output. But we did it in or the service could do it in two minutes. (R1:50).

In that context, R1 further explains that in total it would take someone six hours to arrive to an output, due to the fact that you need to transcribe everything manually and redo it again. With their service of sentiment analysis, however, it only takes minimal time to arrive to an output.

4.9.2 Thoughtful Integration

R1 points out potential benefits and challenges of using sentiment analysis effectively (R1:60). The key point is that sentiment analysis is able to greatly influence customer perceptions provided that the data accurately visualizes the sentiments positively and negatively without facilitation of errors like sarcasm or irony that can drive false positive detections. After all, sentiment analysis can be treated with skepticism as it may not actually reflect customer opinions in all situations, especially if feedback is manipulated or not genuinely reflective of customer feelings:

> … you will be prone to people, then again, being like sarcastic, or they might want to, you know, hurt your product in saying that everything is, you know, really good, but that the reality is that it's really bad. So then you get a false sense of what your actual, I mean, what your customers really, really believe or feel about your product. So I think it's difficult maybe for companies to be, I mean, fully driven by that (R1:60).

Thus, according to R1 the effectiveness of sentiment analysis depends on the setup, the nature of the product, the method of collecting feedback and the trustworthiness of the customer feedback being analyzed (R1:60). R1 means that despite its usefulness, it can be used in moderation and it should not be trusted as a decisive resort that helps to determine a business goal because of a number of pitfalls and the fact that it is difficult to interpret the data.

4.9.3 Benefits for Digital Marketing

All the respondents indicate that sentiment analysis does play a role in digital marketing (R1:52, R2:28, R3:61, R4:26, & R4:20). For starters, R1 notes that sentiment analysis is crucial for their customers' digital marketing strategies, enabling them to have an effective self-marketing through content adjustments based on feedback from R1's digital platform (R1:52 & R1:28).

Like R1, R2 utilizes sentiment analysis to enhance content engagement, but also to proactively manage their company's reputation. The tools collect real-time feedback on the general perception of customers, supporting tailored responses to customer sentiments and strategic adjustments based on competitive analysis (R2:20, R2:22, & R2:30). As mentioned by R2, it is best seen as a means of creating more personalized marketing-content according to what the customers are looking for (R2:28). On top of that, R2 utilizes the tool of sentiment analysis to predict market trends and consumer behaviors. Consequently, they are able to design marketing strategies and apply operational tactics, such as hiring staff, according to their predictions. This predictive capability has significantly expanded their market competitive advantage (R2:32).

R3 also believes that the output of sentiment analysis is precise enough to make valuable business decisions based on it (R3:61) To add on R2's mentioning of predictive capabilities, R3 also states that they use predictive analytics in marketing (R3:49). R3 brings up the example of enhancing the targeting of promotional campaigns such as coupon distribution, which is a benefit of sentiment analysis's role in predictive marketing. R3, explains how firms use sentiment data and customer history to detect and target people who are more inclined to give a positive response to advertising campaigns, thus improving the return on investment (ROI) of marketing campaigns by preventing wasted efforts on those who would purchase regardless of a coupon:

> Um, and so they had examples of like trying to predict who would be most, um, affected by a coupon, something like that, right? Being like, Oh, look, if you can shape this, if you can send coupons to the people who are going to be responsive to coupons and not send coupons that people are going to buy you anyways, and are now getting a discount. Then you can take a marketing program. That'd be a negative ROI and turn

> into positive ROI through better targeting and sentiment analysis. You know, and your customer history was part of that (R3:49).

Additionally, R3 exemplifies the application of sentiment analysis together and NLP in business at large scales, more particularly in car dealership networks with numerous locations:

> … get into like nuanced car dealership networks or something like that, where you've got 10,000 locations that you're responsible for at a high level and you're trying to, you know, do a nuanced, you know, uh, effort in managing and training and staffing and resourcing across this sort of universe, um, getting those hard numbers and sort of understanding the difference between, um, noise, right? Is, is this car, is this sales guy's numbers up this week because it was a really successful, like he's done something great, or is it just like just random chance because this is often, you know, a random function with a small number of observations. And so anything where you can start bringing in the text and understanding what people's experience was helps with that (R3:49).

The example given by R3 highlights how NLP helps in deciphering customer feedback to determine performance at various locations - whether positive sales figures are due to genuine success or merely random variations (R3:49). This use of NLP assists in making informed decisions about management, training, staffing and resource allocation by providing clear insights into customer experiences and feedback across a broad operational scale.

Similar to the previous mentions of sentiment analysis's role of gathering insights from customer feedback and public perception by R1 and R2 (R1:52, R2:20, R2:22, & R2:30), R3 emphasizes how NLP aids in understanding customer reactions and optimizing digital campaigns through methods like A/B testing and analyzing customer feedback from various channels (R3:49). Additionally, R3 underscores the importance of using NLP to identify pain points and optimize workflows by analyzing customer sentiments expressed in reviews and direct feedback. This allows marketers to make more informed decisions for e.g. targeted marketing efforts such as ad placements, choosing the right contexts for the placements to ensure positive association and effectiveness. It also allows marketers to make better marketing strategies overall. Even further, NLP is described by R3 as generally passive - "NLP is all about give me text" (R3:49), but essential in providing actionable insights which can be crucial for real-time interactions such as in call centers or chatbots (R3:49).

R4 says sentiment analysis "falls primarily in the market basket. It does not fall in other entities" (R4:20). R4 outlines how marketing teams use sentiment analysis to inform their strategies and decision-making processes. Similar to what the other respondents express, they focus on the potential actions in which marketing can take based on customer feedback in the case of a product launch. Specifically, R4 describes a scenario where customers were, not unhappy with the product itself, but instead upset about the timing of the launch:

> They were not having a complaint with the product, but they were having the complaint that the product was launched in the middle of the month, and most of the consumers did not have money. Hence, we had a high complaint rate within the sentiment (R4:20).

R4 suggests using this feedback constructively to improve the timing and execution of future product launches, ensuring smoother transactions and possibly better reception from customers (R4:20). Furthermore, R4's mentioning of the marketing team's role in gathering insights from the finding. Questions for the marketing team to think about are quoted “How do we build trust with our customers, or how do we then build brand loyalty with our customers?” (R4:32).

One thing that R2 and R4 underscores is the importance of quality of the output (R2:28 & R4:26). Since the quality of the output has a direct impact on the strategy formulation and campaign optimization, it is significant for marketing decisions. Based on what customers are saying, accurate sentiment analysis assists in identifying areas where products or services need to be improved (R2:28).

4.9.4 Trade-offs of High-Accuracy Sentiment Analysis

For R3 there is a further focus on the balance between speed, cost and computational resources (R3:53). R3 points out that while machines have advantages in speed and cost, the usefulness of these tools becomes questionable when they require comparable resources to a human for similar outcomes. R3 discusses current technological boundaries, noting that while accuracy has improved with new technologies, it often comes at increased costs and higher latency. This further raises issues concerning the usability and value of these high-accuracy schemes for final consumers (R3:53).

4.10 Future Implications

The interviewee’s mentions sentiment analysis and its future implications. R1 discusses how rapidly the field of sentiment analysis is changing, driven by advances in technologies such as those developed by OpenAI (R1:81). While only having a 5% impact for their business, R1 believes it is going to increase (R1:34). R1 predicts significant improvements in overcoming current limitations like detecting irony and sarcasm, which are often missed by existing models (R1:81), and currently it is something that R1 mentions they want to explore and see how they themselves can develop AI further in that regard (R1:44). When describing the system quality, R1 declares that there are opportunities in improving the quality of the tool based on manual quality assessments that they can perform on their models (R1.48). To elaborate on what models, R1 brings up large language models (LLM) and NLP models. Parallel to these models also exists “kind of hybrids where you retrain a model based on a human interfered” (R1:48). R1 believes in future tuning to improve the quality going forward, where manual quality assessments are made on the models. R1 concludes and thinks it will be “an exponential change” in how successful sentiment analysis applications can be in companies (R1:81).

R2 believes something worth mentioning is the importance of “always adapting and innovating further in the field of sentiment analysis, such as customer preferences, communication channels and the involvement of language” (R2:46). R2 believes sentiment analysis must adapt in order to remain accurate and relevant, particularly in light of the always growing amount of data.

R3 briefly mentions that NLP is passive, which R3 elaborates by comparing digital marketing as active - “like it is a choice to put something in front of a customer” (R3:49). NLP, on the other hand, is just analyzing text. Sentiment analysis is changing according to R3, stating the change from models just getting data in and then running it through an engine to also spit out text and communicate with the world (R3:67).

5 Discussion

In the following chapter, we discuss the empirical data that was presented in the previous chapter and tie it with the literature review. This section also includes our own thoughts and reflections around sentiment analysis and its evaluation, as well as its ties to digital marketing.

5.1 Evaluation of Sentiment Analysis

5.1.1 Interrelationships within the D&M Model

Petter et al. (2008) describes the interrelationship between the different dimensions of the D&M Model. This is clear in the discussion, where the evaluation of each dimension is hard to do without including important findings that are also relevant in dimensions. For example, the challenges with sarcasm, irony and cultural nuances are exhibited in the majority of the dimensions. When viewing the headings below, it is hard to miss out the limitations of this language aspect as it poses significant weight in e.g. information quality, which affects system use, which in turn affects net benefits and then goes back to reinforcing system use. This observation strengthens the element of interrelationships and feedback loop in the theoretical framework, as described by the original creators of this model and Petter (Petter et al. 2008).

5.1.2 System Quality

This is the first dimension of the D&M model this chapter will discuss. According to Petter et al. (2008), this dimension measures the desired characteristics of an IS. Key measures include ease of use, system flexibility, system reliability, and ease of learning as well as system features of intuitiveness, sophistication, flexibility and response times. This parameter has been used to evaluate the sentiment analysis tools from the findings of the four respondents. In this regard, the respondents focused on a number of issues including strong model design, user engagement for tool improvement, constant fine-tuning, bias removal and adaptability to cultural and linguistic diversity. These aspects are important in making sure that sentiment analysis tools can be trusted and are accurate enough in achieving their intended purposes. Based on the interviews, we can establish that sentiment analysis tools have a lot of strengths concerning system design and adaptability. The results indicate strong performance of sentiment analysis when used carefully after validating it on metrics in combination with validating different and unique models first on smaller sample sizes before using it on a broader scale. Nevertheless, they also come with significant hurdles in their application. In this regard, while R1 mentions the easy storage of data, more specifically the unstructured text data, the quality of the process is affected by the complexities of dealing with different data types, as well as the inherent hurdle is the biases inbuilt into the tools. This is in accord with issues concerning one of the 5V in big data, Variety, which Sharef et al. (2016) brings up, stating that as various formats of data are being generated, the quality and accuracy of data are factors that should be extra considered. In arguing whether sentiment analysis is good or bad in terms of system quality, these strengths need to be balanced against weaknesses. When it comes to system quality, sentiment analysis may be considered “good” where context allows for control over data types and there is minimal linguistic and cultural diversity. Sharef et al. (2016) mentions this as well, saying that “taming the data is key for big data analytics” (p. 162). However, the drawbacks such as handling sarcasm, slang or even multiple languages can impair efficiency and impartiality in case of global and more diverse settings thus rendering it undesirable. This is inline with existing studies that underscores that unstructured data may contain sarcasm, ambiguity and irony, which the NLP process has a difficult time to interpret (Wankhade et al. 2022). The findings show similar problems to what Wankhade et al. (2022) mentions, where they state that the human language poses an adversity in the complexity for the machines which in turn do not always convey straightforwardness and being precise in the context, tone and cultural nuance. Therefore, sentiment analysis should be approached as a tool that has high potential but at the same time requires constant scrutiny and adjustments especially when used globally. Although overall system quality may be satisfactory due to continuous improvement efforts aimed at addressing inherent limitations effectively.

5.1.3 Information Quality

The second dimension of the D&M Model is Information Quality. Petter et al. (2008) describes that this dimension measures the desirable characteristics of the system outputs. In this study’s case, it refers to the output of the information from utilizing sentiment analysis. Some of these measurements include the outputs relevancy, understandability, accuracy, conciseness, completeness, understandability, currency, timeliness, and usability. When evaluating this dimension, there are some challenges that have to be addressed despite sentiment analysis’ strengths. Firstly, the translation of sentiment across languages introduces inaccuracies due to misalignments and lack of manual intervention which leads to potential errors in sentiment interpretation. However, it still requires human judgment - sentiment analysis is useful but it cannot replace humans completely, especially in multilingual contexts. When taking a closer look at these findings, one comes upon familiar concepts such as sarcasm or cultural nuances. The output of any sentiment analysis system will likely have certain amounts of false positives as it can misinterpret sarcastic data. Once again is Wankhade et al. (2022) relevant to support the findings in the challenge aspects of sarcasm and irony. What’s more, the NLP task oversimplifies complex sentiments into basic categories (positive, negative, neutral), losing nuanced details of the feedback. This simplification hinders the depth of insights derived from the study thereby rendering incomplete data interpretation which may slightly affect business decision-making processes. The fourth challenge is that the output varies based on what kind of content and industries that sentiment analysis looks into. R3 presents in the findings that sectors like news being more accurately analyzed, than others like social media or industry-specific jargon.

Taking this knowledge into account, sentiment analysis is generally accurate when the outputs are summed up, providing a rough consensus of sentiment that can be useful for gauging overall customer mood or satisfaction. It is evident that the accuracy will not be at 100% based on the results and previous studies. When drawing parallels between the findings and existing studies, it is clear that sentiment analysis provides valuable insights from customer feedback, proving the relevancy and usability of the outputs and relating directly to Value in big data where Sharef et al. (2016) highlights the importance of promptly utilizing data and making decisions regarding its value. It helps businesses understand the intensity and nature of complaints or praises, thus aiding in e.g. customer service and product development.

5.1.4 Service Quality

Next up is the Service Quality dimension. The evaluation of this parameter revolves around the quality of the support that sentiment analysis users receive from e.g. the IS department and IT support personnel (Petter et al. 2008). Relevant terms to look at includes responsiveness, accuracy, reliability, technical competence, and empathy of the personnel staff. When gathering the insights from the respondents, we noticed diversity in the infrastructure of support. Overall, while this dimension varies among the different businesses, each provides a level of support and education that contributes to the effective use of sentiment analysis. R3 demonstrated that a good service infrastructure which not only supports users effectively but also engages them in understanding the service deeply, enhances their overall satisfaction and effectiveness in using the technology. Both R2 and R4 have a functional support system that meets the basic needs of the business and its customers. In comparison to the others, it was evident that R1's scenario might limit the breadth of service quality and responsiveness to diverse customer needs. R1 did put significance in educating end-users about the inherent limitations and potential inaccuracies of NLP in general. The best practices highlighted by R3 could serve as a benchmark for the others, emphasizing proactive support, extensive user education, and high availability as key components of excellent service quality in the deployment of sentiment analysis. R3 works as evidence for success in the terms of Service Quality, both internally and externally. In conclusion, it can be argued that service quality for sentiment analysis has succeeded through proactive monitoring as well as comprehensive support mechanisms put in place to address all concerns arising thereof. A company offering continuous support and managing customer expectations by educating them ensures its customers to effectively utilize sentiment analysis tools. The high uptime and quick responses mentioned for R3, coupled with the educational efforts of both R1 and R3, demonstrate a commitment to high service quality. Successful Service Quality has a good influence on the effectiveness of sentiment analysis. By having good training and support programs, it improves users' capacity to make meaningful use of sentiment analysis. Moreover, through ensuring that users are well-informed and supported, businesses can enhance sentiment analysis to improve data interpretation and decision making. It does not mean however that any of its deficiencies should be disregarded. The variety of support systems applied and the mentioned educational gaps show room for improvement. Thus, in order to further enhance service quality, it is possible to focus on some issues like making sure that there is consistent support across different organizations while improving user training so that it embraces more intricate elements about sentiment analysis as a whole.

5.1.5 System Use

Petter et al. (2008) describes this dimension as “the degree and manner in which staff and customers utilize the capabilities of an information system” (p. 239). The examples of measurements include amount and frequency of use, nature of use, appropriateness of use, extent of use, and purpose of use. Regarding the extent to which sentiment analysis is utilized, the findings presented two different extents of use, and one more general. For R1’s business, sentiment analysis is a component rather than the main focus in their services - it accounts for 5% of their business. R3, on the other hand, expresses that sentiment analysis is central to their operations, especially when it comes to monitoring social media and integrating customer feedback into their service improvements and operational adjustments. R2 describes a broader type of application, leveraging sentiment analysis extensively for brand monitoring, inline with Wisneski (2023) and basing the marketing strategies in accord with the predictions of customer behavior. From the perspective of R4, they describe the general use of sentiment analysis, mentioning the regular use to gauge customer responses to new products or branding changes. They highlight its routine application in marketing and customer engagement strategies. Both R2 and R3 suggest a high degree of integration and reliance on sentiment analysis, compared to R1, while R4 describes the technology’s extent of use more broadly. The description of use from R2, R3 and R4 is supported by Shayaa et al. (2018), whose study has shown that sentiment analysis’ main use is to identify and extract subjective information from large datasets, in this case, social media datasets is one of the examples.

Shayaa et al. (2018) and Wankhade et al. (2022) also describe the opportunity to gain an understanding of the unstructured data as paramount, which can support the findings from specifically R2 and R3. According to them, sentiment analysis is declared in how it directly influences strategic decisions, such as staffing, marketing approaches, and customer service improvements. This demonstrates that sentiment analysis is not only used operationally but also plays a critical role in strategic planning and execution. Furthermore, the insights from R2 and R3 mentions the use of sentiment analysis alongside other analytical tools, indicating a well-integrated approach that enhances the overall analytical capability and provides a more nuanced understanding of customer sentiments and market trends.

What is true to all respondents is their acknowledgement of the usage of sentiment analysis, but they also hint at limitations. The focus of challenges lies in accuracy and the handling of nuanced human expressions like sarcasm or indirect dissatisfaction, which is true to the existing study from Wankhade et al. (2022). This reflects an understanding of the technology’s capabilities and its proper place within a broader analytical context. Another important aspect is that the majority of respondents indicated that sentiment analysis, alone, is not enough to utilize as a tool independently. Both R2 and R3 state that their sentiment analysis is used in combination with other tools, such as CRM, and that they compliment each other’s strengths and limitations. This is also something that Shayaa et al. (2018) reports, stating that other data sources need to be integrated along with sentiment analysis.

5.1.6 User Satisfaction

As it sounds, this dimension of the D&M Model measures the users’ level of satisfaction (Petter et al. 2008). Based on the findings, the overall satisfaction level is positively related. To start off, there is an increasing demand for sentiment analysis in R1 and R2’s businesses, suggesting that users find the tool useful especially in enhancing digital marketing strategies and managing company reputations. Furthermore, the practice of sentiment analysis brings many strategic benefits, like increased content engagement, quick reaction to potential backlash, and the increase in competitiveness by making decisions with predictive analytics. But there are aspects that affect the respondents' satisfaction levels. For R2 and R4, the accuracy and data quality is of concern. They mention that handling spam, irrelevant comments, and analyzing sentiment across different languages proves to be difficult. These issues directly affect the reliability and utility of sentiment analysis. R1 and R3 both agree on the challenges of interpreting the results accurately due to sarcasm, irony, and the genuine feedback, which can lead to misinterpretation and false positives. Furthermore, R1 is reserved with caution, but amongst the terms of reliability and the reliability of the machine, they suggest that sentiment analysis is beneficial, but imposes a condition that it should be used as a supplement rather than as a unique source of information for business decision-making because of its limitations. Continuing on this path, Markham et al. (2015) declares that sentiment analysis should be looked upon as a tool and not the solution itself. It should be used thoughtfully. With their statement, we can draw the connection here that R1, R3 and R4 indirectly realizes this, being cautious of the use of sentiment analysis and understanding the grade of value. They reinforce the idea that the value of analytics as a component of a comprehensive decision-making framework, rather than as a standalone solution. Finally, R4 notes challenges specific to certain regions and industries, such as difficulties with language diversity and data formats, which can significantly impact the effectiveness and their satisfaction derived from sentiment analysis tools.

5.1.7 Net Benefits

Petter et al. (2008) describes this dimension by the extent to which IS is contributing to the success of individuals, groups, organizations, industries, and nations. For this thesis, relevant metrics include improved decision making, improved productivity, and cost reductions. What is important to note is that benefits are not always advantageous and positive perks, it can also be negative and provide negative feedback loops.

5.1.7.1 Overall Impact

When it comes to positive net benefits outside of digital marketing, automation and the consequently productivity is one of them. In this thesis' findings, R1 mentions that sentiment analysis is automating the analysis of text data. In this case it means that they do not need any manual labor to go through each text and sort out the sentiments, which the technology now does for them. This process is beneficial, providing significant time savings and efficiency gains which directly contribute to the operational effectiveness of an organization.

Moreover, sarcasm, irony or manipulation can make it impossible for the data to accurately reflect customer sentiments. In conclusion R1 states that sentiment analysis has to be done with great care and integrated wisely in order not to misrepresent customers' opinions and viewpoints. Thus, it is therefore context-specific and the nature of the product being sold as well as the quality of data used also matter a lot in its application. This suggests a conditional benefit, where sentiment analysis is highly valuable but must be employed accordingly to avoid detrimental decision-making based on inaccurate data.

Finally, resource implications of accuracy focus on the trade-offs associated with high-accuracy sentiment analysis or other related issues such as speed, resources and cost. However, sometimes achieving high levels of accuracy may outweigh their benefits when considered against their costs and demands for resources required. Consequently a careful thought needs to be given to allocating resources when high-accuracy modules are implemented in sentiment analysis. Organizations have to assess if increased accuracy justifies additional expenses and possible delays.

5.1.7.2 Sentiment Analysis Role in Digital Marketing

Sentiment analysis has been shown to provide significant advantages in the context of digital marketing. Overall, the findings show that sentiment analysis has quite an impact on decision making in the context of digital marketing. Wankhade et al. (2022) and Shayaa et al. (2018) address the different uses of sentiment analysis in various fields, stressing out on its increasing significance attributed to the internet's growth and social media. This resonates with the findings where digital marketing employs sentiment analysis for improved customer engagement. This is shown by adaptive content strategies that use feedback from sentiments to promote more personalized marketing. However R1 and R2 suggest using sentiment analysis techniques to tailor make content according to customers' liking so as to improve targeting and align promotional activities with user's reviews as stated by Chaffey & Ellis-Chadwick (2022). Moreover, it demands our attentiveness to the audience and a comprehensive knowledge of our customer characteristics and behavior. By doing this, it generates loyal customers as well as improves the further development of the product or service they are offering. Digital marketing is a technology that has its place in informing and refining digital marketing strategies e.g. healthcare, financial sector and among others as a means of developing innovative ways of engaging with its customers (Shayaa et al. 2018 & Wankhade et al. 2022). In addition, Wisneski (2023) shows how sentiment analysis can be used to keep pace with public opinion enabling business entities to handle reputations better and respond to negative comments quickly. This backs what R2 says about the net benefit that implies another core net benefit being able to control and regulate one's reputation proactively. Companies should review the public's perception about their products or brands so that they could be aware of any negative feedback while positive vibes are promoted enhancing a good image for an organization. Additionally, by using sentiment analysis for prediction, firms can outpace market trends as well as consumer behaviors that would give them an upper hand in the market – something R2 highlights as extremely important for maintaining operational excellence and staying relevant in the market.

One of the more tangible net benefits of sentiment analysis in digital marketing, as discussed by R3, involves the optimization of marketing expenditures to enhance the ROI of campaigns. The predictive capabilities of sentiment analysis enable targeted promotional campaigns, such as coupon distribution to consumers most likely to respond. This not only increases the effectiveness of marketing spend but also reduces wastage on unresponsive segments, thereby optimizing overall marketing investments. Moreover, an example provided by R3 about the car dealership network illustrates how sentiment analysis, integrated with NLP, can influence operational decisions across a large-scale business network. By analyzing customer feedback and sentiment, businesses can discern whether fluctuations in sales or performance are due to actual business actions or random variations. In line with Dash et al. (2022) and their mentioning of sentiment analysis impact on decision making, this insight is crucial for informed decision-making regarding resource allocation, training, and management practices.

When it comes to the case of products, Dash et al. (2022) has their relevance here too. They mention that informed decisions due to sentiment analysis can be made to adjust their products. R4's commentary on using sentiment analysis for timing product launches provides insight into strategic market entry, and connects with the study conducted by Dash et al. (2022). Understanding customer sentiment is not just regarding the product, but additional aspects like launch timing, can help companies optimize their product introductions to meet consumer needs better and avoid potential backlash or dissatisfaction, thereby smoothing the path for successful product adoption. Lastly, the impact of the quality and accuracy of sentiment analysis data cannot be understated, as mentioned by R2 and R4. High-quality sentiment analysis can provide the necessary insights for precise strategy formulation and campaign optimization, critical for effective digital marketing. It ensures that decisions are based on accurate and reliable data, reducing risks and enhancing the potential for success. Here, studies about big data come into play. To ensure reliable and accurate data as fundamental pillars for the decisions represents the V of Value in the field of big data, that declares the benefits to businesses of big data insights (Vijayarani & Sharmila 2016).

5.2 Future Role of Sentiment Analysis in Digital Marketing

They outline that the dynamic transformation is mostly powered by the digital improvements based on innovative technologies like those introduced by OpenAI. With the current minimal impact on the company of 5%, they are sure that R1 is the primary nominee expecting situations to behave in a way the company will feel no influence. They further suggest that researchers will manage this through forms of AI alongside machine learning, tackling the issues such as detecting humor or irony in different languages. This is currently overlooked by the existing models and gives a hint for the future program of improving such capabilities through programs of further developing AI. R1 is positive about major steps in model adjustment and increase in quality, and therefore, R1 forecasts huge growth in the profitability of sentiment analysis applications in business sectors in the upcoming years. On the other hand, R3 puts his mind across giving a glimpse of the passive nature of NLPs as compared to the active approach of digital marketing. Here, R3 implicitly demonstrates the active role digital marketing has by choosing the content that the customer might like to watch (R3:49). R3 also notes that the passive sentiment analysis is evolving from merely processing incoming data to generating communicative output that interacts with the world - an active role. With the background of Shayaa et al. (2018) study, it is safe to say that R1 and R3 has a point, as the opportunity to gain an understanding of the data is paramount. Sentiment analysis is important in that regard of text analytics. Additionally, R2 emphasizes the need for continuous adaptation and innovation in sentiment analysis, including aspects like customer preferences and communication channels, to maintain its accuracy and relevance amidst the growing volume of data.

6 Conclusion

This is the concluding chapter where we argue for the success of sentiment analysis and its role for digital marketing.

The purpose of this study was to evaluate the success of sentiment analysis based on the D&M Model and what kind of role it has in the digital marketing context. The literature reviews digital marketing, big data and sentiment analysis, together with the theoretical framework that is the D&M Model for evaluating IS success, which also laid as a base for the semi-structured interviews. The respondents are individuals who had the roles of data analysts and data scientists and were experienced with either developing or using sentiment analysis within their business and digital marketing. Through analyzing our empirical results, the research has systematically explored the multifaceted roles and success of sentiment analysis within businesses and for individual users, particularly within the context of digital marketing. The comprehensive review of literature coupled with interview findings underscores the significant impact of sentiment analysis on enhancing digital marketing strategies and overall business success. We will also argue for the success of sentiment analysis based on the dimensions of the D&M Model.

Sentiment analysis can be considered successful in terms of the dimension “System Quality” when contextual conditions are favorable. More specifically, when there is control over data types and low linguistic diversity. According to us, the tools demonstrate a high degree of sophistication, adaptability, and user-driven improvement, aligning with the key characteristics of system quality. However, sentiment analysis’ effectiveness is conditional in the aspect of this dimension, in the terms that it relies on continuous advancements and adaptations to overcome inherent challenges such as data variety and language complexities. Thus, we argue that while sentiment analysis exhibits substantial strengths that contribute to its success for this dimension, it also requires ongoing scrutiny and adjustment to realize its full potential within the broader context of digital applications.

While sentiment analysis faces challenges that may impact the perfection of its outputs, we argue that it overwhelmingly succeeds in delivering high-quality information that is relevant, timely, understandable, and generally accurate. This makes it an invaluable tool in the arsenal of digital marketing and customer relationship management, aligning well with the "Information Quality" dimension of the D&M Model. The ongoing improvements and adaptations in sentiment analysis technology also suggest a trajectory towards even greater accuracy and applicability, promising to enhance its efficacy and success in the future.

The success of sentiment analysis in the dimension of "Service Quality" is evident through the examples where respondents have put in effort for effective support infrastructure that enhance user competence and satisfaction. These support frameworks not only aid in the direct application of the technology but also foster an environment where continuous learning and adaptation are encouraged. We therefore argue that “Service Quality” is generally good, based on the findings that implies no worries for the characteristics of this dimension. To further this success, there is a need for consistent support across different organizations and an expansion in user education to cover more complex aspects of sentiment analysis. This ongoing enhancement of service quality will ensure that sentiment analysis remains a valuable tool in the arsenal of digital marketing strategies, supporting businesses in navigating the complexities of modern data-driven environments.

The success of sentiment analysis in the dimension of "System Use" within the D&M Model is clearly demonstrated by its extensive and strategic utilization across various businesses. Its role in enhancing decision-making, improving customer engagement, and informing strategic planning underscores its effectiveness as a critical tool in the arsenal of modern digital marketing and business operations. This widespread and strategic use, coupled with ongoing integration with other tools, ensures that sentiment analysis remains a valuable asset in navigating the complexities of today's digital landscape. As follows, we appeal to the success of “System Use”, evaluating this dimension as very high for its purpose of use, and the amount and frequency of use.

The user satisfaction for sentiment analysis is successful when the NLP task is used appropriately and thoughtfully. The satisfaction bases of the fact that the technology provides valuable insights that helps businesses tailor their strategies more effectively and respond more adeptly to market dynamics. However, there is a general user awareness of its limitations. Though, the general user satisfaction does not drop down even with the understanding of the challenges, as the acknowledgement and maturity of the limitations are well known. These challenges are mitigated by integrating sentiment analysis carefully with other data sources and analytical tools to ensure the most reliable and effective outcomes. This blanched approach confirms the success of user satisfaction around sentiment analysis within the digital marketing context, making it a vital tool in the arsenal of modern marketers. With the results provided, we are contented with saying that the user satisfaction is generally high for sentiment analysis use.

Sentiment analysis, when implemented effectively, fulfills the criteria of the "Net Benefits" dimension of the D&M Model by contributing to the success of individuals, groups, organizations, and even industries through improved decision-making, enhanced productivity, and cost efficiencies. While there are challenges such as the need for high accuracy and managing data quality, the overall advantages it offers, particularly in digital marketing, affirm its value and success. The strategic utilization of sentiment analysis in understanding and responding to customer sentiments not only enhances customer experiences but also drives operational superiority and market relevance. Therefore, sentiment analysis is indeed a successful tool within the realms of digital marketing and beyond, as long as it is employed thoughtfully and with consideration to its inherent limitations and challenges.

Sentiment analysis is poised to become even more critical in shaping the strategic initiatives of digital marketing. Its ability to provide real-time, nuanced insights into consumer emotions and preferences will increasingly drive the development of more personalized, responsive, and effective marketing strategies.

Appendix 1 - Interview Guide (Old)

This old interview guide was structured to gain insights in sentiment analysis and its role for digital product development. Its main purpose was to originally answer a redacted research question. As one of the interviews conducted used this guide as its template, this appendix remains for clarity in the first interview conducted (see Appendix 3).

Introduction

- We greet the interviewee and introduce ourselves and our research purpose
- We explain the structure of the interview and estimated duration
- We remind the interviewee about confidentiality and explain the usage of the data that's about to be collected
- We ask for permission to record the interview for accuracy in data collection
- We ask if the interviewee has any initial questions before starting the interview

Interview Questions

Background Information

- Could you please introduce yourself and the company? What is your role and your responsibilities in the organization?
    - How long have you been involved in this role?
- What is the digital product that your organization manages?
    - What goals does the company aim to achieve with [product name]?
    - What kind of association does your role have in ties with the product?
- Any experience of involvement in digital product development for your business?
    - What kind of association does your role have in ties with product development?

Main

Context / Theme	Question	Dimension of IS Success Model (The D&M Model)
Digital Product Development	**Q1a:** What approach / methodology does your organization use in your product development? (Scrum, Lean, etc.)	
	Q1b: Can you walk us through a typical product development cycle in your organization?	
Big Data and Big Data Analytics	**Q2a:** What kind of data do you collect (user insights) and to what extent (platforms)?	
	Q2b: What type of format is the data that you collect in (text/audio/video)?	
	Q3: Have you experienced any challenges associated with managing and analyzing big data? (As a business and/or individually)	
Sentiment Analysis	**Q4a:** Can you give us an overview of how sentiment analysis is applied on the user feedback data that you collect?	
	Q4b: What other tools do you use aside from Sentiment Analysis? Can you compare them? (tools and technologies)	
Evaluating Information Systems Success	**Q5:** To what degree and manner would you say you utilize the capabilities of sentiment analysis? (e.g. amount, frequency of use, nature of use, appropriateness of use, extent of use, purpose of use)	System Use (Intention to use / Use)

Context / Theme	Question	Dimension of IS Success Model (The D&M Model)
	Q6: How do you evaluate the quality of the sentiment analysis tools? (ease of use & learning , system flexibility, reliability, features of intuitiveness, response times)	System Quality
	Q7a: Can you describe the quality of the information you receive from sentiment analysis (specifically from user / customer feedback)? (relevance, understandability, accuracy, conciseness, completeness, understandability, timeliness, usability)	Information Quality
	Q7b: Do you think that the quality of the output influences the decision making?	Information Quality
	Q8a: Can you come up with any examples of how integrating sentiment analysis has changed the way you develop products? (e.g. what stage in product development (design, analysis, etc.))	System Use (Intention to use / Use)
	Q8b: Is this impact measurable or quantifiable?	Net Benefits
	Q9a: Have you observed any benefits of using sentiment analysis in your product development? (specifically any improved decision making process?)	Net Benefits

Context / Theme	**Question**	**Dimension of IS Success Model (The D&M Model)**
	Q9b: Any other benefits in… - product innovation, - customer satisfaction, - productivity - market competitiveness, - improved profits, - economic development, - creation of jobs?	Net Benefits
	Q10: Is the sentiment analysis tool, alone, enough for understanding the custome**r** / user feedback of your product?	System Quality
	Q11: Have you experienced technical issues with sentiment analysis?	System Quality
	Q12: How satisfied are you and your team with the sentiment analysis tools and the information they provide?	User Satisfaction
	Q13: Are there specific areas they find more valuable or challenging?	User Satisfaction
	Q14: What kind of support do you receive for sentiment analysis tools? Can you evaluate the quality of the support service? (e.g. responsiveness, accuracy, reliability, technical competence, empathy of the support staff)	Service Quality

Closing

- "Is there anything else you would like to add that we have not covered, which you think is important for our study?"
- "Thank you for your time and insights. Your participation is invaluable to our research. We may follow up if additional clarifications are needed. Would that be acceptable?"

End

Conclusion

- Summarize the main points discussed and thank the interviewee for their time.
- Explain the next steps (e.g., how and when the results will be shared, how to access the final thesis, etc.).
- Offer to answer any questions they might have.

Appendix 2 - Interview Guide (New)

This updated interview guide was structured to gain insights in sentiment analysis and its role for digital marketing (see Appendix 4-6).

Introduction

- We greet the interviewee and introduce ourselves and our research purpose
- We explain the structure of the interview and estimated duration
- We remind the interviewee about confidentiality and explain the usage of the data that's about to be collected
- We ask for permission to record the interview for accuracy in data collection
- We ask if the interviewee has any initial questions before starting the interview

Interview Questions

Background Information

- Could you please introduce yourself and the company? What is your role and your responsibilities in the organization?
    - How long have you been involved in this role?

Main

Context / Theme	**Question**	**Dimension of IS Success Model (The D&M Model)**
Digital Marketing	**Q1a:** Do you in your business / organization have digital marketing?	
	Q1b: Do you use any kind of platform(s) for your digital marketing? Can you describe it/them? (email, social media, affiliate, paid etc.)	
	Q1c: What reach do you have and to what extent? (what kind of customers)	

Context / Theme	Question	Dimension of IS Success Model (The D&M Model)
Big Data and Big Data Analytics	**Q2a:** What kind of data do you collect and to what extent (platforms)?	
	Q2b: What type of format is the data that you collect in (text/audio/video)?	
	Q3: Have you experienced any challenges associated with managing and analyzing big data? (As a business and/or individually)	
Sentiment Analysis	**Q4a:** Can you give us an overview of your sentiment analysis that you use or provide?	
	Q4b: Do you use any other tools aside from Sentiment Analysis? Can you compare them?	
Evaluating Information Systems Success	**Q5a:** To what degree and manner would you say you utilize the capabilities of sentiment analysis? (e.g. amount, frequency of use, nature of use, appropriateness of use, extent of use, purpose of use)	System Use (Intention to use / Use)
	Q5b: Can you come up with any examples of how integrating sentiment analysis has changed the way you market yourselves digitally?	System Use (Intention to use / Use)
	Q5c: Is this impact measurable or quantifiable?	Net Benefits

Context / Theme	Question	Dimension of IS Success Model (The D&M Model)
	Q6: How do you evaluate the quality of the sentiment analysis tools? (ease of use & learning , system flexibility, reliability, features of intuitiveness, response times)	System Quality
	Q7a: Can you describe the quality of the information you receive (output) from your sentiment analysis? (e.g. relevance, understandability, accuracy, conciseness, completeness, understandability, timeliness, usability)	Information Quality
	Q7b: How important is the quality of the output for your marketing decisions or the customers? Can you give any examples?	Information Quality
	Q8a: Have you observed any benefits of using sentiment analysis in your digital marketing?	Net Benefits
	Q8b: Any other benefits in… - product innovation, - customer satisfaction, - productivity - market competitiveness, - improved profits, - economic development, - creation of jobs?	Net Benefits
	Q9: Is the sentiment analysis tool, alone, enough for understanding the customer engagement?	System Use (Intention to use / Use)

Context / Theme	Question	Dimension of IS Success Model (The D&M Model)
	Q10: Have you experienced technical issues with sentiment analysis?	System Quality
	Q11: What kind of support do you receive / give out for your sentiment analysis tools? Can you evaluate the quality of the support service? (e.g. responsiveness, accuracy, reliability, technical competence, empathy of the support staff)	Service Quality
	Q12: How satisfied are you and your team with the sentiment analysis tools, the information they provide and the service?	User Satisfaction
	Q13: Are there specific areas you find more valuable or challenging that affects your satisfaction levels?	User Satisfaction

Closing

- "Is there anything else you would like to add that we have not covered, which you think is important for our study?"
- "Thank you for your time and insights. Your participation is invaluable to our research. We may follow up if additional clarifications are needed. Would that be acceptable?"

End

Conclusion

- Summarize the main points discussed and thank the interviewee for their time.
- Explain the next steps (e.g., how and when the results will be shared, how to access the final thesis, etc.).
- Offer to answer any questions they might have.

Appendix 3 - Semi-Structured Interview R1

Date: 23-04-2024
Length: 49:06 minutes
Participants: Respondent 1 (R1), Welman Lam (WL) & Sofia Erikson (SE)
Language: English

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
1	WL	Yes, hello. So could you please introduce yourself and the company, more specifically, what is your role and your responsibilities within the organization?		
2	R1	So my name is [NAME] and I work as a senior data scientist at [COMPANY], which is a digital marketing platform, influencer marketing, focusing on games and how they market themselves on different platforms such as TikTok and Twitch and YouTube. And my role in that is to basically be the leader when it comes to how we work with and handle data, anything from sourcing data to implementing dashboards for different kinds of use cases to follow up on internal KPIs and then also implementing machine learning and AI at scale.		
3	WL	All right. You did mention your product a bit. What more, specifically, is the goal with this platform and what kind of association do you have towards this platform?		
4	R1	Yeah, as I mentioned, it's a marketing platform with the goal then, to you as a company or a publisher for us, which is our core customer segment, to basically		

Row	**Person**	**Transcription**	**Context / Theme**	**Dimension of IS Success Model (The D&M Model)**
		market yourself and in this case, your new game towards your potential audience or buyers or what it might be. So it might be everything from a new game release or your latest game in your portfolio to, let's say, a new patch or whatever it might be. And the target can be different gaming channels. So we use them. We match creators, as we call them, based on what game is in scope for you as a publisher and what goals you might have with your marketing activity. So it's all about either reach or different kinds of KPIs that is relevant for the customer.		
5	WL	All right. And your association to this product, what is your role towards this product? I don't know if you did mention it.		
6	R1	I think I mentioned it, but I can mention it again. So we are a very data-driven company, and we want to do things at scale and as automatic and accurate as possible. So a centerpiece of our way of achieving and providing the results that we aim for are based on using the different kinds of data that we then collect. So my association with that is then to build out the different capabilities that helps us achieve that.		
7	WL	All right. So you do have a role tied to this product development of yours, yes. Do you know what kind of approach slash methodology you have in your process of product development? Do you know if you use Scrum or	Digital Product Development	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		Lean or any other?		
8	R1	Yeah, we have been and are currently working according to Scrum. We are, without going into too much details on that topic, sort of adjusting and maybe changing that now, actually, with the reason being that the framework of Scrum can be, of course, quite positive, but it all boils down to what fits us as a company and as the product goals and team dynamics and such. So I would say that we are following Scrum currently, but we are actually revisiting that methodology.	Digital Product Development	
9	WL	All right. In [COMPANY], your company, can you maybe walk us through a typical product development cycle for you?	Digital Product Development	
10	R1	Yes, we work a lot with opportunity scoping and how an opportunity goes through different stages. So it might be an idea that someone in the company have, either it's coming from an external stakeholder or an internal user or part of the commercial team or, like, let's say the sales team or even someone like me from tech. So we raise this kind of idea. We look at that from a product perspective, looking at product market fit and how many potential customers might be interested in this kind of product and how does it tie into our process or portfolio of products? Or it might be an addition to an already existing product, like an improvement or something. So once we have identified how that idea and	Digital Product Development	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		opportunity then can fit our internal or external needs, then we move that into discovery phases and then solution stages where we as a tech team present different kind of solutions and maybe sort of the costs associated with that kind of solution in man hours or time spent on reaching the result. And then that becomes like a feedback loop where we together then with product and stakeholders then like, OK, what are we really aiming for? And then once we all agree on that, we go for implementation and basically go into the whole, you know, regular cycle of demos and informing the stakeholders and stuff like that. So it's a very healthy process, I would say.		
11	WL	Right. Yeah, I assume you are familiar with sprints and stuff, right?	Digital Product Development	
12	R1	Yes.	Digital Product Development	
13	WL	So let's thank you for that. Let's dwell into big data a bit. So for this digital product that you're managing, right? What kind of data do you collect and to what extent? And what I mean by extent is from, for example, what platforms, blogs maybe or online reviews, if you have that. Can you walk us through that?	Big Data and Big Data Analytics	
14	R1	Our main sources are platforms related to gaming channels like streaming and video creation. So like the big ones, you say, as I mentioned, like, our publishers or	Big Data and Big Data Analytics	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		our customers want to reach an audience that consume Twitch or YouTube or TikTok. So in that, like in that lies the answer to your question in that those are the sources that we mainly collect and then build up on our sort of creator index, as we call it. And those are quite different in how they work and how they provide data externally. So we have almost close to real time data from the live streaming services. And then for, let's say, YouTube, it's maybe more on a scheduled basis where we collect data in different kind of aspects. But we are working with millions and millions of rows. And we have a case now where we'll go into the billions when it comes to data volumes as in number of rows, basically. So we are definitely, I mean, touching or are within the big data aspect. But it's not maybe I mean, it's kind of a scale, right? When you look at big data, it can be insane amounts of volume and insane volumes in a data warehouse. I mean, I was I worked with bigger volumes. I would say that we are within the big data category listening to them. Yeah, real time data and different kind of events that occur on these platforms.		
15	WL	All right, this huge vast amount of data that you're collecting, I assume you collect from users slash customers?	Big Data and Big Data Analytics	
16	R1	I mean, it's basically it's mainly about the type of content that's being produced and connections to that. So people watching or	Big Data and Big Data Analytics	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		people commenting, what are they commenting and stuff like that? So it's more on that basis rather than, yeah, if you would define users as that, yeah, sure.		
17	SE	So it doesn't necessarily have to be like insights or opinions. It can just be anything that's like related to the topic of whatever you're interested in?	Big Data and Big Data Analytics	
18	R1	Yeah, pretty much. Since I mean, a lot of it is or everything that we consume is, in a sense, public data. Means that, I mean, when it comes to, let's say, comments on a YouTube video, then that is something that we can collect and consume. The same with the Twitch chat data, for instance. That's something that we collect and that is available.	Big Data and Big Data Analytics	
19	WL	Yes. And does the data you collect have an impact for your product development as well?	Big Data and Big Data Analytics	
20	R1	Yes, I would say it's instrumental.	Big Data and Big Data Analytics	
21	WL	All right, just a quick question. What type of format do you collect? Is it mostly textual data?	Big Data and Big Data Analytics	
22	R1	No, I wouldn't say so. I would say it's more, I mean, statistics connected to a period in time. And whatever data that's connected to that specific point in time. So it's both textual data, if you'd go into like comments or chat messages. But then also, yeah, I mean, statistics connected to that kind of content being produced.	Big Data and Big Data Analytics	

Row	**Person**	**Transcription**	**Context / Theme**	**Dimension of IS Success Model (The D&M Model)**
23	WL	All right. Can you describe, do you have any examples of challenges associated to collecting data as of right now?	Big Data and Big Data Analytics	
24	R1	I mean, yeah, I think collecting data at scale is always going to be a complex topic. And to do that in a smart way, I mean, creates a lot of demands on the kind of tech that you need to enable that and what requirements that our products have on that. So different stages of a product might have different needs in how often data should be collected, for instance, and if you collect it more often than the volumes increase and storing that in an efficient manner. So you can actually use that is, of course, a key component. Otherwise, it's quite wasted.	Big Data and Big Data Analytics	
25	WL	All right, thank you. Let's delve deeper into sentiment analysis. So [COMPANY], just so you can confirm, uses sentiment analysis?	Sentiment Analysis	
26	R1	Yes, we use sentiment analysis.	Sentiment Analysis	
27	WL	Yes. So can you give us an overview of how you apply sentiment analysis on the data that you collect?	Sentiment Analysis	
28	R1	Yes, since we're a marketing platform, which means that our customers want to market themselves through these channels on different kind of mediums. And an important aspect of that is, of course, like, how do you measure success? OK, we have different statistics connected to	Sentiment Analysis	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		how many people view the content or click the link or whatever it might be. And one additional part, since like chat and comment data is available, that opens up the possibility to correlate, OK, what is being said about the content produced and looking at that kind of unstructured text data, it's quite difficult to make sense of it by just scrolling through the several thousands of comments or chat messages. And it's a lot of, I would say, depending on the type of medium, like the junk in the messages being written. On Twitch, for instance, you have a lot of a language that's quite maybe a lot of memes or a lot of a different kind of maybe way of chatting or talking and how you derive the… what's it called? Like the what is actually being said and how do you connect that to what the content was really about, is of course, quite difficult. And that's where models within or approaches within sentiment analysis can help us to aggregate that and summarize it in a sense that can be used to just have a quick look at it and then understand how it really landed with the audience. And then you have additional complexity on that, of course, that a certain channel that we are working with might have sort of a negative attitude, but that is not necessarily meaning that the content and what is being produced have a negative sense of it. It's just the channel itself is like that. So you have the persona of the creator is		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		connected to the persona of the people watching it. So the persona of the messages or the sentiment is probably highly correlated to that kind of persona. But yeah.		
29	WL	So obviously, [COMPANY] uses sentiment analysis, but do you also have other tools that you use aside from sentiment analysis for analyzing this data?	Sentiment Analysis	
30	R1	Can you… can you exemplify that?	Sentiment Analysis	
31	WL	For example, so sentiment analysis is a tool that is encompassed by NLP natural language processing. Are there any other tools or technologies that you use aside from sentiment analysis to analyze this data that you collect? Or is it just only sentiment analysis that you use?	Sentiment Analysis	
32	R1	I- We use a lot. Now we use if you look at like ML and AI and those kind of things, we use quite a lot more than that.	Sentiment Analysis	
33	WL	All right. Let's dig deep into specifically sentiment analysis and the tool that you use. So when it comes to the system use of sentiment analysis, what would you say is to what degree and manner would you say that you utilize the capabilities of sentiment analysis? So this can be everything from the amount of use, frequency of use, right? The nature of use and purpose of use and stuff like that.	Evaluating Information Systems Success	System Use (Intention to use / Use)
34	R1	I wouldn't say that the way that we use it is like the centerpiece of	Evaluating Information	System Use (Intention to use

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		our portfolio or within any of the products. It's more something that we offer and we have as part of our sort of architecture, like infrastructure or portfolio. But it's not a driving service in any of our sort of offerings. It is there, and we definitely identify more possibilities within that area and have it to be more maybe impactful towards our clients and for us as well. But I mean, there are a lot of difficulties since we work on a global scale, so we work across different languages and different countries. And then being able to then process both spoken language and written language in different or sorry, spoken and written language and then make sense of that, I mean, adds on other complexities. So that's definitely a lot more potential than what we currently use it for. It's all about putting it together and actually capturing it in the product. So I would say it's maybe, let's say, five percent impact or like a part of our business. But it's something that's on the rise, something that I think is increasing.	Systems Success	/ Use)
35	WL	Yeah, it is a relatively new tool and technology that you use. Am I correct?	Evaluating Information Systems Success	System Use (Intention to use / Use)
36	R1	You mean for us as a company or?	Evaluating Information Systems Success	System Use (Intention to use / Use)
37	WL	Yeah, exactly.	Evaluating Information	System Use (Intention to use

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
			Systems Success	/ Use)
38	R1	Yeah, I would say I've been at [COMPANY] for almost two and a half years. And I would say we maybe started using it to some degree, say, I mean, within the last year or something. And it's as I said, like we we are quite broad in the area when it comes to the data and AI. So there are a lot of other different capabilities that we explore. But I think this one is now getting more attention than before.	Evaluating Information Systems Success	System Use (Intention to use / Use)
39	WL	Yeah. You mentioned before that it is a complexity in itself of using sentiment analysis. But how do you currently evaluate the quality of the sentiment analysis tool right now?	Evaluating Information Systems Success	System Quality
40	R1	I would say that…	Evaluating Information Systems Success	System Quality
41	WL	I can give you some examples?	Evaluating Information Systems Success	System Quality
42	R1	Yeah, sure.	Evaluating Information Systems Success	System Quality
43	WL	For example, like ease of use, maybe response times, if that is relevant as well, flexibility, reliability and stuff like that.	Evaluating Information Systems Success	System Quality
44	R1	I would say that there are different kind of answers depending on	Evaluating Information	System Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		what service we look at, because we have like two sentiment analysis systems or services in place. One of them is more in production than the other one. The one in production, I would say, is quite potent. The way for us to sort of try to ensure some kind of quality is to use a combination of models where we see that certain models have different strengths and weaknesses. Some of them are more maybe complex and sometimes maybe too complex. Some of them are actually better at capturing, you know, simple signals in the kind of data. So what we try to do is to use a combination of different models as like a voting mechanism. And then the most dominant sentiment score or sentiment output is the one that we flag the text with, basically. And then it's just a matter of, you know, there are, of course, limitations or maybe I would say it like complexity in the kind of text, like detecting sarcasm and irony and things like that are very difficult because it might be the tone of voice that also affects how that text data is actually to be interpreted. So that's a topic that we want to explore further. So now it's way easier to, of course, work with the actual text data. It's quite cheap to, you know, store and work with a set of strings, but add on a level of irony or sarcasm or start analyzing the audio data would be quite interesting to see how we can use AI to do that. So I would say, I mean, yeah, if the data that you're	Systems Success	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		analyzing have a lot of irony and sarcasm in it, it will probably be outputted as quite negative, but maybe the meaning was actually positive. So it's always it's very difficult to define that kind of sweet spot of like a correct representation of what is actually being, you know, said, what's the message or is it positive, negative or whatever is on that? What is the underlying sort of message of it?		
45	WL	Yeah. And that is what you're saying is in tune of what is currently what the research world is also saying that sentiment analysis have a hard time taking interpreting like sarcasm, for example, and irony and stuff like that, as well as like cultural context.	Evaluating Information Systems Success	System Quality
46	R1	Yeah, exactly.	Evaluating Information Systems Success	System Quality
47	WL	Yes. Thank you for that answer. You talked about the tool itself and how you would evaluate the, yeah, like I said, the tool of sentiment analysis. When it comes to the quality of the output of sentiment analysis, can you describe the quality or rather the output of sentiment analysis? How would you evaluate that?	Evaluating Information Systems Success	Information Quality
48	R1	Yeah, I would say it's difficult to do that without any kind of manual or human interference, since you have the aspect of, especially as I mentioned, like we	Evaluating Information Systems Success	Information Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		operate in different languages. Let's say that we are analyzing something in German and we translate that to English and then pass that through downstream sentiment analysis. So some things are prone to that kind of misalignment maybe between what was said in the native language and the translated language and how that is captured. I would say that we could do more on that area where we, yeah, I mean, it's difficult to not do any kind of manual or human quality check of the output, since that's the whole thing that if you don't have an NLP model or a model that is good at capturing, I mean, how certain words are mentioned or like with sarcasm and irony, it's difficult to then of course know that, yeah, now we know that the output is always accurate or a good representation. So I would say it's case to case. The way that we use the service or provide that is towards an end user. So of course, there are cases where the end user raises questions or concerns about the output. And then in those cases, we might look at it and say that, yeah, OK, this is why this text or whatever was captured as this target or this output labeled as in a certain way. And there, I think that looking at the NLP field and you look at like ChatGPT or AI or any kind of LLM or NLP models out there, you have these kind of hybrids where you retrain a model based on a human interfered or like a catered answer or you have		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		quality check the output and then you change that accordingly. So I think for us, it's also an opportunity to tune this model based on the manual quality assessment that we could perform to guarantee or improve the quality going forward.		
49	WL	Yeah. So right now, the output of Sentiment Analysis is not 100% accurate. It's not maybe 100% relevant and like understandability is not also at 100% as well is what you're saying, right?	Evaluating Information Systems Success	Information Quality
50	R1	Yeah, I mean, I think I think within this field, at least currently, there will always be cases that our difficulty will be borderline or outlier cases, anomalies or whatever. And it's, as I said, like, it's difficult to know the output from that kind of service without looking at and quality checking the output with the input. It's, of course, difficult to say that, yeah, this is 100% accurate or whatever. I think that's always the case, but I think in our case, we kind of weight, I mean, doing it full automatically using these kind of applications means that we don't have to do it manually. And if the output is somewhere quite close, I mean, no, it's not exactly the same as if you would analyze it manually and you would capture the sarcasm and irony. But I think it's quite accurate to assume that and that occurs quite seldom. So in the end, the representation is probably quite close to if you did it manually, but we are able to do it. We are able to analyze, let's	Evaluating Information Systems Success	Information Quality

Row	**Person**	**Transcription**	**Context / Theme**	**Dimension of IS Success Model (The D&M Model)**
		say, let's put it, let's just take a number like we can analyze 100 messages per second, or we can analyze a two hour long video in two minutes. But for you, it would take you need to watch the whole video for two hours. You need to maybe, you know, scribble, I mean, transcribe everything manually and then you need to redo it again. So it would take you six hours to arrive to an output. But we did it in or the service could do it in two minutes. And most likely in a large set of cases, if you simulate it, I think the output would be quite close on like a total level. So I think, yeah, that's where I think NLP and sentiment analysis and those kind of things can, it's not you can't guarantee you arrive to 100% accuracy, but you will get the rough sort of consensus of it.		
51	WL	Yeah, exactly. Let's dig into the application of sentimental analysis and how it influences your digital product development of your platform. Would you say that the quality of the output influences the decision making in your product development?	Evaluating Information Systems Success	Information Quality
52	R1	No, since this is not really, we don't apply these kind of services or models on anything that's being said about our products that we deliver. It's rather of the material that is being broadcasted through our product, but it's not connected to our product per se, but rather the customer that wants to market themselves. So it's more about maybe it would rather be the	Evaluating Information Systems Success	Information Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		potential of the customer being able to adjust and change maybe those parts of their product based on the input that people are saying or writing about or commenting about the content that's being shown on the platform. So it's more about our offering of that so they can get that kind of feedback. And that doesn't mean that we couldn't utilize this if we receive feedback on our products, but that's of course a possibility, but nothing that we use as part of our product development today.		
53	WL	All right, so since you are not using sentimental analysis more directly or targeting on your digital product development, you don't have any example of how integrating sentiment analysis into your digital product development, or do you have an example of that, of integrating sentiment analysis in the case-	Evaluating Information Systems Success	System Use (Intention to use / Use)
54	R1	You mean if we would do that, how would use it?	Evaluating Information Systems Success	System Use (Intention to use / Use)
55	WL	Yeah, or yeah, if we talk about today, right, simply do you have any examples of integrating sentiment analysis and how that has maybe impacted the way you develop products or have made any changes? Do you have any examples of that currently?	Evaluating Information Systems Success	System Use (Intention to use / Use)
56	R1	No, since the output of our sentiment analysis services is not correlated or directed towards what we develop, but rather what	Evaluating Information Systems Success	System Use (Intention to use / Use)

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		our customers develop. So you could, if you take the example of you manufacture watches, and you want to create a couple of, you want to market your new watch through YouTube or Twitch, and then people, so you do that through [COMPANY], let's say, and then based on the comments on the creators that made the commercial or ad for your watch, then it's rather the sentiment on the comments made on the segment where your watch was being talked about is more for you to act on as the watch manufacturer rather than [COMPANY] to iterate or change the way that we develop our products. So I don't have an example of that at [COMPANY], but I have examples of that maybe from other companies, and so I think if we would have that, of course, it would be impactful, and I think an important aspect of that, if we would use it, is that how you collect or maybe how you prompt your users on the sort of input you need and the input that you want to apply the sentiment on becomes crucial as well. So if you have, of course, you can have like an open field or form where you can put in whatever, like a Google review, and I mean, that's something that you could utilize that for, but it doesn't apply currently, so I don't have any examples where I could say that it's impactful for us.		
57	WL	Yeah. So are you providing a sentiment analysis service to other individuals or organizations? Is that true?	Evaluating Information Systems Success	System Use (Intention to use / Use)

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
58	R1	Yes.	Evaluating Information Systems Success	System Use (Intention to use / Use)
59	WL	All right. When it comes to benefits of using sentiment analysis, have you observed any benefits of using sentiment analysis? If you go deeper into that, I know you mentioned it before, but are there other benefits that comes with utilizing sentiment analysis?	Evaluating Information Systems Success	Net Benefits
60	R1	Yeah, I would say that if you find sort of a good level where you feel that like the bigger picture is being captured as being, I don't know, let's say positive, negative, whatever, and you feel that they're curious and the quality of those answers are actually representative and not, you know, false positive due to, let's say, again, like sarcasm and irony, then I think it can have a really good, a really positive impact, but it also needs to be maybe, I mean, quite, it shouldn't maybe control or guide it fully since you will be prone to people, then again, being like sarcastic, or they might want to, you know, hurt your product in saying that everything is, you know, really good, but that the reality is that it's really bad. So then you get a false sense of what your actual, I mean, what your customers really, really believe or feel about your product. So I think it's difficult maybe for companies to be, I mean, fully driven by that. So I think it depends on how you set it up and what your product is	Evaluating Information Systems Success	Net Benefits

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		and how you collect that kind of feedback and like the trustworthiness of your customers and how truthful they are in giving that kind of feedback that you apply the sentiment analysis on. So I think it's a, I think it can be a challenge to utilize it fully.		
61	WL	Yeah. So as of today, you, like you mentioned before, you are not using sentiment analysis for your own digital product, but do you have any examples of, let's say, if you have customers that use your sentiment analysis service, how have that impacted their digital product? Do you have any examples of that?	Evaluating Information Systems Success	System Use (Intention to use / Use)
62	R1	No, unfortunately not.	Evaluating Information Systems Success	System Use (Intention to use / Use)
63	WL	All right.		
64	SE	What about, just going back to benefits that we were talking about just before, maybe you've seen an increased like interest of using like the sentiment analysis service. Have you seen anything like that from your customers?	Evaluating Information Systems Success	Net Benefits
65	R1	Yeah, for sure. Both internally and externally, I think it's something that we as humans like, I think. If there are large volumes, again, like this kind of, I mean, unstructured text data, it's difficult to make sense of it. And I think a lot of decision makers are really keen to understand that more. And then whatever it might be	Evaluating Information Systems Success	Net Benefits

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		and whatever the quality, it's still, I think it's still a good indication on an aggregated level, like what is being, what is actually being said amongst all of these messages or like this kind of text. So I think it's, we're definitely seen an increase in demand, both internally in our, like our, our users and, and how we deliver that to our customers in, like the end customer being quite happy about being able to get that kind of service provided to them through us. So it's definitely, I think, as a consumer, it's something that you, within marketing, at least, are really interested in, but it's difficult to make sense of it and maybe really utilize it. And I think that's where, within that, you have a lot of opportunities to really, you know.		
66	WL	If I'm correct, you mentioned that it's not only sentiment analysis alone that you utilize for text or for analyzing the data, right? Is that true?	Evaluating Information Systems Success	System Use (Intention to use / Use)
67	R1	Yeah, it depends on if, yeah, no, yeah, that's right.	Evaluating Information Systems Success	System Use (Intention to use / Use)
68	SE	It could also be like a combination of the sentiment analysis with something else, but just alone. It is not, yeah, okay.	Evaluating Information Systems Success	System Use (Intention to use / Use)
69	R1	I would say that, yeah, looking at our way of working with data, we use a lot more.	Evaluating Information Systems Success	System Use (Intention to use / Use)

Row	**Person**	**Transcription**	**Context / Theme**	**Dimension of IS Success Model (The D&M Model)**
70	WL	When it comes to the utilization of sentiment analysis as a tool, have you experienced any technical issues?	Evaluating Information Systems Success	System Quality
71	R1	I would say that, given the nature of text data, it's quite difficult to utilize it and store it efficiently. I mean, it's quite special compared to sort of regular kind of data. And I mean, it's easy to store, of course, you put it somewhere, but then when you want to use it and when you want to pipe it through a sentiment or the NLP model or whatever, then accessing that is sometimes difficult depending on how you decide to store it and process it. So I think perhaps there we have, I think within that, companies have challenges in really capitalizing on that kind of unstructured data. And then within the sentiment, like when it comes to the actual models or applications, I say, yeah, I mean, again, like with different languages and capturing cultural, as you mentioned, like cultural sort of ways of maybe talking or typing or certain words gets sort of misinterpreted. I think it's more like the consensus of them or the meaning of them. And then again, with like irony or sarcasm that it's easy to create false positives where I think it's more prone to finding negatives that are in truth positives. So I think that kind of limitation is also then the challenge of solving those use cases.	Evaluating Information Systems Success	System Quality
72	WL	All right. We reach the end of the questions. We have just a few	Evaluating Information	User Satisfaction

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		more. So the next questions, we'll talk about the satisfaction of using it as well as if you have any service or like support staff or sentiment analysis and how you would evaluate that. But to start off in general, how satisfied are you and maybe your team if you have with the sentiment analysis as a tool and the information they provide, how satisfied are you?	Systems Success	
73	R1	I think in general, it's quite positive. But I mean, since you can't really guarantee or feel secure in the quality output, like are you, you know, there will be outliers, you know, there will be false positives, because that's just the nature of it. If you don't, you know, really go deep into it and find a very sophisticated way of doing it. As I said, like for us, it's within, it's in our toolkit, but it's not our main focus or like our main deliverability. So therefore, my answer might be a bit biased towards, I mean, connected to that. That's not our focus, but it's an opportunity and part of our offering that we can, we can, you know, deliver. So, but given that, given that you can't really guarantee the quality and accuracy, I would say that the satisfaction level maybe is, I mean, it's not 100% due to that. But for me, in the products I produce or deliver based on that, I always, you know, have the small little, you know, you as a user, think about that. There will be cases when you go into details on certain, let's say, text snippets or whatever, that you won't agree	Evaluating Information Systems Success	User Satisfaction

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		with output, but that's sort of impossible to handle at the current state. I would say that, yeah, given that it's difficult to feel totally satisfied with those kinds of systems.		
74	WL	Do you in [COMPANY] have like any type of support staff when it comes to sentiment analysis or at least a staff that helps you, helps you with sentiment analysis and stuff like that?	Evaluating Information Systems Success	Service Quality
75	R1	You mean as in developers or as in call center support kind of thing?	Evaluating Information Systems Success	Service Quality
76	WL	Yes, maybe more, let's say, simply ask, like, do you receive any support for sentiment analysis? Like, do you, if there is a problem with the tool itself, do you know where to call, for example, or do you know who to talk to, or do you-	Evaluating Information Systems Success	Service Quality
77	R1	No, I think it's important. Maybe we should have talked about that already, that, I mean, the way that we work with sentiment analysis is not using any off the shelf pay as you go kind of service. We use native models and like we implement it from the, I mean, we use pre-trained models and such, but we use, we develop it ourselves. So we're not paying any kind of service or any kind of company for that kind of application. So everything, mostly what we do is entirely out of, I mean, our, me and the engineers build it from scratch, basically.	Evaluating Information Systems Success	Service Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		So no, we don't, we cannot really receive any support connected to that, based on the tools or our services in that sense.		
78	SE	Regarding, just regarding your customers, what kind of support do you offer when your customers use the sentiment analysis?	Evaluating Information Systems Success	Service Quality
79	R1	That's a good question. I think given that it's, we are quite in a somewhat early state in really using this and deliver it and working together with the client and making sense of it. I think that's something that we need to, or will be investigating further, like how can we use that for both, for us and then with, together with the client and really making sense of it. And then, yeah, I think it's just a matter of highlighting what we talked about now that, yeah, there will be cases that are outliers and there will be cases where sarcasm and irony. I mean, all these things that what is the nature of sentiment analysis and NLP, there will be cases where it doesn't really work. So I think it's a matter of educating, I mean, all users in the process that that will be the sort of case throughout that output or result that keep that in mind. So I think it's on that level done with it.	Evaluating Information Systems Success	Service Quality
80	WL	So we are on our last question now, if Sofia doesn't have anything, but our thesis is about sentiment analysis and what kind of role it can have in a digital product development process, right? Do you have anything else		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		that you can add to that, that we have not covered, which you think is important to our study of, like I said, sentiment analysis and what kind of role it has in a digital product development?		
81	R1	I think that it will change very rapidly going forward. I mean, since the boom of OpenAI and I mean, and like LLMs, I think will have a huge impact on what is maybe has been the sort of current tech to provide that. So I think we will see a lot of improvements when it comes to these challenges we see with, let's say, irony and sarcasm and those kind of things. So capturing maybe the human like nature of text and speech to text and those things. So I think that just looking back a couple of years and what was standard and maybe the limitations back then might be difficult to or sort of maybe not true anymore. So I think it will be an exponential change in how successful sentiment analysis applications can be in companies.		
82	WL	I am pretty sure you talked about it before earlier in this interview. But when it comes to sentiment analysis, currently in [COMPANY] or in your organization, it doesn't have any influence in any sprints or so forth. It's mostly about from the customer's end or can you clarify that a bit?		
83	R1	Yeah, since the use case of sentiment analysis for us is to provide that as a service layer to		

Row	**Person**	**Transcription**	**Context / Theme**	**Dimension of IS Success Model (The D&M Model)**
		the end customer, like our customers. There's nothing in the output from those services that impacts the way that we develop and change our sprints or change our product development or milestones and stuff like that. I mean, of course, it can be part of it as in, oh, we need to invest more in developing our sentiment analysis service and improve it because we have demands from the customer that they want to use it more thoroughly or something. But it's not saying that impact says that on our latest feature, we received negative sentiment, so we should change our development for the next coming sprint or something, since that's not really the application for us. It's more providing it rather than using it for our sake.		
84	WL	Right. If I interpret it correctly, it's more about maybe if you have a campaign, what is the feedback you receive from that campaign rather than utilizing sentiment analysis and seeing what kind of feedback you get to your own digital platform.		
85	R1	Exactly.		
86	WL	Alright, Sofia, do you have any other questions?		
87	SE	No, I think we covered everything that we wanted.		
88	WL	Yeah, so thank you. Thank you for your time and insights. Your participation will obviously have an impact on our study.		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		Is it okay if we also mail you if we need any further clarifications in the future for our thesis?		
89	R1	Yeah, that’s fine.		
90	WL	Yeah, we are done, we’ll stop the recording right now, thank you.		

Appendix 4 - Email Interview R2

Date of Receival: 03-05-2024
Participants: Respondent 2 (R2), Welman Lam (WL) & Sofia Erikson (SE)
Language: English

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
1	WL & SE	Introduce yourself briefly by stating e.g your name, your title and your role in your company.		
2	R2	I'm [NAME] and I've been a senior data analyst at [COMPANY] for a little over 5 years. In my role I mainly gather and analyze information from different sources. Once the data is collected I use statistical tools to, for example, analyze key metrics and to measure the effectiveness of campaigns. This involves examining customer behavior or perhaps determining which aspects of our campaigns resonate most with our audience. By doing so, we can make informed decisions which will result in better outcomes only if we know what is working and what isn't. To this effect, my role includes using data insights to optimize marketing strategies and improve customer engagement. My company primarily specializes in providing a range of services for our client's digital marketing needs.		
3	WL & SE	Do you, in your business, have digital marketing?	Digital Marketing	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
4	R2	Yes. Our business heavily relies on digital marketing. Any company should be able to reach out to its target audience through different platforms, or digital channels, as it is for us.	Digital Marketing	
5	WL & SE	Do you use any kind of platform(s) for your digital marketing? Can you describe it/them? (email, social media, affiliate, paid etc.)	Digital Marketing	
6	R2	Yes. We use the typical social media platforms such as Facebook, Instagram, X (former Twitter), even LinkedIn. We also use email marketing platforms and online advertising networks such as Google Ads.	Digital Marketing	
7	WL & SE	What reach do you have and to what extent? (what kind of customers)	Digital Marketing	
8	R2	It varies depending on the target audience and specific campaign objectives. However we always aim to maximize our reach by leveraging the capabilities of each digital marketing platform, and optimizing our campaigns for maximum visibility and engagement.	Digital Marketing	
9	WL & SE	What kind of data do you collect and to what extent? (Big Data and Big Data Analytics)	Big Data and Big Data Analytics	
10	R2	We generate a considerable amount of information concerning our digital marketing activities. It could be anything from age, sex and location demographics to website tracking statistics like which pages are visited by	Big Data and Big Data Analytics	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		customers or how much time they spend on the site. In addition, this can include social media interactions data such as likes, shares, comments, followers and number of posts among others. Such data collection helps us understand the tastes and tendencies of our potential customers, as well as to evaluate how effective our marketing strategies have been.		
11	WL & SE	What type of format is the data that you collect in (unstructured/structured), (text/audio/video)?	Big Data and Big Data Analytics	
12	R2	The structured formats mainly used for storing the collected data are spreadsheets, databases or APIs while unstructured sources include things like customer reviews, social media posts and text feedbacks.	Big Data and Big Data Analytics	
13	WL & SE	Have you experienced any challenges associated with managing and analyzing big data? (As a business and/or individually)	Big Data and Big Data Analytics	
14	R2	Yes. Managing and analyzing big data is quite challenging, mainly because of the sheer volume and variety of the data. It's a complex problem for storage as it requires advanced storage systems. Processing speeds to analyze real-time data is also a challenge as it requires us to be able to immediately have a marketing response.	Big Data and Big Data Analytics	
15	WL & SE	Can you give us an overview of your sentiment analysis that you	Sentiment Analysis	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		provide?		
16	R2	As a sentiment analysis tool that we offer, this is concerned with analyzing information such as textual content in order to determine an attitude taken in it. We apply Natural Language Processing (NLP) algorithms to categorize text data into positive, negative or neutral sentiments. We mostly analyze from social media platforms to sum up sentiments and how customers perceive, not only during, but before and after a campaign as well.	Sentiment Analysis	
17	WL & SE	Do you use any other tools aside from Sentiment Analysis? If yes, can you compare them?	Sentiment Analysis	
18	R2	Yes, apart from sentiment analysis we also utilize other tools such as social listening tools, Customer Relationship Management (CRM)-systems, web analytics platforms and plenty of others. Each tool has its strengths and limitations and can't be compared as they complete, rather than compete with each other. One isn't better or worse than the other. We often use them in conjunction to get a comprehensive understanding.	Sentiment Analysis	
19	WL & SE	To what degree and manner would you say you utilize the capabilities of sentiment analysis? (e.g. amount, frequency of use, nature of use, appropriateness of use, extent of use, purpose of use)	Evaluating Information Systems Success	System Use (Intention to use / Use)
20	R2	Today we leverage our sentiment analysis capabilities to a significant	Evaluating Information	System Use (Intention to use

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		extent, particularly in monitoring brand sentiment, identifying emerging trends or issues and gauging customer satisfaction levels. By analyzing sentiment data we can get a pulse on what people are saying and feeling, and the findings convert to insights for the marketing.	Systems Success	/ Use)
21	WL & SE	Can you come up with any examples of how integrating sentiment analysis has changed the way you market yourselves digitally? Is this impact measurable or quantifiable?	Evaluating Information Systems Success	System Use (Intention to use / Use)
22	R2	One example could be that sentiment analysis has changed our digital marketing approach by detecting and addressing negative sentiment very early. This makes us able to reach out to customers and provide solutions or issue public statements and maintain our reputation and image. By analyzing sentiment trends there is an opportunity to tailor contents and messaging even further to resonate better with the target audience, this consequently leads to higher engagement. For example, let's say a business is using sentiment analysis to find an attributed negative sentiment on their smartphone's battery performance, and later on they acknowledge the concerns and communicate transparently with their customers. This process of acts shows active engagement with customers and their concerns.	Evaluating Information Systems Success	System Use (Intention to use / Use)

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		This can absolutely be measurable through tracking Key Performance Indicators (KPI). They can be sentiment polarity scores, sentiment distribution over time, customer satisfaction metrics etc.		
23	WL & SE	How do you evaluate the quality of the sentiment analysis tools? (e.g ease of use and learning, system flexibility, reliability, features of intuitiveness, response times)	Evaluating Information Systems Success	System Quality
24	R2	We have several criteria in which we conduct thorough testing and validation to ensure that the tools meet our specific requirements and deliver reliable results.	Evaluating Information Systems Success	System Quality
25	WL & SE	Can you describe the quality of the information you receive (output) from your sentiment analysis? (e.g. relevance, understandability, accuracy, conciseness, completeness, understandability, timeliness, usability)	Evaluating Information Systems Success	Information Quality
26	R2	It depends on how accurate the algorithms are, and what kind of data we're working with. In general we always try to aim for solid insights, in which we think truly capture what the customers are thinking and feeling. This makes us able to make decisions based on information or data that's actually useful. Though there are cases where a comment could say "oh great, another launch…", obviously meant in a sarcastic way, but the analysis will interpret that literally. This means that the output will show positive. We always have to take limitations in mind	Evaluating Information Systems Success	Information Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		because it can struggle with sarcasm, but as a whole there are lots of useful insights.		
27	WL & SE	How important is the quality of the output for your marketing decisions or the customers? Can you give any examples?	Evaluating Information Systems Success	Information Quality
28	R2	The quality is important for marketing decisions as it directly influences the strategy formulation or the campaign optimization. Accurate sentiment analysis helps customers identify areas of improvement to adjust and change in products or services as well as refining the marketing messaging to align with the customer preferences based on what the customers are saying about.	Evaluating Information Systems Success	Information Quality
29	WL & SE	Have you observed any benefits of using sentiment analysis in your digital marketing?	Evaluating Information Systems Success	Net Benefits
30	R2	Yes, we've observed several benefits by using sentiment analysis in our digital marketing efforts. Since we want to market ourselves for the customers, we track our own brand sentiment so we analyze online mentions and discussions. We do this primarily because we want to understand how our company is perceived to improve ourselves. This also goes for our competitors, so by getting output from competitors we can have a better understanding of our strengths and opportunities.	Evaluating Information Systems Success	Net Benefits
31	WL & SE	Have you observed any other benefits in areas such as:	Evaluating Information	Net Benefits

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		- product innovation, - customer satisfaction, - productivity - market competitiveness, - improved profits, - economic development, - creation of jobs?	Systems Success	
32	R2	The sentiment analysis helps businesses gain a competitive edge in the market. It can, for example, identify market trends such as what's rising in popularity, what the customers are talking about. With that we can sometimes predict consumer behavior and anticipate customer needs, therefore changing our roadmap for marketing to fit the ongoing trend. When it comes to the marketing aspect it's rather beneficial and mostly helps with marketing. It also gives us hints on how to improve our services and, when it's time, hire more folks to handle the growth.	Evaluating Information Systems Success	Net Benefits
33	WL & SE	Do you have examples of limitations in the output of your sentiment analysis?	Evaluating Information Systems Success	Information Quality
34	R2	There's always going to be a challenge in analyzing cultural nuances, as well as irony and sarcasm because of the complexity in the human language. Sentiment analysis currently has a hard time understanding indirect language, which makes it a limitation. As mentioned before, the sentiment analysis tool has a chance of picking sarcasm up as a positive sentiment even though the underlying meaning was negative.	Evaluating Information Systems Success	Information Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
35	WL & SE	Is the sentiment analysis tool, alone, enough for understanding the customer engagement?	Evaluating Information Systems Success	System Quality
36	R2	Sentiment analysis provides valuable insights for us when it comes to customer engagement, however we also use other tools. Right now it's important to complement it with data sources and analytical techniques to gain a more comprehensive understanding of customer behavior and preferences. Sentiment analysis alone may not capture the full spectrum of customer engagement dynamics especially in complex scenarios as described in the previous example with sarcasm.	Evaluating Information Systems Success	System Quality
37	WL & SE	Have you experienced technical issues with sentiment analysis?	Evaluating Information Systems Success	System Quality
38	R2	Sentiment analysis is not without its technical challenges, just like any other data driven tool. This includes issues related to data quality, noise in unstructured text data, bias in sentiment classification algorithms and also the scalability of these techniques. However we continuously try to refine our methods and algorithms to address these challenges and improve the accuracy and I mean the reliability of sentiment analysis results.	Evaluating Information Systems Success	System Quality
39	WL & SE	What kind of support do you receive / give out for your sentiment analysis tools? Can you	Evaluating Information Systems	Service Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		evaluate the quality of the support service? (e.g. responsiveness, accuracy, reliability, technical competence, empathy of the support staff)	Success	
40	R2	We receive support for our sentiment analysis tools both from internal data science teams as well as external vendors. The quality of the support service can vary depending on the responsiveness and resources available from the support team. Overall we try to prioritize a proactive type of communication, where we try to keep an open dialogue, and share important information with each other ahead of time instead of waiting for questions to arise. This ongoing collaboration with our support partners then allow us to troubleshoot issues as needed.	Evaluating Information Systems Success	Service Quality
41	WL & SE	How satisfied are you and your team with the sentiment analysis tools, the information they provide and the service?	Evaluating Information Systems Success	User Satisfaction
42	R2	My team and I are quite satisfied with the tools that we use, though as with everything else, there's always areas where we see room for improvement. For example adding even more advanced machine learning techniques, or possibly utilizing larger and more diverse datasets to train the algorithms and expanding data sources to get a comprehensive view of the customer perspective.	Evaluating Information Systems Success	User Satisfaction
43	WL & SE	Are there specific areas you find more valuable or challenging that affects your satisfaction levels?	Evaluating Information Systems	User Satisfaction

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
			Success	
44	R2	Personally, my own satisfaction levels primarily involve the quality of the data, sometimes the tool has a hard time analyzing spam, irrelevant comments or slang words. That's where it's important to really train the models and make them generate even more accurate results, though we're continually working towards addressing these challenges and optimizing the sentiment analysis capabilities to deliver better business outcomes.	Evaluating Information Systems Success	User Satisfaction
45	WL & SE	Is there anything else you would like to add that we have not covered, which you think is important for our study?		
46	R2	Something that's worth mentioning is the importance of always adapting and innovating further in the field of sentiment analysis, such as customer preferences, communication channels and the involvement of language. It's essential for sentiment analysis to evolve accordingly to stay relevant and accurate, especially with the data that keeps on generating continuously. Additionally, sentiment analysis alone can't capture the full spectrum, which makes it important to keep in mind that there's a type of collaboration between, for example, data analysts and marketers to unlock the full potential of the tool. By working together with the help of the tools you get a clearer picture of what the customers think.		

Appendix 5 - Semi-Structured Interview R3

Date: 06-05-2024
Length: 53:03 minutes
Participants: Respondent 3 (R3), Welman Lam (WL) & Sofia Erikson (SE)
Language: English

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
1	WL	All right. Could you please introduce yourself and the company, for example, what is your role and your responsibilities within the organization?		
2	R3	Sure. I'm [NAME]. I am Chief Scientist at [COMPANY]. I came in via an acquisition of a natural language processing provider called [COMPANY]. And so now kind of oversee the various efforts to productize and make use of AI and NLP technology both for internal usage and certainly we provide this as a service to customers.		
3	WL	Right. And how long have you been involved in this role, approximately?		
4	R3	So we were acquired about three years ago. I was Chief Scientist for maybe three years before that. I've been in this field for since I graduated and so, I don't know, about 16 years, I would say I've been working in NLP.		
5	WL	All right. And when it comes to your organization, do you have any form of digital marketing for yourself or do you offer services that helps customers with their own digital marketing?	Digital Marketing	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
6	R3	Sure. So we can break those into in terms of internally, I think we engage with all the sort of normal digital channels you would think. And I don't have direct insight into a lot of them, but certainly we're running email campaigns or pushing stuff through LinkedIn, we're doing any number of different things like that. We probably have banner campaigns, we run webinars, so I don't know exactly where you define the boundaries of digital marketing versus other things, but certainly those are all within the purview of a large sort of organization. And then in terms of selling services around that space, we've always been a sort of low level NLP provider providing functionality to understand language, which some of our customers certainly use either for internal digital marketing type of use cases or maybe turn around and resell. We sold to a fair amount of digital marketing sort of agencies and stuff like that over the years, especially in the early days of social media. That was sort of the, you know, as Twitter was blowing up in the original time, that was sort of the wave that we rode into becoming a company. So we've done a whole bunch in, especially tweets, but yeah.	Digital Marketing	
7	WL	Alright, when you, as you are a service provider, can you explain or go into a bit, what kind of reach you have and to what extent, for example, what type of customers do you have and so forth?	Digital Marketing	
8	R3	Sure. We were always very horizontal, meaning we sold into all different industries. If somebody had	Digital Marketing	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		text, we wanted to help. Bio Pharma was a major one, social media was for a while, that sort of social media monitoring space grew and then consolidated and shrank. So we rode that wave and then every time it would shrink, we'd find a new wave to ride. You know, it's been a little bit of everything. The reach has always been, you know, not massive. We were sort of a smallish business, a five to 10 million in revenue year kind of business, sort of by the end there. So we played in a lot of different industries, but never specialized into one. We went into two packs. We did a whole bunch of hospitality. That was another major area for us and then COVID hit and then we had to pivot again. So it's been a little bit of everything under the sun, not never sort of the major player. We're always a little bit niche, a little boutique, but for people who had hard problems, we were usually the ones that ended up finding sooner or later.		
9	WL	So you don't really, you know, specialize in a field, it's like you said, it's pretty horizontal of, you know, the reach of where you provide your services. Is that correct?	Digital Marketing	
10	R3	Yeah. what we got good at was building pipelines and natural life processing pipelines, especially sort of the annotation work. How do we, you know, add a new language? How do we add a new industry? And so once we had that playbook down, we would build new industry packs. We support something like 25, 30 human languages and then tens of industries within it. And it was	Digital Marketing	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		usually just sort of a, you know, a go-to-market process of figuring out who do we need to know, what the language they speak in this industry, right? Like every industry uses different terminology. Once you start talking the same words that they say, they start to trust you. And until you do, they don't trust you. And so there was just sort of this sort of learning curve where we would find some first customers, get good at telling that story, make some headway. They're always too small to sort of, you know, dominate in the industry and then refine through the next one.		
11	WL	All right, let's move on. So the next thing we want to discuss is big data and big data analytics. The first question is, what kind of data do you collect and to what extent? So what I mean by extent is maybe you collect it solely from, let's say, social media or, you know, emails or whatever. So, yeah.	Big Data and Big Data Analytics	
12	R3	Yeah, so we were never in the data acquisition game itself. So our customers have run huge amounts of data. I think we run something like a billion documents a month. And it was even more earlier on. We had a few customers when Twitter was fairly open who were processing a Twitter fire hose. So every tweet that was made, we would process at one point, maybe multiple times because more than one of our customers was offering that as a service. So different instances, the engines, because they were competitors. So it was running sort of multiple times across all that. Yeah, it could be emails. It could be news articles.	Big Data and Big Data Analytics	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		A lot of the NLP space sort of started in news, so you still had those sorts of customers out there, web chats, call transcripts, you know, we've been focusing a lot more on sort of call center lately. It's not exactly digital marketing because it's sort of an internal, you know, data set, but customers are very eager to learn about what, how do I learn, you know, part of this, right, marketing, there's the outreach part of like, how do I get my message and broadcast It? But the other part is sort of the diagnostic, you know, what's resonating, what do my customers care about and stuff like that. And so I would say, you know, emails, especially support emails, support channel transcripts of audio files, stuff like that is increasingly an important data set there. Surveys would be another sort of, it's not a huge data set, the survey is small compared to other things, but exists, you know, internal reports would be another one, you know, we've processed customer interviews, some of our customers would like go out to their customers and run these sort of long form interviews to understand what their customers are thinking and then bring it back, get it tagged up with an NLP engine. So the breadth was extremely wide because we weren't providing it. We didn't have to have those relationships. We would just pull this in from whatever they were providing. So they would have subscriptions to Zapier or whatever, where Genesis are getting the email, you know, the call transcripts through or whatever. And then again, the NLP part, the sentiment part, that		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		was us.		
13	WL	I see. So what you're just to clarify. So what you're saying is that you mostly collect, are you familiar with unstructured data, unstructured data, stuff like that?	Big Data and Big Data Analytics	
14	R3	Yes.	Big Data and Big Data Analytics	
15	WL	So what you're mostly collecting is unstructured data, is that correct?	Big Data and Big Data Analytics	
16	R3	Exactly. Yeah, I would say 99% of what we did is unstructured. We can support structured. So there's now an analyst workbench kind of tool, especially because we got bought by a survey company. So survey is very structured, you know, how would you rate us on, you know, the friendliness of our staff, one to ten? But it's been 99% unstructured, it's been by world and mostly text. So when it comes to audio, we are processing transcriptions. So we'll work with Amazon Transcribe or Whisper or something like that. We do a little bit with image recognition for reviews. But again, mostly if it's not text, that's some sort of partner we're working with. But we're doing almost any form of text you can imagine for sort of the unstructured.	Big Data and Big Data Analytics	
17	WL	I see.	Big Data and Big Data Analytics	
18	SE	Do you work with video as well or is that like very rarely?	Big Data and Big Data Analytics	

Row	**Person**	**Transcription**	**Context / Theme**	**Dimension of IS Success Model (The D&M Model)**
19	R3	Not so much. Yeah, no, I mean, I find that basically the problem with video is still just cost. So I think we're finally getting I mean, it's only in the last couple of years that transcription is becoming cheap enough that people want to do it. And video is still, I think, just kind of out there. Either they'll pull the audio channel off and process that or they, you know, just won't do any of it. I'm sure there are use cases where you've got a small amount of video and there's high value stuff to do, like, I don't know, security cameras or something that people are working in. But for this sort of like large scale, I mean, you've got, you know, YouTube and you've got TikTok, you've got all these video platforms that people are talking through. But usually once the conversation gets to, OK, well, what does it actually cost to source and download and then to process that sort of stuff? And I think existing technology is just too early. Text is so compact that that was a very early field. And I think just now audio is getting cheap enough to do it sort of big data scales. And I don't think video is there other than, you know, certainly Google is doing it for sort of research purposes and internal purposes, but not many people have a Google sized budget. So what we found is probably that's a little early. Now, the technology LLMs and the transformers and stuff like that keep getting faster. So I suspect in the next, I would guess, three to five years, you'll start seeing more video analytics. But I just don't think the cost to benefit is there yet.	Big Data and Big Data Analytics	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
20	WL	Hmm. When it comes to managing and analyzing big data, are there challenges today in that?	Big Data and Big Data Analytics	
21	R3	Oh, yeah. I mean, you know, it's funny, it's any large scale infrastructural problem, any sort of large scale IT problem, right. It's auto scaling and it's reliability, it's robustness. When you're processing that amount of data, you see every crappy document you can imagine. So there were all sorts of bugs over the years that were just like weird things. People would send movie files in, for example, right. Like not not transcribed, just like MP, you know, 4 or whatever. They were just like upload into the server and they go, “it took forever”. And “I didn't get anything”. It's like, yeah, that was just binary data. Like, there's no connector for that. There was another bug where it turned out if you had like 80,000 greater than symbols, that would cause some stack thing inside our engine to crash. And when we finally found the document that was causing the issue, it was the Star Wars, the original Star Wars transcript, except everybody's lines, except for C3 POs had been replaced with right characters. Like it was somebody studying to be C3PO or something like it was just his lines. There's just like pages and pages of this like replacement character for everybody else's lines. I don't know why that existed and why someone fed that to the engine. But when you're dealing with data at that quality with scale, billions of documents, you know, a year, everything shows up and, you know, you need to be robust against	Big Data and Big Data Analytics	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		that. Part of that's fail safes, right? So that, you know, something going wrong doesn't take the whole cluster down. But also it was just making the code robust to all that. Yeah, you know, I think auto scaling is always a challenge. High reliability. You know, we have like 99.99, whatever uptime service level agreements with our customers. So, you know, there's efforts on that. There's updates, you know, there's updating in live running systems and how do you minimize disruptions there? We did this on premise behind firewalls for customers because some of them were data, you know, sensitive. And so that creates hard debugging situations and things like that. That sort of scaling out of, you know, OK, I'm supporting something that I don't have access to is challenging. God, we had bugs around, you know, things overflowing from 32 to 64 bit sort of stuff because there was more than, you know, X of those, those are a little earlier on. But yeah, I think anything at this scale is a little hard, whatever you're doing.		
22	WL	No, it's in line with theory that currently exists today. You're talking about volume and veracity. And, you know, there's a theory about, you know, you know, there's five big challenges in big data and it's called the five V's, I believe. So you describe, you know, some challenges that are in line with with what the journal and the conference papers are talking about today. Thank you for that.	Big Data and Big Data Analytics	
23	R3	It's 99 percent just the same everywhere. Structured versus	Big Data and Big Data	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		unstructured. We have like these cool, you know, LLMs and these cool algorithms in the middle, like machine learning. I've always found really sexy and neat, but you have like 99 percent of the code is just the same as if you were running a giant CRUD web page or something like it. Just dealing with gigantic scales, just dealing with gigantic scales. And that problem is the same, whether it's text or video or anything else.	Analytics	
24	WL	Yeah, thank you for that talk about big data. Let's let's head into sentiment analysis. So just to clarify, you are using or providing sentiment analysis as a service. Is that correct?	Sentiment Analysis	
25	R3	Yeah, yes, it is.	Sentiment Analysis	
26	WL	So can you give us an overview of your sentiment analysis that you provide? How does it work and stuff like that?	Sentiment Analysis	
27	R3	Yep, so there's a little complexity, but the baseline is we have sort of at this point two versions, I would call it, that we're in the process of reconciling because you have two different use cases. One is around quality. And so that's a sort of clause based sentiment model. We use an English BERT for English. We use a multilingual sentiment BERT for other languages. We're scoring at the clause, so sentence effectively. And then we're also usually looking for things like overlap with tags or entities. So did this tag tend to show up in mostly positive or mostly negative contexts in this document? We've always highlighted using the	Sentiment Analysis	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		entities or the tags as the more interesting thing, right? That document level sentiment is fine, but tends to be a very blunt instrument. So you're usually interested in a little bit more and like, okay, but who was it good for or what context was it good, right? The customer liked certain things in a review or they didn't like other things. They're just saying like, eh, you know, medium neutral is less useful than like, here's the positives, here's the negatives. There's also still a phrase based sentiment model, which is based on unsupervised learning, there's Peng and Lee, there's a paper back when we got started out detailing how to do this. And so it was an unsupervised, you know, use web scale data to find correlations between seed, positive and negative words, and then have a bunch of interns and people like that sort through the list and look at other documents, see what was going wrong, stuff like that. We still support that because it's blindingly fast compared to running BERT. And some of our customers are very sort of latency sensitive or scale sensitive, right? There's some real time chat bot type use cases where even BERT's not slow, but it's enough slow that it becomes a pain point or where the cost of running GPU machines is a little prohibitive. So there's a little bit of two pieces there. Either way, we're giving you scores for various aspects, certainly a document level overall, how is it, but trying to, as much as possible, steer customers towards, you know, look at the entities, look at the companies, look at the products and track		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		sentiment based on those. That's a short version. We do it all natively. That'd be the other thing is rather than running Google translate and then doing sentiment on the English version, we create these data files in each language. So the engine speaks Mandarin. I do not, but it's really cool to drop text in and see it come out with like, yeah, that's positive. I'm like, yeah, it's probably right. I can't confirm. This is true, but you know, 80% of the time it's true. So that's probably a positive document right there about that word.		
28	WL	We will talk about the quality of the output later. You just got the 80%. Yeah. First, but first off, let's talk about the, the, the tool use, right? So what would you say is the degree in manner? Yeah. So to what degree and manner would you say that you utilize sentiment analysis or provide it rather in this sense or in this content?	Evaluating Information Systems Success	System Use (Intention to use / Use)
29	R3	Yeah, it's probably the most important feature. I'd say it's the marquee feature. Um, you know, NER and identity recognition is probably number two, but I would say sentiment has been the dominant thing that people have been interested in in extracting from text. So I would say it's, it's the reason most people come to us. Um, and then the other ones of tagging classification, they're all necessary and useful, but sentiment gets a lot of the focus.	Evaluating Information Systems Success	System Use (Intention to use / Use)
30	WL	Um, let's see, when it comes to, for example, I don't know if you did answer it before, but when it comes	Evaluating Information Systems	System Use (Intention to use / Use)

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		to like the amount of use, the nature of use, purpose of use, appropriateness of use, like, can you, in those aspects,how do you, how would you say that you provide sentiment analysis or utilize it?	Success	
31	R3	So in terms of sort of volume of usage, in terms of like the ways it gets interacted with, uh, can you clarify a little bit about what the question is?	Evaluating Information Systems Success	System Use (Intention to use / Use)
32	WL	Um, let's see. So, as you are a provider of sentiment analysis, I would, I would assume that the frequency of use is nonstop, right? Because you provide it-	Evaluating Information Systems Success	System Use (Intention to use / Use)
33	R3	Yeah. Sort of like one of the centerpieces of our business.	Evaluating Information Systems Success	System Use (Intention to use / Use)
34	WL	Oh, that's important. Yeah, centerpiece of your business and the purpose of use, um, why do your business use sentiment analysis?	Evaluating Information Systems Success	System Use (Intention to use / Use)
35	R3	Right. And so that's where it becomes like hugely open-ended and this is that sort of horizontal play, right? So I mentioned social media monitoring early on, like that was a phase where everyone was like, are there problems showing up with my brand that I'm unaware of, right? If you're a fortune 500 company, the scale, the number of executives you have who can be putting their foot in their mouth is massive. And at the time, at least there was a sense of if you get ahead of things, if you're apologizing on day one, right? You can start to shape the messaging. If	Evaluating Information Systems Success	System Use (Intention to use / Use)

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		this has been going on for two months and there's boycotts and everyone hates you, then it's much harder at that point to then, you know, gain control of the messaging again. So there was this sort of sense of like, we need to know right away something bad is happening, right? Sentiment was a very easy marker for that. Do I have a shooting up in negatives? Another piece of this is a lot of companies have sort of CX programs, customer experience. And again, this sort of feeds into the learning, what's your customer part of digital marketing. And traditionally those were built around NPS [net promoter score] or CSAT [customer satisfaction], you know, [net] promoter score, customer satisfaction, asking people what they thought about your brand and then using that signal to optimize your business. Well, people don't really fill out surveys anymore. It's expensive. There's certain demographics that are hard to get to, Gen Z, stuff like that. And so there was already all this existing infrastructure and interest in, great, if I have the signal, I can work with it. If I know, you know, I've identified the 800 different topics as a hotel, right? So we've got a gigantic tag set for hotel. I know as a hotel, this is where customers interface with, and I could ask them, you know, how was the front desk experience? Were the flowers fresh, right? Did, you know, were the, did you have enough towels? But if I can actually just score and see in reviews online or in feedback we get, just free text field, sort of free, you know, feedback, then I know how to run my business.		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		I can identify whatever they do. Right. So once it becomes like what they do with that information, that's where my part of the journey ends. So how they use this for training or resourcing or whatever, is a little unclear to me, but that's been a major use of sentiment. It's just like a NPS [net promoter score] replacement. And there were early studies that said, yeah, you know, these are pretty much, you know, correlated. These are highly correlated. If you have good NPS [net promoter score], you're going to have very positive sentiments. If you have bad NPS [net promoter score], you have negative sentiment. It's kind of intuitive, but that, just that signal is very useful. I'm sure there's a dozen other use cases. There were people doing predictive analytics. There were people doing trainings for, you know, call center employees and stuff like that. This is how, you know, you should, when someone says this to you, here's what you should say. And then if you're being negative, your sentiments negative, then they're going to ding you on that and tell you to be more positive to the customer or stuff like that. So it's pretty wide ranging. What those use cases are.		
36	WL	I see. When it comes to a use case for digital marketing, do you have any examples of how you have provided sentiment analysis to a customer and how that has changed, how they market themselves digitally? Do you have any examples of that?	Evaluating Information Systems Success	System Use (Intention to use / Use)

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
37	R3	Yeah, that's a good question.	Evaluating Information Systems Success	System Use (Intention to use / Use)
38	WL	If you don't, it's okay.	Evaluating Information Systems Success	System Use (Intention to use / Use)
39	R3	Yeah, no, I'm trying to think of it because we, we certainly had a lot of sort of digital marketing, like ad agencies, marketing agencies who are our customers and had interesting customers to their own. I never had a lot of visibility into what exactly they were offering to their customers. So I guess it's as I'm trying to think, I don't actually have a ton of good anecdotes around digital marketing specifically. I know it was useful. I don't know what for.	Evaluating Information Systems Success	System Use (Intention to use / Use)
40	WL	Yeah, that's okay. So thank you. We talked, you talked about the 80% accuracy before. Currently, how do you evaluate the quality of the sentiment analysis tool? This is not about the output. It will come later, but this is about the quality of the tool itself. Right.	Evaluating Information Systems Success	System Quality
41	R3	Yeah. Is the quality of the tool meaning like the code itself? Or like the formative job? There's sort of two pieces.	Evaluating Information Systems Success	System Quality
42	WL	Yeah. So for example, flexibility, reliability of the tools, intuitiveness of using, we don't really know how it works to use it. Right. But, you know, ease of use and learning response times.	Evaluating Information Systems Success	System Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
43	R3	Got it, got it, got it. Yep. So again, most of those are either product, you know, management, product development, whatever you want to call that sort of stuff of trying it, interviewing customers, thinking, trying to put the customer's hats on and, okay, what would be intuitive here? What do we expect here? We've had conversations about waiting, right? Some of our customers are survey customers that tend to use sort of waiting schemes of, well, only 2% of the data is from Gen Z, but that actually makes up 20% of our customer base. So let's reinterpret these numbers relative to that. And that comes up with all these weird edge cases of like, but what does that mean when it comes to like tag frequency? Is that number that should be weighted? Stuff like that. So there's a whole like, is the product easy to use as a configurable that comes down to asking customers or trying to make guesses about it. You know, this was always something we sold ourselves as, you know, highly tunable, highly configurable, and often it came down to, okay, but is that too much work, right? Do the customers understand it? Support channel, you know, is another source of that, of, you know, what are people getting confused about. And then the latency and the uptime and stuff like that. I mean, it's just sort of normal IT problems at that point. So there's any number of, you know, Grafana [multi-platform open source analytics and interactive visualization web application] databases for response time, for lag time, for turnaround. There's a whole ops [operation] team who's worrying	Evaluating Information Systems Success	System Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		about the, you know, is it always up and how long does it take to get the results? And, you know, is this, you know, dashboard or this view of the data, you know, nice and snappy, which of our customers are the biggest, how do we get their performance load better? There's often lots of just, you know, backend, you talked about big data problems, right? And so it's like, oh, this customer has this sort of problem. So let's move them over here to a separate, you know, in dedicated instance, stuff like that. There's a whole QA infrastructure for making sure it's functional, right? So unit tests and all those sorts of things, interaction tests for the UI, but then also suggest develop a written test as well. So I would say the process of it's a software tool mostly. And so, you know, again, setting aside the accuracy numbers, it's just a, how would you run a software business? And it's lots of testing, lots of product ideation, lots of customer interviews.		
44	WL	Now we can talk about the output of Sentiment analysis. So can you describe the quality of the information you receive?	Evaluating Information Systems Success	Information Quality
45	R3	Yeah. So it's all over the board. I threw out 80% is just like a discussion number as opposed to something firm. We've always tried to push customers as conversations got towards accuracy towards like measure it because everyone's data on structured data is so dissimilar. Right. And so what we want to get away from was a lot of the field had sort of moved towards these	Evaluating Information Systems Success	Information Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		standardized data sets. IMDB sentiment, right. Being the classic one, right. That became the testing ground in the space because it was hard because it's movies, movie reviews. So you can have lots of, you know, blood and gore and terrible villains. And it's actually a positive review. So that was an interesting academic data set to try to do a good job on. And so some competitors were like, Hey, look, you know, on these standard benchmarks, we're at 89%. And it was always like, yeah, but that, are you a movie review company? Like you're probably doing something weird. You're like an oil and gas exploration company. I can't tell you what's going to do well on that. Certainly has gotten to like, I'm a French hospitality. I'm a French hotel or something like, okay, great. I can guess I can give you some baseline numbers for the data we gathered, right? We're seeing, you know, X percent accuracy on that. And that varies, you know, certainly English, you know, news was the highest. Tweets are always kind of noisy because there's so many of them are just unintelligible. So, you know, you always got your grade got down, brought down by those. And as you moved into weird industries, you know, it would be lower because they had their own special, special language. Cisco was a customer and like security, like it was all hacks and denial of service and hackers and catastrophic, you know, failure and like, no, no, no, that's not bad. That's our field, right? That's just, those are just terms of art. So you'd have to tune it, either train it or put it in configurations or		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		whatever. So we always struggled to give like a here's the top line number. And in fact, just sort of got away from it because it was like, Hey, we've got like 30 numbers of tracking internally and none of them are applicable to you. And whether or not they would, we also just found pragmatically that, you know, becoming in like a, well, we're 88%. Well, no, we're not 89. It was not a terribly useful fight to get in with the customers. We wanted like more value proposition or business kind of value. Here's why it's a good tool. Here's why you need something reliable and configurable with high up times. Here's why we're cost competitive, yadda, yadda, as opposed to getting in debates about accuracy numbers. So for those reasons, you know, we track them and like, they're not even like top of mind, I feel like with sentiment 80, I used 80 because that was sort of like the magic number that we're always trying to get to anything above that was sort of impossible, like it just humans usually disagree on about that percentage. So, um, unless you had a very tightly curated set, like you had trained humans, you had a clear definition of what it was. You can get it up higher if you build the processes for it. But if you ask people, Hey, is this good or bad or neutral? 80% agreement is usually what you get if you haven't done more work. So that was always sort of our target number. And especially with BERT stuff, it can get pretty close to that.		
46	WL	When it comes to limitations of the output, do you, um, do this, would	Evaluating Information	Information Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		you say that, do you know of any limitations when it comes to the output? I know you described a lot in your answers before.	Systems Success	
47	R3	Oh yeah, that's all more of them. Yeah. No, I mean, certainly like sarcasm still even GPT struggles with sarcasm is just a hard problem. A lot lack of context, um, something I thought was interesting was a lot of sentiment in Japanese is sort of indiscernible to outside readers because like a fair amount of, um, conflict is expressed through misuse of honor effects and stuff like that. So if you're mad at your boss, you might call him as if he was your inferior sort of report or something. Well, without knowing your relationship, without knowing who the same bill is too, and like this outside context of how the two of you are related, like the data is not there, the information and the same with, with, um, you know, sarcasm sometimes the same with a lot of these, like, if you get like a little snippet of a larger conversation that happens a lot on tweets, right? Somebody's agreeing. Yeah, a hundred percent. Absolutely. Well, okay. That doesn't have sentiment. Like maybe it does if they're lying to something that was good or bad, but without that other context, it's, it's useless. Um, I think sentiment is also a somewhat limited, you know, it's, we're turning it into just a binary or, you know, it's a, it's a floating point number, but it's just like a one dimensional sort of access. And so there's a bunch of use cases where that's applicable, but there are other cases where you're losing nuance,	Evaluating Information Systems Success	Information Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		right? We're just saying it's good or bad is not really expressing what the user was trying to express and you're losing information. So I think inherently it's lossy. That's its benefit. I think, you know, we have things like themes, we have topics, we have stuff like that, but then you're just overwhelming the human with information that they can't process. So there's a benefit to having something as simple as like a polarity, but it also means, you know, this is a positive tweet only tells you like a little tiny bit. Um, accuracy is certainly a challenge. And mostly what we told people there was look, it'll average out in the end, right? You're talking about posting hundreds of thousands, millions of articles. So yes, any one of them is probably, you know, wrong at a reasonable clip, but unless you have some pre, you know, reason to assume that it's getting positive or negative, more incorrect. It doesn't really matter. We always found pretty good. We aim for sort of a symmetrical error function because as long as your error is random, then it cancels out. And if, and the customers usually weren't that precise, we could always, you know, spot check and figure out what that deviance was, if it was sort of a real issue. Um, yeah, there's some of the limitations.		
48	WL	And what you're saying is also in line with the current studies, like sentiment analysis, of a problem with sarcasm, irony, cultural nuance, like you described before with the japanese, you know, they have like a structure, right, or hierarchy like you	Evaluating Information Systems Success	Net Benefits

Row	**Person**	**Transcription**	**Context / Theme**	**Dimension of IS Success Model (The D&M Model)**
		said, when talking with the people, bosses, family, inferiors, whatever. So yeah, thank you. When it comes to, so I know you said before that, you might not have a, on top of your head, examples of how sentiment analysis have helped customers in the digital marketing. But can you say like any, you know, observed benefits that sentiment analysis have had for customers? Once again, I think I did say this, or ask these questions, but yeah, once again, do you have any on top of your head?		
49	R3	Yeah, there was a bunch of different ones. If we're talking benefits in general, I think the predictive analytics people were a good example of that. Like they were running models to predict outcomes on customers and sentiment was a useful, you know, metric that was not capturing other signal. Um, and so they had examples of like trying to predict who would be most, um, affected by a coupon, something like that, right? Being like, Oh, look, if you can shape this, if you can send coupons to the people who are going to be responsive to coupons and not send coupons that people are going to buy you anyways, and are now getting a discount. Then you can take a marketing program. That'd be a negative ROI and turn into positive ROI through better targeting and sentiment analysis. You know, and your customer history was part of that. Um, certainly, you know, I kind of come back to the most common use case I see for sentiment for NLP has been an understanding one has been a, what are my customers thinking, what does this feedback	Evaluating Information Systems Success	Net Benefits

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		mean, where are we doing well, where we're doing poorly, especially as you get into like nuanced car dealership networks or something like that, where you've got 10,000 locations that you're responsible for at a high level and you're trying to, you know, do a nuanced, you know, uh, effort in managing and training and staffing and resourcing across this sort of universe, um, getting those hard numbers and sort of understanding the difference between, um, noise, right? Is, is this car, is this sales guy's numbers up this week because it was a really successful, like he's done something great, or is it just like just random chance because this is often, you know, a random function with a small number of observations. And so anything where you can start bringing in the text and understanding what people's experience was helps with that. There's a whole bunch of cases like that, where you're trying to, um, even digital marketing, like you're trying to run different ad campaigns, you're trying to AB test, you're trying to understand what's working, what's not anything to get you a little more clarity around how the customer's reacting, what their opinions are, um, optimizing workflows, right? Like especially like a website, again, this is getting out of digital marketing exactly, but customers will tell you, customers will tell you what went well, what went badly. They will tell you directly. They will put it in reviews. They'll tell you a million places. And so this promise of like, yeah, look, listen to them. Oh, there's too much data. Okay. Let's		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		synthesize it. Let's get it down, but understand where the pain points are. Understand where the frictions are. We have effort models to try to track, you know, where are customers complaining about friction? You know, where are your weights too long? Where are you losing customers? Because then I had to get in the phone and they will tell you when they're annoyed with those sorts of things, when there's experiencing friction. And so learning and optimizing, I think there's a huge part of it. Like NLP generally is sort of a, um, passive, right? That's where the connection to digital marketing gets a little bit nuanced. Cause I usually think of digital marketing as sort of an active, right? Like it is a choice to put something in front of a customer. It is an action you're taking. And NLP is all about give me text. And so there are certain use cases. I think, um, you know, chat bots and web chat and stuff like that call center. There are certain areas where the interaction is happening live and you can bring the analysis and, um, the interaction together. Um, but to a large extent, most NLP is a little after the fact. It might be just barely after the fact. I know that with social media, they always, you know, focused on timeliness. We always said, you know, within 15 minutes or something, it's already become not useful anymore was sort of the thought process, whether that was true or not. Um, but it's still sort of a, okay, am I doing well? Am I missing things? It's a signal to watch the world. And then I think mostly in terms of digital marketing, in terms		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		of like, okay, then how do I use that signal to be more active? There have been a few cases number of we did it or not. If it was just discussions around more nuanced placement, if you can get, you know, if your banner ads and stuff like that, you don't just want to be on a site about, you know, um, cars. If you're a car site, you want to be a positive car article. You don't want it to be people talking about how cars a scourge of cities and then, Oh, check out the new, you know, Ford focus 500 or something. You'd like it to be a little bit more nuanced there where you're placing it. So I'm sure customers were using it for that, but I'm not sure offhand. Um, there was one early on who was using it for, um, uh, finding, you know, useful URLs and stuff like that. Like they were buying up URLs, sort of the mean squatters and wanted to know what these meant and therefore like what to use them for sort of stuff. Um, so that was another kind of digital marketing one. Um, but yeah.		
50	WL	Oh, thank you. Lengthy answer. We like that. Um, so, um, when it comes to understanding, you know, customer's engagement of our product or service, um, you know, or what kind of, what kind of like what customers think of something, uh, would you say the sentiment analysis alone is enough to do that, to understand-	Evaluating Information Systems Success	System Use (Intention to use / Use)
51	R3	Yeah at least when it's connected to tags and stuff like that. You need some other piece. There's lots of different ways of going. I mean, people go all the way to simple	Evaluating Information Systems Success	System Use (Intention to use / Use)

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		things like word clouds and that provides something centered by itself is a very limited measure. You can probably make use of it. If you're using it in a sort of experimental sense, right. Of let me intervene, let me run an experiment and then see if the sentiment can change. Like if, if, if there's an active experiment, fine. But other than that, you usually want to tie it to something, uh, tags, entities, we use key phrases, right? Like any number of different things. Um, but you know, you're, you're trying to tell them a more nuanced story. I would say nuance has been one of the major challenges that LLMs are finally starting to help with, but it was always like, yeah, okay, right. Especially cause it was like, Oh, it looks like people aren't happy about the long waits, like, yep, yeah, they don't like that. Oh, but you know, um, the, the good customer service that's positive. And like, yep, people are usually glad when they're nice to them. So you're trying to find something more nuanced. If it's part of an experiment is trying to tracking that's one thing, but people want to know what they don't know, right? The unknown unknowns is always a major ask. I'm like, okay, but what is the data telling me that I don't already know? And I think just the, what is good or what is bad is intuitive to the customer. And that was a major challenge was just getting customers to understand how much of experts they already are and how much, you know, the sort of simplistic understanding of the LL- the pre LLM stuff could bring was not really going to move the needle for them.		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
52	WL	Um, yeah. So, um, any technical issues with sentiment analysis? I don't know, as we don't really know how it works in applying and using it, but do you have any technical issues right now with sentiment analysis?	Evaluating Information Systems Success	System Quality
53	R3	Um, so certainly the ones you talked about cultural nuance and things like that, and all the industries you want to attack, like just the scale, the, how to do well across, you know, all human languages, all industries is a sort of unsolvably large problem. So that's a challenge. Uh, and then the performance envelope, right? I always thought of it in terms of, um, speed and cost being the main advantages the machine has, right? As soon as you become comparable to a human, which is an extreme amount of compute, but fine either way, then they just read it yourself, right? And by the same token, like we didn't work on, you know, if you had 10,000 articles or a thousand reviews or a thousand surveys, like I'd probably just read those, right? Like we came into play hundreds of thousands, millions, um, our bottom tier change over time. But it was like, there has to be some reason that the human can't deal with this. And so that means that you're struggling, I think, with the trade-off between giving more results, more accurate results, LLM powered results that explain things with the bill going up and the latency going up, right? So, um, it's very easy now with some of these technologies to get quite high accuracy, but is it worth it for the end goal? Does that still make a compelling, um, solution for the	Evaluating Information Systems Success	System Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		user? So I feel like as we've gotten new technologies, certainly that pre to boundary has improved and there are certain areas of solutions that exist that didn't exist before. Um, but you're still making these trade-offs. And so there's still regions where, yeah, I would love to have super accurate sentiment, uh, for almost free and right. And it needs to have a ton of nuance and stuff like that, but I don't have time to configure it. Okay. Like, well, the tech still isn't there. So the baseline of being able to score these things, tag these things to reasonable accuracy, I think is, I mean, I want to say solid because you can always do better, but it's like, okay, this is a useful piece of technology that you can just use today. And now it's mostly a question of, okay, can we get more out of it? Can we get more configurability with less human effort at lower costs, at bigger scales, and that's where the engineering effort goes.		
54	WL	Um, uh, so you're a provider, like I've said one million times, it feels like, but, as you are a provider of sentiment analysis, do you have like any kind of support that you give out to your customers that make use of your service in sentiment analysis? And if that, if that is the case, can you also evaluate the quality as well?	Evaluating Information Systems Success	Service Quality
55	R3	Of the support? Yeah, we always got very well, uh, regarded for support. Um, so I don't know exactly how to, uh, demonstrate it other than, you know, it was in terms of repeat customers in terms of the customers who went elsewhere. To a new job	Evaluating Information Systems Success	Service Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		and then pulled us in, you know, those sorts of things. Um, we had very low attrition among our customers and, you know, part of that technology, the big part was support quality. Um, this was, you know, uh, I forget the hours, but, you know, very generous hours of being open, very short response times, and then a willingness to really dig in to solving these problems. Um, again, we were a startup and this was one of the places that we could have an advantage was by providing high quality support. Um, the guy who sort of ran that early on was just a people pleaser at heart. And so we were able to, I think he really put his fingerprints on the support, uh, efforts for a long time, even after he was gone because yeah, it was just sort of this attitude of customers being unhappy, being a major issue that we needed to get engineers on, you just solve these problems. Um, so yep, support's important explaining the results, why they're seeing them, why it's not working, if they're having a problem, figuring out what it is. Often it was something in their setup, but, you know, they didn't know that especially because our stuff was somewhat involved. So figuring out where the issue was often required some degree of hand holding and, you know, we were usually there for that.		
56	WL	What about the internally, do you offer support internally for you guys?	Evaluating Information Systems Success	Service Quality
57	R3	Um, sure.	Evaluating Information	Service Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
			Systems Success	
58	WL	Do you have like a support staff, for sentiment analysis or maybe NLP field?	Evaluating Information Systems Success	Service Quality
59	R3	Yeah, it's, yeah, it's a support staff for NLP in general. Um, and they support internal and external customers. Internal was less of an issue when we were just as tiny startup. Now that we're part of a larger company, I almost consider them a customer, you know, as sort of a concept, obviously we're the same team and we're working together and I, you know, interface with them as colleagues, but I also think of them as a customer, our sort of main customer of this product. And so the same sort of learning from them, the same sort of supporting them absolutely applies. And yeah, even from the very early days, you know, I don't know which number, but employee eight or something probably was a support person. Right. It was always a, you know, a part of the team.	Evaluating Information Systems Success	Service Quality
60	WL	Uh, just a few questions left and the questions we have talk about your satisfaction. So in general, how satisfied are you and your team with the tools or sentiment analysis tools and the information that they do provide, how satisfied are you?	Evaluating Information Systems Success	User Satisfaction
61	R3	Um, it's a weird question because I'm providing it. So I'm not, I try not to be though. Like this is a, a, you know, I shouldn't be satisfied if I'm happy what we're doing, then, you	Evaluating Information Systems Success	User Satisfaction

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		know, that's a problem. Like then what are we doing here? And then to the extent that stuff gets solved and we're, we're done. Right. So, uh, I, I see lots of issues. I see having worked in this field for 15 years, I've seen a lot of growth. Uh, I think I'm most impressed with the increasing maturity of the field, right? Like I look back at the early days where, um, God, like the, like the, the mid 2000s had that like machines can't be racist, like it's just the data. They just process data. And it's like, no, like I've been fighting that fight for so long, but finally, like people have realized like, okay, no one, like even if the data is the problem, like that doesn't absolve everything downstream from the data and two, like these things can focus exclusively on the generic tasks, you know, you know, exemplars over, you know, the, the minor sort of variance. Uh, so, you know, it's a problem anyways. So I guess I'm, I'm pleased with the improved maturity of how you're representing this, the understanding of sarcasm and stuff like that, the limitations, right? Um, I think the education has been going well in terms of like this exists and what it is the early days of selling sentiment was just like, Hey, this is a thing. This exists. And that was a cycle was like something called sentiment analysis exists and maybe you want it by the end there, it was like, well, you should choose us, but you know what sentiment analysis is. So in all those ways, I think there's been a lot of successes. I think it's like a youthful, I think the signal is accurate enough to make business decisions off of. I think		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		that's awesome. I think the opportunity now to pair it with LLMs, there's, you know, a lot of excitements going on there. So like, I'm excited about all those sorts of things, but at the same time, every time I put a document in and it gets something wrong, I'm like, uh, right. A little bit of chalk, you know, fingers in the chalkboard there. So I'm not satisfied, but I'm the weird person to be asking that question of.		
62	SE	Maybe, maybe have an example of like your customers being satisfied or something that you noticed.	Evaluating Information Systems Success	User Satisfaction
63	R3	Certainly, you know, I mean, certainly the support, you know, burden is lower on terms of like, why did I get this wrong? I mean, it does a better job. I think having the industry packs was a huge change for our, you know, positioning of this, um, we have happy customers, like we were, we lost more customers because they went out of business than I think left us, right? Like that was sort of who we were. So I think that the overall satisfaction of this stuff is, is pretty high. I would say tunability is, you know, uh, a dissatisfaction in general. Like people want it to be better, but they don't want to put the work in. Um, and then there's certainly nuanced cases, right? I keep coming back to that. You have to evaluate relative to the text you're processing on. We've had unhappy customers who just had weird data sets that had something weird about them. Um, one of them was, you know, um, OCR content. We ended	Evaluating Information Systems Success	User Satisfaction

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		up building a system to correct OCR issues, but it turns out if you have garbage texts that they can't read the words, it does a bad job and the customer can read it as a human, you figure out what those errors are and you don't even think about them, but they tripped up the machine. So that was a problem, right? So, um, yeah, I think overall the customers are pretty happy with what it is though, as long as they understand it, and as long as they're not in one of these weird niches and our job is to make it so that there are fewer of those weird niches where it doesn't work well.		
64	WL	Yeah. The last question was about, you know, if there are any specific areas you find challenging or valuable, even that affects your satisfaction levels and you quite answered that, but do you have, like you talked about maturity wise, it's good. It has been better, right? That was an example. But just to close it off, do you have any other areas, more specifically that you maybe think is valuable that positively contributes to your satisfaction level? I know you said that, you know, if you do think of yourself that, yeah everything's going perfect then it's something wrong, right? Because you always want to develop, right? But if there are any specific areas where you find valuable that, how do I say it, that positively contribute to your satisfaction level, do you have any?	Evaluating Information Systems Success	User Satisfaction
65	R3	Yep. What I, what I would say really here is, is the cross modality, the omnichannel of, um, NLP, I think is really coming to the forefront. And I	Evaluating Information Systems Success	User Satisfaction

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		think is one of the things we've been pitching for a long time and is starting to finally show up in the marketplace, especially in terms of what customers are asking for, right? So this idea that we would often be selling in the past to a team, to the marketing team who had a specific goal and had a specific data set, and you might eventually sell to a different team with different data and different needs and stuff like that. And a lot of these organizations, you have a CX team who is running surveys and you have a different team who is responsible for interacting with, you know, uh, reviews and stuff like that. And you have a third team who's running the call center and these are different teams, these are different datas, you know, old data lake and data lake house and all that sort of stuff is a somewhat new thing to actually have organizations succeeding at. We've obviously been talking about them for decade plus, but, you know, it took a long time for that to happen. And I think we're seeing the same sort of thing where a lot of these programs have traditionally been lots of disparate signals feeding into, you know, into individualized teams for these results, but NLP is very broad. And once you bring it to tags and sentiment, stuff like that, it becomes very easy to compare across modalities, across different unstructured sources. And so I think, you know, that to my mind is sort of the biggest, um, current benefit is just like, yeah, bring in your call center records, bring in your web chat records and bring in your surveys and bring in your views.		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		And let's try to find a more nuanced, more complete understanding of what's going on with your business. These signals are going to catch different things. You're going to have different audiences. Um, they're going to have different degrees of leading time versus different ability to, to, you know, uh, drive the conversation, different places, surveys nice, cause you can ask whatever you want, but it takes a long time to run these. It can be expensive versus, you know, just seeing what people are saying online and your reviews. Um, so that fact that unstructured is, is very just, it's all unstructured. Like so much of stuff is text and then just the centrality of text, like just this idea that text is sort of innately human and is some of like the most valuable stuff in our organization. Like I would never give a new hire like a spreadsheet of numbers. You give them manuals and you give them emails and stuff like that. So, um, I think, you know, it's sort of, uh, just this, the baseline value, I think is, is high of this and as tools are getting better and as LLM is coming to existence, like the amount of stuff we can do with them is just sort of exploding. Um, and so I think it's very exciting time to be working on this stuff. And I think the foundation is there, right? Like, I think that, you know, we have a good foundation for structured, repeatable, you know, ability to reason about text that is now dovetailing nicely into the sort of generative AI world.		
66	WL	Hmm. Yeah, thank you. For this, this interview, just to close it off, since		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		we are writing a bachelor thesis about sentiment analysis, you know, what kind of role it has for digital marketing and stuff like that, do you have anything else that might be valuable to our thesis? This can range, you know, it can be anything like. Maybe future implications or, you know, that's where…		
67	R3	Yeah. So I would say that as I think about digital marketing, like it seems like the next frontier is agents and chat bots and stuff like that. You see it in both positive forms and you see it in sort of the negative forms of, um, chat bot, like, you know, if you say something on Reddit now about a product, it's a reasonable chance that some sort of bot is going to show up and start talking up or down that product. Um, so I think sort of the trustworthiness information and the sort of responsibilities of marketing, digital marketing is going to change. And I think certainly where I see the sort of next vista is in the fact that we can have computers talk for us, can have conversations and stuff like that. And so, like I said, sentiment is a passive thing, right? That's finally changing, right? So this model of get the data in and then run it through an engine is changing when the engine can then spit out text and communicate with the world. And, you know, I, I usually, when I talk about people at AI, I'm always sort of focused on like, AI isn't doing anything new yet, maybe, you know, never will or whatever, but usually when you look at like cutting edge AI stuff, it's, it's bringing down the barrier to entry, it's bringing down the cost, it's taking		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		what is a very sort of marquee premium approach and then making that widely available to everybody, like that's sort of where AI is today, you know, it can write poems, but so can humans, but it can write 50 million poems in an hour and a human can't do that. So that kind of goes back to that. It's a volume play and it's a cosplay. And so that's going to be, I think the question for digital marketing going forward is, okay, great. Well, now you have these things that can generate realistic text, but also have a million limitations around hallucination and being able to get hacked into saying terrible things, like there's been so many failed digital marketing attempts to like have a chat bot and have it recommend poisoned sandwiches to people. And this at the end of the thing, like you'll find another Tay, right? Like there's been so many high visibility failings of trying to use chat bots in the marketing realm, but at the same time, like this is something new under the sun that people are going to figure out how to do. And this idea that the highest value marketing, the highest value sales tends to be very individualized, right? Like spearfishing, if somebody is a really valuable prospect, you put a human in charge of communicating with them. If they're low value, if you don't care, if it's a numbers game, then fine. You throw up a digital, you know, you just have to put a, you know, whatever, some, some ads somewhere, but okay. Now you can start doing that sort of individualized marketing, outreach, targeted reach in a much more individualized and		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		smart way. And so like, that's the piece I would look to, I think of sentiment as probably always the building block of this in terms of like giving you a score. But as I look at like digital marketing, it's like, great. How, how do LLMs fit into this? Because that's what's going to change this field.		
68	WL	Yeah, [NAME], thank you for your time and insights. I mean, your participation is invaluable for our research. If we do want to follow up with some questions, is that...		
69	R3	Yeah.		
70	WL	Yeah, I will stop the recording now.		

Appendix 6 - Semi-Structured Interview R4

Date: 08-05-2024
Length: 23:01 minutes
Participants: Respondent 4 (R4), Welman Lam (WL) & Sofia Erikson (SE)
Language: English

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
1	WL	Okay, so first question. Do you in your business or organization have digital marketing or are you providing for another business that have digital marketing?	Digital Marketing	
2	R4	Yeah, for my company, I think every company is into digital marketing. I think traditional marketing is very hard to keep track of. If you have a billboard, you don't know how many people will use your billboard. But if you have an Instagram post, you don't know exactly how many people will use your post. So you make the decision based on data. Yeah, digital. Yeah, every company is digital.	Digital Marketing	
3	WL	Next question. So, do you in your organization use any kind of platforms for digital marketing and can you describe them?	Digital Marketing	
4	R4	Okay. There is a company that I consulted, it's called, it's a logistic e-commerce company. Within this company, what was your question again?	Digital Marketing	
5	WL	What kind of platforms are you using for digital marketing or your customer?	Digital Marketing	
6	R4	Okay, we, for [CUSTOMER], remember they used, they are all on major platforms, TikTok, Instagram, Facebook, WhatsApp. Depending on	Digital Marketing	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		the type of service they are selling, they are usually on V2C and then they are on Instagram or Facebook or Twitter also. And TikTok, depending also on the content. Yeah.		
7	WL	And when it comes to your own organization, what kind of data do you collect and to what extent. So for example, the data that you collect, do you collect it from social media or emails or etc?	Big Data and Big Data Analytics	
8	R4	For sentiment, you scrape data from social media. So there is a software that allows you to scrape. Ideally, if you say hashtag Gold Drop, what it does is it takes all the weddings that are related to that entity, then you do an analysis based on that entity, picking out the keywords. Because usually when a customer is frustrated, usually say hashtag Amazon, hashtag Facebook, just to make sure that it falls into that segment of complaints.	Big Data and Big Data Analytics	
9	WL	And when it comes to this data, what type of format is the data? Is it text or is it numbers, video, audio?	Big Data and Big Data Analytics	
10	R4	It's usually text. It's usually text or sentiment usually with text.	Big Data and Big Data Analytics	
11	WL	I see, I see. Thank you. When managing and analyzing data, have you experienced any challenges associated to that?	Big Data and Big Data Analytics	
12	R4	Ideally, when you're doing it for the first time, the first time is when the challenge is, usually because you are on unfamiliar ground and you have to learn from other people that have done it before. And along the way	Big Data and Big Data Analytics	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		you make mistakes, you figure things out. But there are challenges, especially when you're doing it for the first time. If you're running the time and it's successful, then the first time becomes a good thing.		
13	WL	Yes, I see. Thank you. Let us delve deeper into sentiment analysis. So can you give us an overview of your sentiment analysis that you use and slash or provide?	Sentiment Analysis	
14	R4	Okay. Ideally, within my sentiment analysis, I had to scrap. This was data that I had to scrap online. Ideally, it's not particularly for my company because I don't think it's feasible to put your company's information out there because not everyone speaks good about their company. This was data that I scraped from Amazon, just so I build a blueprint so I can roll it into the company. Now, within this data, you had close to 400 complaints. Now, within these 400 complaints, one would then read the first five. But reading 400 complaints is cumbersome. And these are just one month of data. So if you are doing a whole year, then that's close to four times 12, 40 times 12. That's close to three, 400 data points. So yeah, you have to prepare the data, clean it, read the first four lines, read the last four lines. And then once you read the first four lines, as a human, you know how I'm writing these texts. Am I happy or am I angry or am I having a question or am I having a complaint or am I having a good review? You read the first four lines and then you can manually score them. What sentiment allows you to	Sentiment Analysis	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		do is it gives a relationship between words. So if I'm saying good service, then automatically that's in the green. If I say bad service, those two words, the relationship between those two words, the bad and the service, it's already in the red. It's a scoring system that allows you to score words and then it gives a threshold that okay, from all the words, is it in the green or is it in the red? Hopefully I've answered your question.		
15	WL	And you have. So thank you, thank you. When it comes to, you know, text analysis, do you use other tools except for sentiment analysis?	Sentiment Analysis	
16	R4	For text analysis, I use what you call Jupyter Notebook. It's a coding software. What it allows you, it's more or less machine learning. So you take a sample of the data. Again, as I mentioned, you can take five complaints within these five. Consentment is something that is emotional. We take these five or complaints and then you analyze, score them based on the five complaints and then you see. I was scoring on the first one. Is it a good complaint or is it a bad complaint? So you can just test if the sentiment is giving you the correct answer. Again, as I mentioned, I'm not happy with the service. That is a bad sentiment. Ideally, then you know the system is doing the right job and then you run scripts, you code, you break the text down, you see how the software is. The language processing is aligning to the giving scores based on that, on the sentences, individual words. And then what it does is from	Sentiment Analysis	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		there, you then run the script, then it divides that. Okay, from five you run to 100, you run to 400. Then you can give an overview, a baseline and say, okay, from these 50% of them are saying sad, they're saying happy, they're saying angry, they're saying frustrated. These are the keywords that you are picking up. Some are saying, okay, who are happy? 5%. So that's an overview of, but I usually use a large language processing model.		
17	WL	Okay, thank you. That was a good insight into the overview of sentiment analysis that you use. When it comes to evaluating sentiment analysis, right? So my first question is to what degree and to what manner would you say that you utilize the capabilities of sentiment analysis? So I can give you examples. How much do you use it? Why do you use it? And stuff like that.	Evaluating Information Systems Success	System Use (Intention to use / Use)
18	R4	Ideally, I think it's something that you run on a six, three, four months basis. Also depending on the product. If I've launched a new product and I want to see how other people are responding to the new service or new product that I have offered to my consumers. Ideally, you launch, what's your favorite product? What do you like? Coffee, for example, coffee. The coffee decides to change its branding, necessarily decides to change its branding. So you want to find out what's the sentiment customers have to the new branding. Then you do a sentiment analysis to say, okay, are the customers reacting so well with a	Evaluating Information Systems Success	System Use (Intention to use / Use)

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		new change? Or are the customers angry with a new change? Ideally, no one will come knock to your company and say, no, I don't like the change. But if you take that Twitter response, or their Instagram comments, and you have them on Excel file, you can then score say look, actually, 40% are angry, 30% are actually happy with a new change. And then the 30% are actually not sure. Exactly. So you can have it for an overview of a company, you can have it for a product. Just depends on how you want to see the response from your customer and the engagement. Because if you have to launch a product and the customers are not engaging, they are not complaining, it's also not good. You want to because you want to have brand loyalty.		
19	WL	I see. Yes, thank you. Can you come up with any examples of how integrating or using sentiment analysis has changed the way you or your customers have marketed themselves?	Evaluating Information Systems Success	System Use (Intention to use / Use)
20	R4	Ideally, it's twofold. Sentiment analysis falls primarily in the market basket. It does not fall in other entities. So if marketing has an overview of how customers feel about the product, it's twofold. They can change, or they can say, look, at one point, the customers will adapt and adjust. But it's always good to say, okay, future decision making, you can then say, look, customers on our previous sentiment analysis, customers were angry that we launched the product. They were not	Evaluating Information Systems Success	System Use (Intention to use / Use)

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		having a complaint with the product, but they were having the complaint that the product was launched in the middle of the month, and most of the consumers did not have money. Hence, we had a high complaint rate within the sentiment. But then how do we then, when we are going to launch our next product, how do we then use that feedback to expedite and make sure that it's a smooth transaction for our next product?		
21	WL	Yes, thank you. Thank you. When it comes to the tool, sentiment analysis tool, how would you evaluate this sentiment analysis tool? So this can be, for example, ease of use, ease of learning, flexibility, reliability, response times, and so forth.	Evaluating Information Systems Success	System Quality
22	R4	Sorry, pose your question again.	Evaluating Information Systems Success	System Quality
23	WL	Yeah, so how would you evaluate the quality of the sentiment analysis tools? For example, is it easy to use and learn? Is it flexible? Does it have a good or bad response time?	Evaluating Information Systems Success	System Quality
24	R4	Ideally, it's a model that you can always, again, as I mentioned, train from a sample. You can analyze the whole population. What you do is you analyze, you take a sample, you analyze, and then you see what are the feedbacks that you have. What is the quality of response, the quality of the output of your model? So if your model is giving that quality sentiment, and it's giving a bit of, it's giving 70% of accuracy or 90% of accuracy, then what you do, then you	Evaluating Information Systems Success	System Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		roll it out to the whole, to the whole population. And then this then allows you to, as I mentioned, it's only difficult at the first, but once you build a model that you can see that it's quality analysis, then it's essential to run it again in a six lib, and it's not that complex. If you analyze and you understand the analytics language, it's not complex. If you can't, then it's best to outsource because you might have false positives.		
25	WL	Yeah, false positives is our current theme that we have noticed when it comes to the output. And there's also theories and journal articles that describe a lot about the false positives, like you say, right? So that is good. But when it comes to the output, again, can you describe more of the output of sentiment analysis? You say, you talked about before, the accuracy and stuff like that. And I want you to talk more about accuracy. Also, if the information you get from sentiment analysis is understandable, relevant, complete and stuff like that.	Evaluating Information Systems Success	Information Quality
26	R4	Yes, I know information from sentiment analysis is super relevant. Ideally, it's super relevant. It helps you with decision making. Secondly, also, it gives you an overview of the, in terms of technicality, gives you an overview of the quality, the quality of words being used by your customers. You can also determine if your customers are using high level English, very frustrated, using strong grammar that can be used. These are people that took the time to write the complaint. So you are dealing with very, very, very unhappy customers	Evaluating Information Systems Success	Information Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		due to the intensity and the scoring, because you are scoring the language, right? Either you are scoring it, is it neutral, is it negative, or is it positive? And secondly, also, should one then use languages that are not too strong, then you can see, okay, this is just someone that is giving a slight complaint. But if someone sends you a 500 essay, that is serious business, compared to someone that is giving you three sentences, four sentences. Yes, he is frustrated, but not compared to someone that took the time to write a 30 minute essay. Ideally, hopefully that has answered your question.		
27	WL	We have about three, four questions left. So the next question is about if you are using, or if you have experienced technical issues with sentiment analysis.	Evaluating Information Systems Success	System Quality
28	R4	Technical issues, yes, especially in, I would say in Africa, we, language, we have a lot of slangs. So the system, the model might not be able to distinguish what the customer is trying to say. So those are things that you pick up, yes. Unlike when you have places like in the States [United States of America] where English is mandatory, here you might find that language might be one of the barriers. How a customer express himself, maybe a mixture between two languages, and the model is unable to pick up. What does this language mean? Is it good? Is it bad? And that gives a bit of bias, not bias, but kind of the capping system. And not the cap, but you can see it's kind of those gray areas where you really don't know what to say, ideally. So	Evaluating Information Systems Success	System Quality

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		that's the drawback, especially in Namibia, where you have 14 languages in one country.		
29	WL	Oh really? 14?		
30	R4	14, yes.		
31	WL	That is a lot. Thank you for that. When it comes to the service qualities, do you first of all receive any kind of support for sentiment analysis, both internally or externally?	Evaluating Information Systems Success	Service Quality
32	R4	Ideally when you're doing the sentiment analysis, at the end of the day, again, as I said, I hardly use it in the space that I am in now, due to different factors. But however I have applied it in different sectors, I have run it in different countries, especially in Europe and American countries, you kind of find that the data is quite clean, it resonates, the language, the grammar. So there are no challenges yet, and the support usually just comes from IT. Help me scrape data off LinkedIn, off what what, so that I can compile it into an Excel file or CVM file, and then run it into a software. You only need IT's help, and then you need marketing at the end of the site to tell them, marketing, this is how your customer feels about your service. Are you able to, how do we then build trust with our customers, or how do we then build brand loyalty with our customers?	Evaluating Information Systems Success	Service Quality
33	WL	I see. Almost the last question. How satisfied are you with sentiment analysis and the information that it provides?	User satisfaction	

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
34	R4	I'm 100% satisfied. I think it's not perfect, but it's a glimpse on how your customers feel about your service or product. It's the only way, rather than running a survey, a survey is strictly biased because you tend to have a tendency of saying how your customer should think based on the questions that you are presenting to the customer. But if it's an open, freely system where someone can air out or vent what he really feels, I think that for me gives an overview of, okay, this is what your customers feel. And these are the type of words that your customers are using, which are strong words or which are soft words. So it gives you an overview. It scores the words, which is one thing I like about it. So if you are getting a lot of angry words in a survey, you might really not get harsh words, cruel words, vulgar words. But if you can see that, you can see how extremely your customers are unhappy with the service, with the sentiment analysis. But with a survey, you can only see that, yes, there's a disengagement from our customers, but how angry are they? You are unable to determine that. But with a sentiment, you can determine that, okay, we are on the bridge of chaos or no. We are unable, customers are angry, but they are not on the extreme side of the fence. Yes. So that's why I like sentiment analysis.	Evaluating Information Systems Success	User Satisfaction
35	WL	Yeah. Last question. Are there any specific areas that you find more valuable or challenging that affects your satisfaction levels?	Evaluating Information Systems Success	User Satisfaction

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
36	R4	That boils down only to language. For me, it's only language and I think also the receiver of the report. Ideally, they are not taking that, especially the guys from marketing, which is you guys. If you feel that the sentiment is not aligning to your core, then it becomes a waste of the analysis. But it's for me, primarily, it's just the grammar. That's one of the biggest challenges. And also, secondly, is maybe the source of data. There's so many ways how people complain, you know, sometimes through videos, through audios. So you can't really script everything. Only those that are educated, especially we in Africa, not everyone would want to write how they feel. You know, the other A to their friends or something like that. So it's very niche, quite a small niche of complaints. Yeah. So you can't really build on that. But big data from Europe, America, it's always good. But for us, continental, it's a bit challenging.	Evaluating Information Systems Success	User Satisfaction
37	WL	Yeah, I see. All right. I forgot to ask you if you could please introduce yourself and your company. What kind of role? What is your role and responsibilities in that organization?		
38	R4	Okay. My name is [NAME]. I'm an analyst. I'm an analyst in a business intelligent at a telecom company in Namibia. I do mostly customers, engagement, just to see how we engage with the service, product analysis, models, risk analysis, all of those boring stuff.		
39	WL	Yeah, I see. All right. Yes, thank you for your time and insights. Your		

Row	Person	Transcription	Context / Theme	Dimension of IS Success Model (The D&M Model)
		participation is going to be valuable for our thesis. So I will end the recording now.		

Appendix 7 - AI Contribution Statement

AI-based tools have been utilized to some degree to produce this bachelor's thesis. The tools that have been used are Whisper and ChatGPT. Whisper is an automatic speech recognition system, developed by OpenAI (OpenAI, 2022). This tool has been used for transcribing MP4 files, the format in which our interviews that are described further in Methodology and the appendixes (see Appendix 3 & 4) were converted to and saved as after the interviews on Zoom. ChatGPT has also been utilized in addition to Whisper. ChatGPT, also developed by OpenAI, was mostly used to aid the writing process. For example, it has been beneficial to give ChatGPT prompts about the structure and logical sequence of our text. This is especially true in our interview guides, to make it easier for the interviewee to see the coherent following of questions. For instance, after structuring our interview guides based on the sequential following of the D&M Model dimensions, ChatGPT aided us in re-structuring the questions to have a more comprehensive common thread. When it comes to the "Results" and "Discussion" chapters, ChatGPT was utilized to remove redundancies and make these chapters more readable with a better structure and sequence. To exemplify it in "Results", we first drafted our own text based on the findings from the interviews, and later pasted the text we wrote into ChatGPT to remove overlapping information and give us better paragraphs without recurring and redundant information. It was necessary to also manually correct the text given by ChatGPT, in terms of not losing valuable insights from the findings that would impact the discussion chapter. In addition to helping us structure our thesis, it has also been used to summarize journal articles and conference papers. This has been done in parallel with reading abstracts, but to get a better sense of each source we have used ChatGPT to speed up the holistic understanding of each and every relevant data source.

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