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The effect of sentiment analysis in social media

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Preface

Working on this thesis has been an incredibly rewarding and educational experience. We found a common interest in marketing during our initial discussions about the dissertation. Finding the right direction for our dissertation proved challenging, going back and forth as we tried to find an interesting way to angle our research question. With the outstanding help and valuable guidance of our tutor, Elham Ghazimatin, we were able to contact the Stavanger Crisis Center and interview one of their employees. The interview was a turning point for us in finding the research question we landed on.

The process has been very time-consuming and challenging. It felt impossible to complete at times. However, after countless hours of research, reading, and writing, we pulled through. We now sit with a deep understanding of the material and a completed bachelor's thesis.

Good communication and teamwork have been a very important aspect of completing this work. Without the hospitality and kindness of the Stavanger Crisis Center, our thesis would not look the way it does.

We would like to express our utmost gratitude to our tutor, Elham Ghazimatin, for her invaluable input and guidance, and the seamless cooperation we achieved with Stavanger Crisis Center granted by our contact person.

Stavanger, 10/05/2024
Eirik Iversflaten og Kasper Tveter

Abstract

This dissertation examines the effect of sentiment analysis on social media engagement, with a focus on Norwegian crisis centers. We analyzed 164 posts from three crisis centers: Stavanger, Molde, and Bodø using The Lexical Suite to measure sentiment variables such as valence, extremity, emotionality, and certainty. ANOVA tests were conducted to assess the differences in sentiment across centers, as well as correlation tests to see how the variables interacted with each other. Additionally, a Poisson regression was also conducted to further view how the variables influenced the number of likes received per post.

The findings suggested that higher levels of positive valence and consistent emotions are associated with an increase in likes highlighting the impact of positive and neutral sentiment in promoting engagement. Furthermore, posts with either low or high certainty levels have interacted with more likes, meaning that keeping an overall assertive sentiment does not impact likes positively. Notably, extremity and emotionality did not show any significant correlations with likes, which tells us that an excess of strong emotions and words, whether positive or negative, did not necessarily increase engagement levels.

What can be concluded from this study is that a strategically planned management of sentiment in posts can improve the overall engagement that the crisis centers receive on their Instagram communications, which most likely could be applied to other social media platforms. For institutions such as crisis centers that have an inherent sensitive nature, it can be especially relevant to provide a basis for more effective digital communication strategies.

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Definition List

The Lexical Suite – “The Lexical Suite analyzes people's language in order to understand their underlying opinions.” (Rocklage M. , 2022)

β – Beta coefficient

R-value - Pearson correlation coefficient

P-value – Significance level

η^2 - Eta-squared

LS - shortening for “Lexical Suite.”

EL - shortening for “Evaluative Lexicon.”

CL - Shortening for “Certainty Lexicon.”

IDE - Shortening for “Integrated development environment.”

Stavanger Crisis Center - "The crisis center provides support to all individuals experiencing violence in close relationships.” (Stavanger kommune, 2024)

Instagram - "Instagram is a free photo-sharing service and social network launched on October 6, 2010. The service allows users to take a photo, add simple effects, and then share it with other Instagram users connected on the social network." 2024).

Sentiment analysis - is the process of detecting positive or negative sentiment in text. It’s often used by businesses to detect sentiment in social data, gauge brand reputation, and understand customers (MonkeyLearn, 2024).

Valence - is used to categorize words or phrases that appear negative or positive in sentiment analysis. The words “Happy”, “Love” or “Excellent” are associated with positive valence. In contrast, words such as “Sad”, “Hate” or “Terrible” are associated with negative valence.

Certainty - is an individual’s subjective sense of confidence or conviction (Petrocelli et al., 2007). A greater certainty in the text is indicative of a greater likelihood that the sentiment expressed is accurate.

Emotionality - “Emotionality is the observable behavioral and physiological component of emotion. It is a measure of a person's emotional reactivity to a stimulus” (“Emotionality,” 2024). Examples of emotions include happiness, sadness, and gratitude.

Extremity - refers to the degree of intensity or mildness of the sentiment expressed in the text. In this context, the extremity is measured from the midpoint of valence (4.5 on the valence scale).

1. Introduction

This bachelor's thesis examines the impact of sentiments used in marketing on social media, and how a message can reach an audience with full potential. Because of its location, we will mainly focus on Stavanger Crisis Center. We have looked at what the crisis center does to promote its messages and what they do on social media. Furthermore, we interviewed a staff member who explained how they operate and the issues they face both externally and internally. We have developed an understanding that aided in thoroughly investigating our research question.

The study aims to identify the most effective format of sentiments the crisis center can use to communicate with people through their Instagram accounts. We conducted and analyzed a sentiment analysis to gain insight into the sentiment expressed in posts on the Instagram profiles of the Stavanger Crisis Center, Molde Crisis Center, and Bodø Crisis Center.

A text analysis tool called "The Lexical Suite" has been utilized to better understand the sentiments conveyed through the words used in their posts. Which is described by themselves as: "The Lexical Suite analyzes people's language to understand their underlying opinions. It packages together the Evaluative Lexicon with the all-new Certainty Lexicon. It keeps the original ability to measure the emotionality, valence, and extremity of people's opinions and now also captures the confidence people have in their opinion" (*The Lexical Suite*, n.d.).

The objective of this study is to gain insight into the relationship between sentiment and their interaction with people on social media.
By doing so, we will be able to provide valuable insights for the crisis centers and help them understand which wording to prioritize and which to avoid. We aim to find evidence of what certain type of messages constitutes more engagement by the number of likes metric. More engagement will lead to a higher turnover in the awareness rate related to domestic violence awareness, which hopefully can lead to the ability to help more people.

1.1 Research Question

A crisis center typically offers protection, advice, support, a place to stay, and guidance from vocational professionals, for individuals who have or experience violence in close relationships.

At the beginning of the 1970s, the women's movement brought attention to the issue of domestic violence, which at that time was referred to as household conflict (Botnedal & Nilsen, 2008). Discussions within the group led to transparency about the private violence many experienced at home, and the first crisis center in Norway was established in 1978 in Oslo. This first center led to a wave of new centers across the country; between 1980 and 1985, six to seven new centers opened each year (Ryste, 2019).

In 2023, the Stavanger crisis center reported having 965 daily users and 631 one-on-one phone conversations. Additionally, they reported 188 women staying for longer periods, with a total of 2941 overnight stays. 25 men were staying for extended periods, with a total of 329 overnight stays.

These numbers are derived from self-reports filled out by users and residents upon arrival at the Stavanger Crisis Center. The reports were provided by our contact at the Stavanger Crisis Center. See Attachment 1 and 2 under "Automated reports from Stavanger Crisis Center."
(One criterion for opting out of the registration is that at least four of all the questions in the questionnaire must be answered for it to count)

From September 2022 to September 2023, the crisis center on Stavanger's website had 3,655 visits. It is noted that most of the visitors, over 3,000, find the site through searches, which suggests that those in need of information can find it.

The need for crisis centers in Norway is present, and the numbers for the Stavanger Crisis Center webpage indicate that a large part of the need within the geographic area served by the center is being addressed. However, the information available on the website is always the same and is rarely updated. Through social media, a crisis center can reach more vulnerable individuals through diversifiable posts. What distinguishes social media from the website is that the information can be more relatable, provoke stronger reactions and a community for those at risk can be created. Important, useful, and educational information can be more easily shared through social media.

Hence, in our dissertation, we aim to conduct a sentiment analysis on the crisis center's Instagram posts to examine how different sentiments expressed in their posts affect the engagement of Instagram users, as indicated by their number of likes received. In addition to this key question, we aim to find an answer to some side questions as well, which are listed below:

- **"Which variable has the most influence on the number of likes?"**
- **"Are there any significant differences between the centers' engagement strategies?"**
- **"What causes the biggest extremes from the valence?"**
- **"How should a crisis center utilize the results from the analyses?"**

From an interview we had with our contact at the Stavanger Crisis Center, we were informed that the employees handle all the social media work individually. Our contact person mentioned in the interview that she does not have deep knowledge regarding the use of social media. We think that our research could help the center bridge this knowledge gap. Furthermore, we believe that our research could assist the center in reaching more individuals who need their services.

1.3 Project Boundaries

When you are in the research phase it is important to define the boundaries of your work. This way you will conduct a more effective, focused, and high-quality academic output (Llego, 2023). Time is an important resource and must therefore be allocated wisely. In this context, it is helpful to consider the role of project boundaries. Limiting your research allows you to explore your topic in depth, rather than skimming the surface. It also prevents the work from going in other unrelated directions.

1.3.1 Geographical Boundaries

The task is limited to three crisis centers spread across Norway. We have chosen to stay within the national borders of Norway because we believe it will provide us with a more accurate comparison without introducing any unforeseen sources of error in our analysis. It will also eliminate any differences in language used in the posts.
Since our analysis primarily focuses on the use of words and phrases, we want the crisis centers to be as similar as possible. By limiting our scope in this way, we can more easily identify and map errors that may make our analysis less valid.

An important criterion for the selection of the centers was that all had an active Instagram account with evenly distributed posts over a longer period. This allowed us to have an even sample size across the three organizations.
We chose a specific period during which the posts were made. This period was from September 2022 to March 2024. This period was determined after the posts from the first center were collected. We set a goal of 50 posts, and thus that date was established.

1.3.2 Boundaries for The Lexical Suite

Lexical Suite (LS) has a built-in limitation in the software, designed to focus on details as opposed to absolute text. This means that if the program does not encounter an "LS-word," it will not provide an assessment of the text it has been assigned (*The Lexical Suite*, n.d.). For this thesis, it means that some of the Instagram posts will not contain data from LS that can be used in further statistical analysis. This is something we considered throughout the thesis.

2. Theory

In this chapter, the theoretical foundation for the thesis is presented. The chapter largely contains sentiment analysis and argues about its importance. Previous research in the field is introduced, as well as how the research question in this thesis could benefit from it. The Lexical Suite tool that we use is explained in detail so that the analysis part will be more comprehensible to the reader.
Essentially, the theory chapter is meant to explain potential findings that emerge later in the thesis.

2.1 Sentiment Analysis

Sentiment analysis, or opinion mining, is the process of analyzing text to determine a person's thoughts and beliefs behind a text. By doing a sentiment analysis of a text you can gain an understanding of attitudes, opinions, and emotions. It is widely used among other things, in social media analytics, because sentiment is the most essential characteristic to judging human behavior (Chakraborty et al., 2019).

In the last 10 years, the online search for sentiment analysis has increased by many thousand percent (*Google trends*, 2024). It's the same with books that discuss the topic (*Google Books Ngram Viewer*, 2024).
The topic of sentiment analysis is being recognized more and more as the data tools are getting better. Measuring people's attitudes via neutral language has influenced how marketing is practiced on a day-to-day basis (Rocklage et al., 2023).
At present, we are faced with huge amounts of information and data as communications technology is growing. The World Wide Web is constantly evolving, and new information is constantly being put out there (Iglesias & Moreno, 2019).
"Since humans express their thoughts and feelings more openly than ever before, sentiment analysis is fast becoming an essential tool to monitor and understand sentiment in all types of data." (MonkeyLearn, 2024)

Today, companies use sentiment analysis on reviews, comments, emails, customer support, and other volumes of data that can help them understand what their customers think of their product (Amazon Web Services, 2024)
In this study, we aim to use sentiment analysis to identify what sentiments can generate higher engagement among people viewing Stavanger Crisis Center's Instagram posts. We measure this engagement by the number of likes that each Instagram post received. Receiving a greater number of likes means that the message has been heard by the audience, has resonated with them, and hence, the message has effectively been communicated. Measuring engagement through comments is deliberately excluded. This is because the posts have so few comments on them. The reason for this will most likely be connected to anonymity. To conduct our analysis, we are going to use The Lexical Suite.

(See attachment 3 for an overview of how the comments are distributed across the posts.)

2.1 Importance Of Sentiment Analysis In Social Media

Through social media, crisis centers can reach a broader audience. Social media can offer people education and awareness about the topic of domestic violence. It allows for the creation of online communities and for people to feel safer. We learned from our interview with the Stavanger Crisis Center that people are often afraid of showing up at their door or hesitating to give them a call. We learned that 70% of the victims take 4 years before they reach out to a center. 20% of the victims use 1 year, and only 10% reach out after the first incident of violence. Social media platforms can offer anonymity for people who want to reach out anonymously without alarming an abuser. (Krisesenteret i Stavanger, personal communication, March 7, 2024).

"Opinions are central to almost all human activities because they are key influencers of our behaviors. Whenever we need to make a decision, we want to know others' opinions" (Liu, 2012, p. 5). As a consumer, you want to know other people's opinions before you buy a product, or before you vote for the next prime minister.

When reading a blog or a long post about a product where the volume of text is considerable, the average reader will have difficulties with identifying and filtering text relevant to opinions. Automated sentiment analysis is therefore needed (Liu, 2012).

As a result of a well-done analysis, an organization can get consistent results about people's opinions. In our example, it is the crisis centers, and we are interested to know 1) how they can benefit from creating engagement and 2) how and why they can increase their audience engagement on social media.

Currently, the Stavanger Crisis Center lacks a specific focus on the sentiment they use on social media. Analyzing in this regard can provide them with some helpful insights to assist individuals in need.

Online word of mouth is another thing that is worth mentioning in this thesis. Online word of mouth is about the consumer's opinion or thought on a topic. A good example of online word of mouth is product reviews or Instagram comments, in our example, it is Instagram posts. Some studies on the topic of word of mouth, people tend to be more influenced by the negative than the positive word of mouth they receive (East et al., 2015). This can be connected to the theory introduced by Kahneman and Tversky in 1979, called loss aversion. Losses loom larger than gains is a famous line from Kahneman and Tversky. If word of mouth can affect consumers' willingness to pay (Li et al., 2022). It can perhaps also be connected to people's willingness to ask for help.

2.2 The Lexical Suite

The founders of the lexical suite, Rocklage, He, Nordgren, Rucker, and Fazio have published two papers about their research on the topic of sentiment analysis (Rocklage et al., 2023) and (Rocklage et al., 2018). In these papers, they present important research about what sentiment analysis is, what it was, and what they want it to become. The articles are deeply connected to their text analysis tool and describe in detail how the lexicon is made.

Different sentiment analysis tools are made up of several different methods, LS is made with a lexicon-based approach. A lexicon-based approach involves a pre-made lexicon where each word has an associated sentiment score (Kannan et al., 2016).

One of the things LS can calculate is valence. Valence shows if the text is positive, negative, or neutral. More generally, it determines one's attitude towards a topic. The scoring for valence in EL ranges between 0 and 9, where 0 is very negative and 9 is very positive.
The range is important because we have countless words that express both positivity and negativity. We can perhaps say that we 'like' or 'dislike' something, or we can put more energy into it and say 'wonderful' or 'disgusting' (Rocklage & Fazio, 2015), which expresses more extreme valence.

LS can also detect extremity and emotionality. Extremity measures the degree of positivity or negativity in a post. In other words, it measures how strongly a post is formulated. Words like "Absolutely fantastic" have greater extremity scores than "Pretty good". This concept helps determine the intensity of the sentiment.

Emotionality refers to the extent the text expresses emotions. For example, consider the words "Joyful," "Angry," and "Neutral." The first two words have high emotionality, while the last one has low emotionality. In real life, when we express our feelings through a conversation, we can often read other people's faces and listen to vocal gestures (Hu et al., 2013). We do this in text too, but it is not easy to capture without a text analysis tool. By measuring emotionality, a crisis center can benefit from using more emotional and empathic words to engage people.

A good example of how EL works is an "individual who used the adjective "Fantastic" would score a 6.64 out of 9.00 on emotionality, 8.57 out of 9.00 on positivity, and 4.07 out of 4.50 on extremity" (Rocklage et al., 2018, p. 2). "On the other hand, an individual who used the adjective "Valuable" would score lower on emotionality (3.98) as well as on both positivity (7.68) and extremity (3.18)" (Rocklage et al., 2018, p. 2). Both present a positive attitude, and the last one is less emotional and not as extreme (Rocklage et al., 2018).

"By quantifying both the emotionality and extremity of the adjectives people use, Rocklage and Fazio found that more emotional reactions tend to be more extreme in their positivity or negativity." (Rocklage et al., 2018, p. 3). The lexical suite could detect if the words used are extreme from the valence. Any deviation from this midpoint of the valence (4.5) indicates a more extreme rating. The extremity score goes up to 4.5.

"Words are of immense importance to our understanding of others. They provide a window into people's thoughts and feelings, their intentions and their biases " (Rocklage & Fazio, 2015, p. 1). Words can be expressed in considerable amounts but can be of similar meanings. Therefore, it is important to create a variable that can distinguish between all the different yet similar words that exist out there. This is what Rocklage and the rest of the founders of LS have done through several studies where adjectives have been the focus. The first version they came out with was called The Evaluative Lexicon 1.0. After several conducted experiments with both participants and judges, the result of the studies from EL was a list of 94 adjectives. Later on described as: "A size which can limit its application in natural text" (Rocklage et al., 2018, p. 3).

EL 1.0 had its weaknesses, including a limited number of words in its lexicon, which specifically led to a common sentence being misinterpreted because only a few of the words were registered. This led to the development of The Evaluative Lexicon 2.0.

2.2. The Evaluative Lexicon 2.0

EL 2.0 was made to fill the gaps that EL 1.0 had. "The key objective of the present work was to increase the size and scope of the EL dramatically and to then validate the expanded wordlist as a measure of individuals' attitudes and their emotionality." (Rocklage et al., 2018, p. 3). The first thing they did was to choose evaluative words from real-world sources. The volume of these sources is substantial, and in a 24-hour time, taken together these five sources resulted in 1.5 billion words and 6.2 million unique words. (Rocklage et al., 2018) From each of the five sources, they picked out 10.000 most frequently used words. Words such as "Fantastic" and "Amazing" are evaluative words. The next step was to filter these words, firstly through trained judges, then they used the judged words as seeds to find other evaluative synonyms. Thirdly, they used data-driven programs to find out if the evaluative words can be found consistently across topics in real-world contexts.

After several instances of filtering, sorting, and judging the words through participants, there were 1541 unique words remaining. These words today constitute The Evaluative

Lexicon 2.0. (See Table 1 under attachments for a summary of the number of words added and removed at each stage)

2.2.2 The Certainty Lexicon

The second part of the two-piece Lexical Suite consists of The Certainty Lexicon. CL is made with the thought of moving sentiment analysis beyond valence. Even though valence is important in sentiment analysis, some believe that considering valence alone can be a weak, incomplete, and misleading way to predict a person's behavior (petty & Krosnick, 1995;Tormala & Rucker, 2018). The purpose of CL is to look at the certainty or confidence people hold in their beliefs.
The more certain a person is in their beliefs, the more is it that the attitude or belief will drive behavior (Tormala & Rucker, 2018). The research that has been conducted on this topic is relevant to this task, considering that we want to examine if sentiment analysis can change the behavior or the mindset of people who have some sort of problem that can concern a crisis center. Tormala and Petty published a research in 2002 that showed that there is a stronger connection between attitude and behavioral intentions when attitudes are held with more certainty than less certainty (Tormala & Petty, 2002;Rocklage et al., 2023). Tormala and Petty's research also included that higher certainty contributed to attitudes being more persistent over time and more resistant to change. (Rocklage et al., 2023;Rucker et al., 2008;Tormala, 2016;Tormala & Petty, 2002).

A good example to show how CL distinguishes between certainty in sentences where different words are used is: "I've sorta disliked my experience with that brand" contra "I've often disliked my experience with that brand" (Rocklage et al., 2023, p. 3-4). The difference in the sentences is clear, but the words contribute to different uncertainty in the text. Whereas "sorta" gives a certainty score of 1.96 and "often" gives a certainty score of 6.5. A person using "Often" in their sentence is therefore considerably more certain in their beliefs. In other words, a higher score indicates a higher level of certainty.

The CL is made with billions of words and millions of reviews from millions of people (Rocklage et al., 2023). See Table 2 for an overlook of how the words were generated in each of the steps.

3. Method

This section of the dissertation will concern the methodology used in the research. A quantitative method is primarily used to analyze the data collected from Instagram posts made by three different crisis centers in Norway, using both The Lexical Suite and SPSS. We complement this study with an interview with our contact person from the Stavanger Crisis Center, allowing for a deeper insight into the application of communication tools that they use.

3.1 Choice of Method

Selecting the research method that fits our needs starts by identifying the research question and aim of the study (Shorten A, 2017). We take a quantitative methodology as the research will rely heavily on datasets to be analyzed. The nature of the research prompted some interest in an interview held with our contact person at the Stavanger crisis center as well. Conducting an interview with our contact person at the Stavanger Crisis Center, coupled with using The Lexical Suite to analyze the wording on the Instagram posts from multiple crisis centers, will yield a greater understanding of the topic. Since our research question focuses on how different words and their meanings can influence people, employing quantitative data analysis is essential (Albers, 2017). This approach will allow us to examine broader trends and patterns emerging from the Instagram posts of various crisis centers (Andreotta et al., 2019). With the use of SPSS, we analyzed the data collected from the Instagram posts of three crisis centers in Stavanger, Molde, and Bodø. Also included is data collected from the Stavanger Crisis Center containing user information, provided by our contact person following an interview held at the center.

3.2 Quantitative Method

Employing a quantitative methodology is essential for this type of research, where we need to investigate numbers on a bigger scale to derive statistically significant patterns and trends. Quantitative methodology enables the object measurement of data, providing a strong framework for testing hypotheses and validating relationships within the data

(Bhandari, 2020). Although an interview was conducted to gain preliminary insights, the primary focus remains on numerical data analysis to ensure the scalability and generalizability of the findings. This approach is supported by Meadows KA (2003), who asserts that quantitative methods are pivotal when seeking to extrapolate data findings to a larger population.

We utilized a set of variables from Instagram posts to conduct our analysis. These variables include not only basic engagement metrics such as the number of likes, comments, and follower counts but also a detailed sentiment analysis. The sentiment variables, such as valence and extremity scores, provide insight into the emotional context of the posts, with specific measures for both positive and negative sentiments.

3.3 The Interview Guide And The Interview Process

The preliminary research on how to conduct an interview consisted of an interview guide. A guide from the Department of Sociology at Harvard let us take some considerations regarding the way of creating the questions and how to ask them. This would prove very beneficial as it allowed us to shape the interview into a free-flowing conversation rather than questioning the person we interviewed (Nelson, 2012).

The interview was held at the Stavanger Crisis Center where we met with our contact person. To be able to access the conversation at a later date, the correct ethical considerations were taken (Pascoe Leahy, 2022). The early decision to conduct an interview prompted us to look for questions that we would like to ask our contact person. A list of around twenty questions was created around the marketing theme that we had originally planned to write about with the help of Mr. Nelson’s interview guide.

The decision to interview our contact person at the Stavanger Crisis Center proved to be very insightful. During the interview, we asked our contact person “How can Stavanger Crisis Center utilize communication tools to increase domestic violence awareness and access to support services?” Some things had not been considered to the full extent such as if they had an existing marketing branch and how they marketed themselves. This was all assumed from the start. As stated by our contact person: “We have been allowed to have social media but have to operate them ourselves”. She also added later in the interview that they had not received any training in marketing or the use of social media to reach out to a target audience efficiently. Some marketing ideas were presented such as posters at bus stops, which would be a cheap and effective way of making people aware of the topic. However, as our contact person explained, it could cause the victims who deal with domestic violence to walk on “eggshells” around their abusers as they would become aware of it as well.

A notable point worth mentioning regarding a question that later came up is the demographic that uses their services the most. Around 60% of the users come from a non-Norwegian culture, where they have different values and beliefs. Our contact person mentioned that it is very important for them as a crisis center to have this in mind when speaking publicly. As a crisis center with a low threshold offered to anyone who needs it, they cannot openly express any opinions. Our contact person emphasized the need to maintain neutrality so no one may feel offended and discouraged from using their services (Krisesenteret i Stavanger, personal communication, March 7, 2024).

3.4 Ethical Guidelines

The goal of a Crisis center in Norway according to law is to provide a low threshold offer to any women, men, or children experiencing domestic violence (Krisesenterlova, 2009, § 1). It is worth mentioning how they must operate according to Norwegian law. Concerning information handling, everyone working at a crisis center is bound by confidentiality when it comes to the users of the services they provide. Employees who breach confidentiality are subject to legal consequences (Werner, 2024). This is explicitly mentioned in the Act on Municipal Crisis Center Services section 5 (Krisesenterlova, 2009, § 5).

When dealing with an institution like a Crisis center, there are certain ethical aspects one needs to consider. These institutions rely on anonymity for their users no matter what the situation they are dealing with is (Ellsberg & Heise, 2002). These are delicate matters that must be handled correctly. We need to ensure that any information shared during the research process does not compromise this anonymity or the trust between the center and its users. To address these concerns, all data gathered through interviews or observations have been anonymized to remove any identifiers that could trace back to specific individuals. Additionally, it is important to emphasize the aggregate data and general insights rather than specific instances or events that might unintentionally disclose sensitive information (Sullivan & Cain, 2004). It's necessary to note that no users of the services at the Crisis center were contacted directly. The only parties with whom we communicated or exchanged data were our contact person, a center employee, and ourselves. Ethical considerations also extend to the consent process; receiving informed consent from all participants is necessary, ensuring that they fully understand the purpose of our research and how their information will be used. Language can place difficulties in communications, which is one of the reasons we chose not to expand our scope internationally. Lastly, it is important to work closely with the Crisis center to establish boundaries for the research, respecting their guidelines and any restrictions they may place on the use of the data shared. This collaborative strategy helps maintain the integrity of the research while respecting the delicate nature of the work done by Crisis centers, aiming to protect the interests and privacy of all parties involved. (Marshall, 2006).

3.5 Controlling Potential Research Bias

Reliability in research is something one should always have in mind when gathering data and conducting various statistical analyses. It tells you how consistently the method you use measures something. When applying the same method to an identical sample that has the same conditions, it should yield the same results. If this does not happen and the results differ from the original results, the method may be unreliable and holds potential bias (Middleton, 2019).

People are affected by different events that occur around the world every year. An event that influences you could similarly influence me, though the effect may differ or might not occur for me at all. When collecting the data from the three Crisis centers' Instagram posts, we made sure to only include a certain range for the years in which the posts were made. By including the years 2022-2024 for all centers and posts we limit the bias that may occur from the effects of world events that affect people, e.g. the COVID-19 pandemic influenced user behavior on different social media platforms that affected how they sought information and provided support (Azer et al., 2021).

Another factor to consider is the amount of traffic they receive on their pages. As of 2023, around 57% of Instagram users in Norway consisted of females (NapoleonCat, 2013). We can assume that most of the accounts that interact with these crisis centers' Instagram accounts are females since 88.3% of the adult users at Stavanger Crisis Center are female. When looking at the number of comments on each post from the three centers we see that 70.1% have no comments at all (Krisesenteret i Stavanger, personal communication, March 7, 2024). This lack of interaction with each post may be attributed to the stigma that follows the topic (Overstreet & Quinn, 2013). The lack of comments may pose an issue when doing the analyses of each post related to the effect of word usage.

Regarding the fanbase of each center, something to consider is the clear discrepancies the three centers have in their following amounts. Where the center in Stavanger has 279 followers, Molde has 333 followers, and Bodø has a very large 1159 in comparison. This may affect the scores when doing the analyses as more followers would mean the content posted will appear for more people compared to those with fewer followers.

The EL 2.0 (see Table 1.) may have had an overly limited selection of words as there were multiple variables with missing values in our analysis conducted with The Lexical Suite. These missing values appear scattered and are likely to be attributed to some words not being used, as they were not included in The Lexical Suite's selection of words. It is important to note that this may affect the outcomes of analyses we have conducted due to bias in the values when the relationship and correlation between certain variables are missing. Especially when conducting a Poisson Regression, when one value in a variable is missing, it will exclude all cases where there is a missing value causing a significant reduction in N cases.

3.6 SPSS

The statistical program known as SPSS (Statistical Package for the Social Sciences) was developed specifically for the Social Sciences and is now used by various fields such as market researchers, health researchers, government entities, marketing organizations, and more to conduct statistical data analysis. SPSS Inc. launched the software in 1968 and was later acquired by IBM in 2009 (Jordan, 2021).

The data we collected previously from the three crisis centers' Instagram accounts were put into an Excel spreadsheet and sorted accordingly. The next step was then to use the

Lexical Suite to analyze the wording used from each center's posts from the timestamp March 2024 – September 2022. This would then give us the different variables we would need to complete the different analyses. These variables previously mentioned are valence, extremity, emotionality, and certainty as well as word count, likes, and comments. Using SPSS for the next step, we ran tests of correlation, ANOVA, and Poisson regression to investigate how they correlate to each other and the relationship between each variable to the likes and comments on the posts.

4. Analysis

In this section, we will look at the statistical examination of all data collected from the three crisis centers in Stavanger, Molde, and Bodø using various tests. The data from all the posts were analyzed through The Lexical Suite which provided the variables necessary to complete the analysis. Tests such as ANOVA, Poisson Regression, and correlation will be discussed in this section of the paper.

When analyzing variables using these different methods, certain values are used to determine whether something is statistically significant or not. For most statistical tests you get a test statistic or a p-value that will tell you if the findings are significant enough to warrant further examination. To determine the significance of a variable, we must examine the significance level, which is usually 0.05 (Andrade, 2019). For this paper, we will be looking for significant findings with $p \leq .05$.

4.1 Measures

To measure how each center receives engagement on their posts, we will use the sentiment variables obtained from The Lexical Suite. These sentiment variables will be analyzed using ANOVA, correlation tests, and Poisson regression to examine how they interact.

Valence:

Valence_min: the value of the least positive word in the text

Valence_max: the value of the most positive word in the text

Valence_avg: The weighted average valence of the text

The valence scale goes from 0-9.

Extremity:

Extremity is calculated as the absolute deviation of the word from the midpoint of the valence scale (4.5 on the valence scale). This scale goes up to 4.5.

Extremity_min: the least extreme EL word used, regardless of valence. In other words, this is the least extreme positive or negative word.
Extremity_max: the most extreme EL word used, regardless of valence. In other words, this is the most extreme positive or negative word.
Extremity_avg: the weighted average extremity of the EL words, regardless of valence
Extremity_min_pos: the extremity of the least positive word that is above the midpoint of the EL scale.
Extremity_max_pos: the extremity of the most positive word that is above the midpoint of the EL scale.
Extremity_avg_pos: the weighted average extremity of those words above the midpoint of the EL scale.
Extremity_min_neg: the extremity of the least positive (most negative) word that is below the midpoint of the EL scale.
Extremity_max_neg: the extremity of the most positive (least negative) word that is below the midpoint of the EL scale.
Extremity_avg_neg: the weighted average extremity of those words below the midpoint of the EL scale.

Emotionality:

Emotionality_min: the least emotional word, regardless of valence
Emotionality_max: the most emotional word, regardless of valence
Emotionality_avg: the weighted average emotionality of the EL words, regardless of valence
Emotionality_min_pos: the emotionality of the least positive word that is above the midpoint of the EL scale.

Emotionality_max_pos: the emotionality of the most positive word that is above the midpoint of the EL scale.

Emotionality_avg_pos: the weighted average emotionality of those words above the midpoint of the EL scale.

Emotionality_min_neg: the emotionality of the least positive (most negative) word that is below the midpoint of the EL scale.

Emotionality_max_neg: the emotionality of the most positive (least negative) word that is below the midpoint of the EL scale.

Emotionality_avg_neg: the weighted average emotionality of those words below the midpoint of the EL scale.

Certainty:

Certainty_min: the value of the least certain (most uncertain) word in the text

Certainty_max: the value of the most certain (least uncertain) word in the text

Certainty_avg: the weighted average certainty of the text

(All variables are taken directly from LS's PDF titled «LS_variables (*LS_variables.Pdf*, n.d.))

In the subsequent stages of this project, we will employ the statistical software SPSS to conduct an in-depth analysis of the data furnished by LS. With multiple variables like the ones above, we will be able to delve deeper into the details of what all the numbers and variables mean for the crisis centers.

4.2 ANOVA

Analysis of variance (ANOVA) is a commonly used statistical method when there are three or more groups to be compared. This method compares the means of the independent groups to determine if there are any statistically significant differences between them, which makes it highly suitable for testing the means of the three crisis centers discussed thus far. Using ANOVA will also minimize the risk of making a Type I error as it compares all the groups simultaneously, rather than the use of multiple t-tests (Kim, 2014).

Using SPSS to categorize the three centers into groups 1-3, allowed for the application of ANOVA to compare all the variables found using The Lexical Suite. Running the ANOVA tests included standard ANOVA with three distinct groups, the effect sizes, and Tukey's HSD results. This allows for observing the mean difference and determining whether they are statistically significant. To further understand the magnitude of the observed differences, we included the effect sizes where we calculated Eta-squared, Epsilon-squared, and Omega-squared for both fixed and random effects. Following the ANOVA and effect size analysis, we then conducted Tukey's HSD tests to locate which specific groups – or center pairings differed significantly. The focus will be on statistically significant result findings.

4.2.1 ANOVA Using Extremity Variables

One-way ANOVA to compare the following variables across the three Crisis Centers: Number of likes as dependent variable. Extremity minimum positive, extremity minimum negative, extremity maximum positive, extremity maximum negative, extremity average negative, extremity positive average as independent variables.

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
numberoflikes	Between Groups	611.935	2	305.967	3.663	.028
	Within Groups	13448.870	161	83.533		
	Total	14060.805	163			
extremity_min	Between Groups	19.775	2	9.888	11.252	<.001
	Within Groups	93.148	106	.879		
	Total	112.924	108			
extremity_max	Between Groups	4.512	2	2.256	4.131	.019
	Within Groups	57.879	106	.546		
	Total	62.391	108			
extremity_avg	Between Groups	8.188	2	4.094	8.705	<.001
	Within Groups	49.857	106	.470		
	Total	58.045	108			
extremity_min_pos	Between Groups	3.313	2	1.656	2.521	.086
	Within Groups	58.477	89	.657		
	Total	61.790	91			
extremity_max_pos	Between Groups	2.251	2	1.126	2.635	.077
	Within Groups	38.024	89	.427		
	Total	40.275	91			
extremity_avg_pos	Between Groups	2.417	2	1.208	2.977	.056
	Within Groups	36.123	89	.406		
	Total	38.540	91			
extremity_min_neg	Between Groups	23.528	2	11.764	8.102	.001
	Within Groups	52.269	36	1.452		
	Total	75.797	38			
extremity_max_neg	Between Groups	5.972	2	2.986	2.414	.104
	Within Groups	44.528	36	1.237		
	Total	50.500	38			
extremity_avg_neg	Between Groups	12.422	2	6.211	5.823	.006
	Within Groups	38.397	36	1.067		
	Total	50.819	38			

Included in the table:
Sum of Squares, degrees of freedom (df), Mean Square, the F-statistic, and the significance level (p-value).

Dependent variable “numberoflikes”, is included in every ANOVA but will only be mentioned for the first one as it yields the same results. The number of likes shows a significance, although only moderately ($F(2, 106) = 3.663$, $p = .028$). The F statistic shows us that there is a difference across the centers regarding the amount of likes they receive. Even though the p-value does not appear highly significant, it is enough to warrant further investigation.

For extremity, we found that there are several significant findings when conducting an ANOVA test. Across the three centers, we observed highly significant differences in minimum extremity levels ($F(2, 106) = 11.252$, $p < .001$) with words that express a mild sentiment such as “pleasant”, it can also be a mild negative word such as “underwhelming”. The F value points to a significant variation in the three centers’ minimum extremity expression, suggesting that certain conditions may influence the lowest level of response.

The maximum extremity levels displayed a significant difference across the three crisis centers as well ($F(2, 106) = 4.131$, $p < .019$), suggesting a significant variation in the usage of the most intense sentiments expressed across the three centers. Words that make up intense sentiment are for instance “disastrous” as a negative and “stunning” as a positive.

There is a strong and significant difference when looking at the average extremity for the three centers ($F(2, 106) = 8.705$, $p < .001$). This indicates that the overall level of intensity used in the language is a key discriminator among the centers.

There is a large variability found in the minimum negative extremity ($F(2, 106) = 8.102$, $p = .001$) for the three centers. Lastly, there is a significant difference in the means of the average negative extremity ($F(2, 106) = 5.823$, $p = .006$). It shows that there is a difference in the average intensity of negative expressions.

There are several insignificant results from this ANOVA including minimum positive extremity, maximum positive extremity, and average positive extremity. These variables did not display any statistically significant differences across the three crisis centers; however, a potential effect could be observed with a larger sample size.

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	Upper
numberoflikes	Eta-squared	.044	.000	.112
	Epsilon-squared	.032	-.012	.101
	Omega-squared Fixed-effect	.031	-.012	.100
	Omega-squared Random-effect	.016	-.006	.053
extremity_min	Eta-squared	.175	.055	.292
	Epsilon-squared	.160	.037	.279
	Omega-squared Fixed-effect	.158	.037	.277
	Omega-squared Random-effect	.086	.019	.161
extremity_max	Eta-squared	.072	.002	.170
	Epsilon-squared	.055	-.017	.155
	Omega-squared Fixed-effect	.054	-.017	.154
	Omega-squared Random-effect	.028	-.008	.083
extremity_avg	Eta-squared	.141	.034	.255
	Epsilon-squared	.125	.015	.241
	Omega-squared Fixed-effect	.124	.015	.239
	Omega-squared Random-effect	.066	.008	.136
extremity_min_pos	Eta-squared	.054	.000	.152
	Epsilon-squared	.032	-.022	.133
	Omega-squared Fixed-effect	.032	-.022	.132
	Omega-squared Random-effect	.016	-.011	.071
extremity_max_pos	Eta-squared	.056	.000	.155
	Epsilon-squared	.035	-.022	.137
	Omega-squared Fixed-effect	.034	-.022	.135
	Omega-squared Random-effect	.017	-.011	.073
extremity_avg_pos	Eta-squared	.063	.000	.166
	Epsilon-squared	.042	-.022	.147
	Omega-squared Fixed-effect	.041	-.022	.145
	Omega-squared Random-effect	.021	-.011	.078
extremity_min_neg	Eta-squared	.310	.064	.486
	Epsilon-squared	.272	.012	.458
	Omega-squared Fixed-effect	.267	.011	.451
	Omega-squared Random-effect	.154	.006	.291
extremity_max_neg	Eta-squared	.118	.000	.295
	Epsilon-squared	.069	-.056	.256
	Omega-squared Fixed-effect	.068	-.054	.251
	Omega-squared Random-effect	.035	-.026	.144
extremity_avg_neg	Eta-squared	.244	.025	.427
	Epsilon-squared	.202	-.030	.395
	Omega-squared Fixed-effect	.198	-.029	.389
	Omega-squared Random-effect	.110	-.014	.241

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

The effect size for the minimum extremity was quite large, with an Eta-squared (η^2) value of .175. This shows that around 17.5% of the variance in the dataset can be explained by differences in minimum extremity levels across the centers. What this tells us is that this significant effect size suggests that the least intense levels of emotional expression in the posts are key predictors of how the messages resonate with the audience. It shows that it is important to moderate negative tones to fit the sensitivity of the audience.

Furthermore, the average extremity was also found to have a significant effect size, with an Eta-squared (η^2) value of .141. Accounting for 14.1% of the variance, it shows us that the average level of extremity is an important component in the model. The average intensity of the language used in their posts is a significant part of capturing the audience's engagement.

Additionally, the maximum negative extremity shows us an Eta-squared (η^2) value of .118. Slightly lower than the minimum extremity, however still expressing a meaningful portion of the variance, at 11.8%. What this shows us is that peaks of negative emotional expression still have a considerable effect on how the posts are perceived by the audience even though it's less frequent. The implication for what this tells us is that one needs to understand that both the minimum and average levels of extremity are significant predictors of the engagement received on their posts. The insight into maximum negative extremity suggests a need for more careful moderation, especially how the negative emotions are conveyed. Finding a balance could lessen or prevent potential backlash or any negative reactions to the posts.

Tukey's Honestly Significant Difference (HSD) test:

The included variables (each block), groups compared (1-3), Mean Difference (I-J), Std. Error, Sig., 95% confidence interval.

Multiple Comparisons

Dependent Variable		(I) center_groups	(J) center_groups	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
numberoflikes	Tukey HSD	1.00	2.00	-2.840	1.828	.269	-7.16	1.48
			3.00	-4.663*	1.725	.021	-8.74	-.58
		2.00	1.00	2.840	1.828	.269	-1.48	7.16
			3.00	-1.823	1.725	.542	-5.90	2.26
		3.00	1.00	4.663*	1.725	.021	.58	8.74
			2.00	1.823	1.725	.542	-2.26	5.90
extremity_min	Tukey HSD	1.00	2.00	-1.08736*	.23768	<.001	-1.6523	-.5224
			3.00	-.71138*	.21026	.003	-1.2112	-.2116
		2.00	1.00	1.08736*	.23768	<.001	.5224	1.6523
			3.00	.37598	.22469	.220	-.1581	.9101
		3.00	1.00	.71138*	.21026	.003	.2116	1.2112
			2.00	-.37598	.22469	.220	-.9101	.1581
extremity_max	Tukey HSD	1.00	2.00	-.28893	.18736	.276	-.7343	.1564
			3.00	-.47606*	.16574	.014	-.8700	-.0821
		2.00	1.00	.28893	.18736	.276	-.1564	.7343
			3.00	-.18713	.17712	.543	-.6082	.2339
		3.00	1.00	.47606*	.16574	.014	.0821	.8700
			2.00	.18713	.17712	.543	-.2339	.6082
extremity_avg	Tukey HSD	1.00	2.00	-.62394*	.17389	.001	-1.0373	-.2106
			3.00	-.56053*	.15383	.001	-.9262	-.1949
		2.00	1.00	.62394*	.17389	.001	.2106	1.0373
			3.00	.06340	.16439	.921	-.3274	.4542
		3.00	1.00	.56053*	.15383	.001	.1949	.9262
			2.00	-.06340	.16439	.921	-.4542	.3274
extremity_min_pos	Tukey HSD	1.00	2.00	-.53091	.23652	.069	-1.0947	.0329
			3.00	-.27028	.20488	.388	-.7586	.2181
		2.00	1.00	.53091	.23652	.069	-.0329	1.0947
			3.00	.26063	.20777	.425	-.2346	.7559
		3.00	1.00	.27028	.20488	.388	-.2181	.7586
			2.00	-.26063	.20777	.425	-.7559	.2346
extremity_max_pos	Tukey HSD	1.00	2.00	-.30145	.19073	.259	-.7561	.1532
			3.00	-.37444	.16521	.066	-.7682	.0193
		2.00	1.00	.30145	.19073	.259	-.1532	.7561
			3.00	-.07300	.16754	.901	-.4723	.3263
		3.00	1.00	.37444	.16521	.066	-.0193	.7682
			2.00	.07300	.16754	.901	-.3263	.4723
extremity_avg_pos	Tukey HSD	1.00	2.00	-.40799	.18590	.078	-.8511	.0351
			3.00	-.34138	.16103	.092	-.7252	.0424
		2.00	1.00	.40799	.18590	.078	-.0351	.8511
			3.00	.06661	.16330	.912	-.3226	.4558
		3.00	1.00	.34138	.16103	.092	-.0424	.7252
			2.00	-.06661	.16330	.912	-.4558	.3226
extremity_min_neg	Tukey HSD	1.00	2.00	-1.50900*	.59698	.041	-2.9682	-.0498
			3.00	-1.58917*	.43242	.002	-2.6461	-.5322
		2.00	1.00	1.50900*	.59698	.041	.0498	2.9682
			3.00	-.08017	.64139	.991	-1.6479	1.4876
		3.00	1.00	1.58917*	.43242	.002	.5322	2.6461
			2.00	.08017	.64139	.991	-1.4876	1.6479
extremity_max_neg	Tukey HSD	1.00	2.00	-.71673	.55100	.404	-2.0635	.6301
			3.00	-.81606	.39912	.116	-1.7916	.1595
		2.00	1.00	.71673	.55100	.404	-.6301	2.0635
			3.00	-.09933	.59199	.985	-1.5463	1.3477
		3.00	1.00	.81606	.39912	.116	-.1595	1.7916
			2.00	.09933	.59199	.985	-1.3477	1.5463
extremity_avg_neg	Tukey HSD	1.00	2.00	-1.09127	.51166	.097	-2.3419	.1594
			3.00	-1.15669*	.37063	.010	-2.0626	-.2508
		2.00	1.00	1.09127	.51166	.097	-.1594	2.3419
			3.00	-.06542	.54973	.992	-1.4091	1.2783
		3.00	1.00	1.15669*	.37063	.010	.2508	2.0626
			2.00	.06542	.54973	.992	-1.2783	1.4091

*. The mean difference is significant at the 0.05 level.

Looking at the minimum extremity results after conducting Tukey's HSD test, we see that Molde Crisis Center exhibits higher levels of minimum extremity compared to Stavanger Crisis Center by a mean difference of +1.087 ($p < .001$), which suggests that the Molde

Crisis Center's posts tend to start at a more intense emotional tone. The Stavanger Crisis Center displayed lower minimum extremity levels compared to the one in Bodø by a mean difference of -0.711 (p = .003), which indicates that they have a more subtle approach in their initial post-expressions.

Our results show us that the Bodø Crisis Center has a slightly higher level of maximum extremity compared to the Stavanger Crisis Center by a mean difference of +0.476 (p = .014), telling us that Bodø's Crisis Center consistently posts more provocative content, or rather more intensity at its peak.

For the average extremity, we see that the Stavanger Crisis Center has a lower value compared to the one in Molde, with a mean difference of -0.624 (p = .001), which suggests that Stavanger Crisis Center's posts generally have a lower average emotional extremity compared to Molde Crisis Center. We also see a difference in the mean between Bodø Crisis Center and Stavanger Crisis Center, where the mean difference is +0.561 (p = .001), which means that the Bodø Crisis Center is maintaining a higher level of emotional intensity compared to the one in Stavanger.

Lastly, looking at the negative extremity metrics we find that the minimum negative extremity for Stavanger Crisis Center is slightly significantly less compared to Molde Crisis Center by a mean difference of -1.509 (p = .041), suggesting that the posts from Stavanger Crisis Center have a less intense negative tone at their lowest in comparison to Molde Crisis Center. We also see a significant mean difference of 1.589 (p = .002) between Bodø Crisis Center and the one in Stavanger. This means that Bodø Crisis Center exhibits a significantly higher minimum negative extremity compared to Stavanger Crisis Center. What this suggests is that Bodø Crisis Center's posts are more intensely negative than Stavanger Crisis Center's posts are, pointing to a more direct approach.
The last variable to prove statistical significance is the average negative extremity where we can see that there is a significant difference in the mean between Stavanger Crisis Center and Bodø Crisis Center. The mean difference being -1.157 (p = .010), means that Stavanger Crisis Center on average displays a more cautious or positive approach in their posts compared to Bodø Crisis Center.

4.2.2 ANOVA Using Emotionality Variables

One-way ANOVA to compare the following variables across the three Crisis Centers: Number of likes as dependent variable. Emotionality minimum, emotionality maximum, emotionality average, emotionality minimum positive, emotionality maximum positive, emotionality average positive, emotionality minimum negative, emotionality maximum negative, emotionality average as independent variables.

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
numberoflikes	Between Groups	611.935	2	305.967	3.663	.028
	Within Groups	13448.870	161	83.533		
	Total	14060.805	163			
emotionality_min	Between Groups	61.235	2	30.617	11.552	<.001
	Within Groups	280.939	106	2.650		
	Total	342.174	108			
emotionality_max	Between Groups	7.612	2	3.806	1.511	.225
	Within Groups	267.063	106	2.519		
	Total	274.675	108			
emotionality_avg	Between Groups	25.866	2	12.933	6.711	.002
	Within Groups	204.285	106	1.927		
	Total	230.150	108			
emotionality_min_pos	Between Groups	43.207	2	21.603	7.610	<.001
	Within Groups	252.657	89	2.839		
	Total	295.864	91			
emotionality_max_pos	Between Groups	14.558	2	7.279	3.020	.054
	Within Groups	214.542	89	2.411		
	Total	229.100	91			
emotionality_avg_pos	Between Groups	26.899	2	13.449	6.508	.002
	Within Groups	183.926	89	2.067		
	Total	210.824	91			
emotionality_min_neg	Between Groups	20.762	2	10.381	3.335	.047
	Within Groups	112.065	36	3.113		
	Total	132.827	38			
emotionality_max_neg	Between Groups	1.850	2	.925	.273	.763
	Within Groups	122.080	36	3.391		
	Total	123.930	38			
emotionality_avg_neg	Between Groups	7.697	2	3.848	1.342	.274
	Within Groups	103.231	36	2.868		
	Total	110.928	38			

We can see that there is a significant difference in minimum emotionality in the ANOVA test across all three centers ($F(2, 106) = 11.552$, $p < .001$). Words that have low intensities of emotions are referred to as minimum emotionality, and can be both negative and positive, e.g. “table”, “routine” and “bland”. We gather from the F value that there is a significant variation in the minimum emotionality expression among the three centers.

The next variable that shows a strongly significant difference across the three crisis centers is minimum positive emotionality ($F(2, 106) = 7.610$, $p < .001$). In contrast to minimum emotionality does this variable only refer to positive low emotional words. This suggests that there is a significant level of difference in variance between the centers regarding the use of positive emotionality in the three centers’ posts.

Another variable that shows a significant difference across the three crisis centers is average positive emotionality ($F(2, 106) = 6.508$, $p = .002$), which refers to the weighted average emotionality of the positive words used. The average positive emotionality is statistically significant and varies across the three centers.

Lastly, we look at the minimum negative emotionality which shows significance, although only slightly ($F(2, 106) = 3.335$, $p = .047$). This variable projects the emotionality of the most negative word that is below the midpoint of the scale. There might be a significant difference in variance between the three centers with how minimally negatively emotional their posts are.

The rest of the variables, maximum emotionality, maximum positive emotionality, maximum negative emotionality, and average negative emotionality are not statistically significant and will not be examined further. It is worth noting that with a larger sample size, maximum positive emotionality ($F(2, 106) = 3.020$, $p = .054$) may show significant results as its significance level is close to 0.05.

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
numberoflikes	Eta-squared	.044	.000	.112
	Epsilon-squared	.032	-.012	.101
	Omega-squared Fixed-effect	.031	-.012	.100
	Omega-squared Random-effect	.016	-.006	.053
emotionality_min	Eta-squared	.179	.058	.296
	Epsilon-squared	.163	.040	.283
	Omega-squared Fixed-effect	.162	.040	.281
	Omega-squared Random-effect	.088	.020	.164
emotionality_max	Eta-squared	.028	.000	.101
	Epsilon-squared	.009	-.019	.084
	Omega-squared Fixed-effect	.009	-.019	.084
	Omega-squared Random-effect	.005	-.009	.044
emotionality_avg	Eta-squared	.112	.018	.221
	Epsilon-squared	.096	-.001	.207
	Omega-squared Fixed-effect	.095	-.001	.205
	Omega-squared Random-effect	.050	.000	.114
emotionality_min_pos	Eta-squared	.146	.029	.270
	Epsilon-squared	.127	.007	.253
	Omega-squared Fixed-effect	.126	.007	.251
	Omega-squared Random-effect	.067	.003	.144
emotionality_max_pos	Eta-squared	.064	.000	.167
	Epsilon-squared	.043	-.022	.148
	Omega-squared Fixed-effect	.042	-.022	.147
	Omega-squared Random-effect	.021	-.011	.079
emotionality_avg_pos	Eta-squared	.128	.019	.249
	Epsilon-squared	.108	-.003	.232
	Omega-squared Fixed-effect	.107	-.003	.230
	Omega-squared Random-effect	.056	-.001	.130
emotionality_min_neg	Eta-squared	.156	.000	.339
	Epsilon-squared	.109	-.056	.302
	Omega-squared Fixed-effect	.107	-.054	.297
	Omega-squared Random-effect	.056	-.026	.174
emotionality_max_neg	Eta-squared	.015	.000	.117
	Epsilon-squared	-.040	-.056	.068
	Omega-squared Fixed-effect	-.039	-.054	.066
	Omega-squared Random-effect	-.019	-.026	.034
emotionality_avg_neg	Eta-squared	.069	.000	.230
	Epsilon-squared	.018	-.056	.187
	Omega-squared Fixed-effect	.017	-.054	.183
	Omega-squared Random-effect	.009	-.026	.101

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

The largest effect size comes from minimum emotionality with an Eta-squared (η^2) value of .179. We see that 17.9% of the variance in our dataset is explained by differences in minimum emotionality across all three centers. This tells us that the minimum level at which emotionality is expressed varies considerably between the three centers. Showcasing the variability in how they each approach their least intense emotional content.

In the average emotionality variable, there is an Eta-squared (η^2) value of .112. Slightly lower than the other variables, however still significant with an 11.2% variance among the groups. What we can take from this is that the three centers may approach the overall strategies in emotional engagement differently. Minimum positive emotionality shows a more significant level of variance from the dataset with an Eta-squared (η^2) value of .146. This shows that 14.6% of the variance is explained by the differences captured in minimum positive emotionality across the centers. A quite significant result from this effect size is minimum negative emotionality with an Eta-squared (η^2) value of .156. The minimum negative emotionality used across the centers explains 15.6% of the variance in the dataset. Notable differences in how negatively each center expresses emotion at its lowest value.

Finally, looking at the average positive emotionality with an Eta-squared (η^2) value of .128. Explaining 12.8% of the variance in the dataset across the centers suggests that the average positive nature of messages conveyed differs among the three centers. A higher average positivity might be a better way to maintain support for their audience.

Tukey’s Honestly Significant Difference test:

The included variables (each block), groups compared (1-3), Mean Difference (I-J), Std. Error, Sig., 95% confidence interval.

Multiple Comparisons

Dependent Variable		(I) center_groups	(J) center_groups	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
numberoflikes	Tukey HSD	1.00	2.00	-2.840	1.828	.269	-7.16	1.48
			3.00	-4.663*	1.725	.021	-8.74	-.58
		2.00	1.00	2.840	1.828	.269	-1.48	7.16
			3.00	-1.823	1.725	.542	-5.90	2.26
		3.00	1.00	4.663*	1.725	.021	.58	8.74
			2.00	1.823	1.725	.542	-2.26	5.90
emotionality_min	Tukey HSD	1.00	2.00	-1.85229*	.41277	<.001	-2.8335	-.8711
			3.00	-.27937	.36516	.725	-1.1474	.5886
		2.00	1.00	1.85229*	.41277	<.001	.8711	2.8335
			3.00	1.57292*	.39022	<.001	.6453	2.5005
		3.00	1.00	.27937	.36516	.725	-.5886	1.1474
			2.00	-1.57292*	.39022	<.001	-2.5005	-.6453
emotionality_max	Tukey HSD	1.00	2.00	-.59343	.40245	.307	-1.5501	.3632
			3.00	.01955	.35603	.998	-.8268	.8659
		2.00	1.00	.59343	.40245	.307	-.3632	1.5501
			3.00	.61298	.38046	.245	-.2914	1.5174
		3.00	1.00	-.01955	.35603	.998	-.8659	.8268
			2.00	-.61298	.38046	.245	-1.5174	.2914
emotionality_avg	Tukey HSD	1.00	2.00	-1.15628*	.35198	.004	-1.9930	-.3196
			3.00	-.07729	.31138	.967	-.8175	.6629
		2.00	1.00	1.15628*	.35198	.004	.3196	1.9930
			3.00	1.07899*	.33275	.004	.2880	1.8700
		3.00	1.00	.07729	.31138	.967	-.6629	.8175
			2.00	-1.07899*	.33275	.004	-1.8700	-.2880
emotionality_min_pos	Tukey HSD	1.00	2.00	-1.20755*	.49164	.042	-2.3794	-.0357
			3.00	.47419	.42588	.508	-.5409	1.4893
		2.00	1.00	1.20755*	.49164	.042	.0357	2.3794
			3.00	1.68175*	.43187	<.001	.6524	2.7111
		3.00	1.00	-.47419	.42588	.508	-1.4893	.5409
			2.00	-1.68175*	.43187	<.001	-2.7111	-.6524
emotionality_max_pos	Tukey HSD	1.00	2.00	-.59428	.45304	.392	-1.6741	.4856
			3.00	.38211	.39244	.595	-.5533	1.3175
		2.00	1.00	.59428	.45304	.392	-.4856	1.6741
			3.00	.97639*	.39797	.042	.0278	1.9250
		3.00	1.00	-.38211	.39244	.595	-1.3175	.5533
			2.00	-.97639*	.39797	.042	-1.9250	-.0278
emotionality_avg_pos	Tukey HSD	1.00	2.00	-.91116	.41947	.082	-1.9110	.0887
			3.00	.41778	.36336	.486	-.4483	1.2839
		2.00	1.00	.91116	.41947	.082	-.0887	1.9110
			3.00	1.32894*	.36848	.001	.4507	2.2072
		3.00	1.00	-.41778	.36336	.486	-1.2839	.4483
			2.00	-1.32894*	.36848	.001	-2.2072	-.4507
emotionality_min_neg	Tukey HSD	1.00	2.00	-.97664	.87412	.510	-3.1132	1.1600
			3.00	-1.60614*	.63317	.041	-3.1538	-.0585
		2.00	1.00	.97664	.87412	.510	-1.1600	3.1132
			3.00	-.62950	.93914	.782	-2.9250	1.6660
		3.00	1.00	1.60614*	.63317	.041	.0585	3.1538
			2.00	.62950	.93914	.782	-1.6660	2.9250
emotionality_max_neg	Tukey HSD	1.00	2.00	-.34773	.91234	.923	-2.5778	1.8823
			3.00	-.46856	.66086	.760	-2.0839	1.1468
		2.00	1.00	.34773	.91234	.923	-1.8823	2.5778
			3.00	-.12083	.98021	.992	-2.5168	2.2751
		3.00	1.00	.46856	.66086	.760	-1.1468	2.0839
			2.00	.12083	.98021	.992	-2.2751	2.5168
emotionality_avg_neg	Tukey HSD	1.00	2.00	-.70101	.83896	.684	-2.7517	1.3497
			3.00	-.95774	.60770	.269	-2.4432	.5277
		2.00	1.00	.70101	.83896	.684	-1.3497	2.7517
			3.00	-.25673	.90137	.956	-2.4599	1.9465
		3.00	1.00	.95774	.60770	.269	-.5277	2.4432
			2.00	.25673	.90137	.956	-1.9465	2.4599

*. The mean difference is significant at the 0.05 level.

In Tukey's HSD test for emotionality, there are nine statistically significant results in the comparisons between the centers.

Minimum emotionality when comparing Stavanger Crisis Center to Molde Crisis Center, we get a mean difference of -1.852 ($p < .001$), which suggests that Stavanger Crisis Center has a lower minimum emotional intensity compared to Molde Crisis Center. This indicates that Stavanger Crisis Center has a more subtle approach in their least intense language used.

We can also look at Molde Crisis Center and compare it against Bodø Crisis Center, which shows a mean difference of +1.573 ($p < .001$). This suggests that Molde Crisis Center uses more emotionally engaging language in their posts even at the minimum level when compared to Bodø Crisis Center.

The next variable, average emotionality, shows a mean difference of +1.156 ($p = .004$) when comparing Molde Crisis Center to the one in Stavanger. What this tells us is that Molde Crisis Center's posts are more emotionally intense on average than that of Stavanger Crisis Center's posts.

There is also a significant difference when looking at the mean difference between Molde Crisis Center and Bodø Crisis Center. Where the mean difference is +1.079 ($p = 004$), suggesting that Molde Crisis Center uses more emotionally intense language on average than the one in Bodø as well. This indicates that Bodø overall has a higher level of average emotionally charged messages in their posts than the two other centers.

Further examining variables, we find that there is a significant difference between Stavanger Crisis Center and Molde Crisis Center for the minimum positive emotionality with a mean difference of -1.208 ($p = .042$), which indicates that Stavanger Crisis Center uses less emphasis on positive emotional expressions at their minimum than that of Molde Crisis Center. We also see that Bodø Crisis Center acts the same when compared, however more significantly, to Molde Crisis Center, where we find a mean difference of -1.682 ($p < .001$)—suggesting an even lower level of minimum positive expressions.

Maximum positive emotionality shows significance when comparing Molde Crisis Center to Bodø Crisis Center, where the mean difference is +0.976 ($p = .042$), indicating that Molde Crisis Center uses a higher level of positive emotions than Bodø Crisis Center.

In the average positive emotionality variable, we compare Bodø Crisis Center to the one in Molde and find a mean difference of -1.329 ($p = .001$), suggesting the average emotional tone used in Bodø Crisis Center's posts is lower than in Molde Crisis Center's posts.

The final variable in this test, minimum negative emotionality, shows a significance between Stavanger Crisis Center and Bodø Crisis Center. We get the mean difference of -1.606 ($p = .041$). This tells us that Stavanger Crisis Center's posts hold a lower level of minimum negative emotions.

Variables such as maximum emotionality, maximum negative emotionality, and average negative emotionality did not display any statistically significant findings worth exploring any further.

4.2.3 ANOVA Using Valence- And Certainty Variables

One-way ANOVA to compare the following variables across the three Crisis Centers: Number of likes as dependent variable. Extremity minimum positive, extremity minimum negative, extremity maximum positive, extremity maximum negative, extremity average negative, and extremity positive average as the independent variables.

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
numberoflikes	Between Groups	611.935	2	305.967	3.663	.028
	Within Groups	13448.870	161	83.533		
	Total	14060.805	163			
valence_min	Between Groups	112.804	2	56.402	7.086	.001
	Within Groups	843.737	106	7.960		
	Total	956.541	108			
valence_max	Between Groups	62.362	2	31.181	7.228	.001
	Within Groups	457.257	106	4.314		
	Total	519.619	108			
valence_avg	Between Groups	83.775	2	41.887	9.134	<.001
	Within Groups	486.113	106	4.586		
	Total	569.888	108			
certainty_min	Between Groups	7.157	2	3.578	2.204	.116
	Within Groups	165.623	102	1.624		
	Total	172.780	104			
certainty_max	Between Groups	1.573	2	.786	1.443	.241
	Within Groups	55.569	102	.545		
	Total	57.142	104			
certainty_avg	Between Groups	2.147	2	1.074	2.367	.099
	Within Groups	46.261	102	.454		
	Total	48.408	104			

Included in the table:

Sum of Squares, degrees of freedom (df), Mean Square, the F-statistic, and the significance level (p-value).

At first glance, the only significance in this ANOVA test lies with the valence variables. There is no inherent significance to any of the certainty variables, so they will not be examined any further.

Taking a look at the minimum valence variable, we can see that it is certainly statistically significant ($F(2, 106) = 7.086$, $p = .001$). There is a clear variation in the use of minimum valence expression among the three centers, meaning the most negative sentiment expressed in the dataset. Words that express negative valence are along with other “Pain” and “Hate”.

Maximum valence shows a similar variation between the centers ($F(2, 106) = 7.228$, $p = .001$). F statistic indicates that the difference across the centers in the maximum valence variable is significant and worth examining further. Words containing positive valence are along with other “Joy” and “Love”.

Finally, the last variable to yield significant results, average valence ($F(2, 106) = 9.134$, $p < .001$). The F statistic shows us that this variable holds the most statistical significance out of the three valence variables. This indicates that the mean sentiment across the centers is very varied.

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
numberoflikes	Eta-squared	.044	.000	.112
	Epsilon-squared	.032	-.012	.101
	Omega-squared Fixed-effect	.031	-.012	.100
	Omega-squared Random-effect	.016	-.006	.053
valence_min	Eta-squared	.118	.021	.228
	Epsilon-squared	.101	.002	.213
	Omega-squared Fixed-effect	.100	.002	.212
	Omega-squared Random-effect	.053	.001	.118
valence_max	Eta-squared	.120	.022	.230
	Epsilon-squared	.103	.003	.216
	Omega-squared Fixed-effect	.103	.003	.214
	Omega-squared Random-effect	.054	.002	.120
valence_avg	Eta-squared	.147	.037	.261
	Epsilon-squared	.131	.019	.248
	Omega-squared Fixed-effect	.130	.019	.246
	Omega-squared Random-effect	.069	.009	.140
certainty_min	Eta-squared	.041	.000	.127
	Epsilon-squared	.023	-.020	.109
	Omega-squared Fixed-effect	.022	-.019	.109
	Omega-squared Random-effect	.011	-.010	.057
certainty_max	Eta-squared	.028	.000	.102
	Epsilon-squared	.008	-.020	.085
	Omega-squared Fixed-effect	.008	-.019	.084
	Omega-squared Random-effect	.004	-.010	.044
certainty_avg	Eta-squared	.044	.000	.131
	Epsilon-squared	.026	-.020	.114
	Omega-squared Fixed-effect	.025	-.019	.113
	Omega-squared Random-effect	.013	-.010	.060

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

The size effects for our valence variables show much significance. The Eta-squared (η^2) value of .118 for minimum valence accounts for approximately 11.8% of the variance in the minimum valence levels among the centers.

Maximum valence yields an Eta-squared (η^2) value of .120, which equates to 12% of the variance in the dataset, indicating that the differences between centers explain a large portion of the variability in the highest level of positive sentiment expressed in their posts.

The Eta-squared (η^2) value of the average valence, which explains 14.7% of the variance in the dataset, suggests that a significant amount of the variance in the sentiment levels across all centers is explained by the variations in the centers' posts. The high effect size indicates that the average sentiment stated is significantly influenced by center association, suggesting that each group's language use might be related to a different overall emotional strategy.

Tukey's Honestly Significant Difference (HSD) test.

The included variables (each block), groups compared (1-3), Mean Difference (I-J), Std. Error, Sig., 95% confidence interval.

Multiple Comparisons

Dependent Variable		(I) center_groups	(J) center_groups	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
numberoflikes	Tukey HSD	1.00	2.00	-2.840	1.828	.269	-7.16	1.48
			3.00	-4.663*	1.725	.021	-8.74	-.58
		2.00	1.00	2.840	1.828	.269	-1.48	7.16
			3.00	-1.823	1.725	.542	-5.90	2.26
		3.00	1.00	4.663*	1.725	.021	.58	8.74
			2.00	1.823	1.725	.542	-2.26	5.90
valence_min	Tukey HSD	1.00	2.00	-2.53529*	.71533	.002	-4.2357	-.8349
			3.00	-1.82112*	.63282	.013	-3.3254	-.3169
		2.00	1.00	2.53529*	.71533	.002	.8349	4.2357
			3.00	.71416	.67625	.543	-.8933	2.3217
		3.00	1.00	1.82112*	.63282	.013	.3169	3.3254
			2.00	-.71416	.67625	.543	-2.3217	.8933
valence_max	Tukey HSD	1.00	2.00	-.65457	.52660	.431	-1.9064	.5972
			3.00	-1.73830*	.46586	<.001	-2.8457	-.6309
		2.00	1.00	.65457	.52660	.431	-.5972	1.9064
			3.00	-1.08373	.49783	.080	-2.2671	.0997
		3.00	1.00	1.73830*	.46586	<.001	.6309	2.8457
			2.00	1.08373	.49783	.080	-.0997	2.2671
valence_avg	Tukey HSD	1.00	2.00	-1.62605*	.54297	.010	-2.9167	-.3354
			3.00	-1.98918*	.48034	<.001	-3.1310	-.8474
		2.00	1.00	1.62605*	.54297	.010	.3354	2.9167
			3.00	-.36313	.51330	.760	-1.5833	.8570
		3.00	1.00	1.98918*	.48034	<.001	.8474	3.1310
			2.00	.36313	.51330	.760	-.8570	1.5833
certainty_min	Tukey HSD	1.00	2.00	-.34065	.32606	.551	-1.1162	.4349
			3.00	-.59255	.28336	.097	-1.2665	.0814
		2.00	1.00	.34065	.32606	.551	-.4349	1.1162
			3.00	-.25189	.33059	.727	-1.0382	.5344
		3.00	1.00	.59255	.28336	.097	-.0814	1.2665
			2.00	.25189	.33059	.727	-.5344	1.0382
certainty_max	Tukey HSD	1.00	2.00	.23970	.18887	.416	-.2095	.6889
			3.00	-.08123	.16414	.874	-.4716	.3092
		2.00	1.00	-.23970	.18887	.416	-.6889	.2095
			3.00	-.32093	.19149	.219	-.7764	.1345
		3.00	1.00	.08123	.16414	.874	-.3092	.4716
			2.00	.32093	.19149	.219	-.1345	.7764
certainty_avg	Tukey HSD	1.00	2.00	-.03637	.17232	.976	-.4462	.3735
			3.00	-.30778	.14976	.104	-.6640	.0484
		2.00	1.00	.03637	.17232	.976	-.3735	.4462
			3.00	-.27141	.17472	.271	-.6870	.1441
		3.00	1.00	.30778	.14976	.104	-.0484	.6640
			2.00	.27141	.17472	.271	-.1441	.6870

*. The mean difference is significant at the 0.05 level.

When testing the valence variables using Tukey's HSD test there are five statistically significant findings when comparing the three centers.

First, we look at minimum valence and compare Stavanger Crisis Center to Molde Crisis Center and find a mean difference of -2.535 (p = .002), suggesting quite a substantial reduction in the level of least positive sentiment expressed in their posts compared to that of Molde Crisis Center. The other significant difference is found between Stavanger Crisis Center and Bodø Crisis Center, with a mean difference of -1.821 (p = .013). This means that Stavanger Crisis Center also has a lower level of the least positive sentiment expressed when compared to Bodø Crisis Center. For maximum valence, we only yield one significant result, which is between Stavanger Crisis Center and Bodø Crisis Center with a mean difference of -1.738 (p < .001). A quite substantial significance that indicates Bodø Crisis Center's posts hold a much larger peak when it comes to their level of positivity in comparison to those of Stavanger Crisis Center. Finally, looking at the average valence we find a mean difference of +1.989 (p < .001) between Bodø Crisis Center and Stavanger Crisis Center, indicating that Bodø Crisis Center generally posts more positive messages in their posts. We also find a mean difference of +1.626 (p = .010) when comparing Molde Crisis Center with Stavanger Crisis Center. From this, we can gather that the same applies to Molde Crisis Center when compared to Stavanger Crisis Center regarding the average levels of positivity used in their posts.

4.3 Correlation

Correlation refers to the degree of relationship between variables. Variables that are correlated show that a variation in one variable is linked with a variation in another, either increasing together or moving in opposite directions. The directions in which the variables are moving are labeled as having a negative or positive correlation. The correlation coefficient, usually denoted as r, quantifies the degree of linear relationship between two variables. This coefficient can range from -1 to +1 where: +1 indicates a strong positive linear relationship, -1 indicates a strong negative linear relationship, and 0 suggests no linear relationship (Schober et al., 2018).
R-values between 0.0 and 0.3 indicate a weak positive linear relationship. When the value is in the negative, it indicates a weak negative linear relationship.
R-values between 0.3 and 0.7 indicate a moderate positive linear relationship. It's the same with negative values.

R-values between 0.7 and 1.0 indicate a strong linear relationship, where 1.0 indicates a perfect linear relationship. It’s the same with negative values. (Ratner, 2009)

The values from SPSS are separated into 4 categorical tables. Valence followed by extremity, emotionality, and certainty.

4.3.1 Valence

		number of likes	valence_min	valence_max	valence_avg	extremity_min	extremity_max	extremity_avg	y_min_pos	extremity_max_pos	y_avg_pos	extremity_min_neg	_max_neg	y_avg_neg
number of likes	Pearson Correlation	1	0,120	.314**	.276**	0,038	0,077	0,061	0,086	0,138	0,134	0,092	0,050	0,074
	Sig. (2-tailed)		0,213	0,001	0,004	0,699	0,424	0,525	0,415	0,191	0,203	0,580	0,763	0,655
	N	164	109	109	109	109	109	109	92	92	92	39	39	39
valence_min	Pearson Correlation	0,120	1	.541**	.873**	.377**	-0,169	0,118	.442**	0,176	.353**	-.674**	-1.000**	-.917**
	Sig. (2-tailed)	0,213		0,000	0,000	0,000	0,079	0,222	0,000	0,092	0,001	0,000	0,000	0,000
	N	109	109	109	109	109	109	109	92	92	92	39	39	39
valence_max	Pearson Correlation	.314**	.541**	1	.846**	-0,012	.256**	0,130	.502**	1.000**	.829**	-0,145	0,057	-0,058
	Sig. (2-tailed)	0,001	0,000		0,000	0,900	0,007	0,177	0,000	0,000	0,000	0,379	0,730	0,726
	N	109	109	109	109	109	109	109	92	92	92	39	39	39
valence_avg	Pearson Correlation	.276**	.873**	.846**	1	.259**	0,029	0,153	.514**	.417**	.536**	-0,199	-0,230	-0,252
	Sig. (2-tailed)	0,004	0,000	0,000		0,007	0,764	0,113	0,000	0,000	0,000	0,224	0,160	0,122
	N	109	109	109	109	109	109	109	92	92	92	39	39	39

		emotionality_min	emotionality_max	emotionality_avg	emotionality_min_pos	emotionality_max_pos	emotionality_avg_pos	emotionality_min_neg	emotionality_max_neg	emotionality_avg_neg	certainty_min	certainty_max	certainty_avg
number of likes	Pearson Correlation	-0,025	-0,065	-0,039	-0,084	-0,062	-0,064	0,118	0,000	0,046	0,125	0,090	0,120
	Sig. (2-tailed)	0,796	0,505	0,690	0,425	0,557	0,543	0,474	0,998	0,779	0,202	0,361	0,224
	N	109	109	109	92	92	92	39	39	39	105	105	105
valence_min	Pearson Correlation	.295**	-.225*	-0,009	.232*	-0,125	0,058	-.593**	-.750**	-.737**	0,220	-.342**	-0,002
	Sig. (2-tailed)	0,002	0,019	0,924	0,026	0,237	0,582	0,000	0,000	0,000	0,050	0,002	0,985
	N	109	109	109	92	92	92	39	39	39	80	80	80
valence_max	Pearson Correlation	-0,048	0,166	0,045	-0,023	.224*	0,089	0,043	0,106	0,072	0,044	0,071	0,082
	Sig. (2-tailed)	0,619	0,085	0,640	0,830	0,032	0,399	0,793	0,522	0,662	0,701	0,529	0,467
	N	109	109	109	92	92	92	39	39	39	80	80	80
valence_avg	Pearson Correlation	0,168	-0,053	0,017	0,154	-0,039	0,066	-0,026	-0,111	-0,105	0,188	-0,158	0,070
	Sig. (2-tailed)	0,080	0,582	0,860	0,143	0,715	0,533	0,877	0,500	0,524	0,094	0,162	0,534
	N	109	109	109	92	92	92	39	39	39	80	80	80

Correlations between variables with extensive discrepancies regarding N cases will mostly be overlooked as there may be bias in the values, e.g. maximum negative extremity and average emotionality (N = 22), as these cases may not be representative of the general population and can lead to a Type II error (false negatives) (Smith, 2012).

Maximum valence indicates a moderate positive correlation with number of likes ($r = .314$, $p = .001$), indicating that more positively charged words such as “excellent” and “fantastic” tend to generate more likes for each of the centers. Average valence shows a significance in correlation to the number of likes with a weak positive correlation ($r = .278$, $p = .004$). While the association between average- and maximum valence with number of likes is not as strong, it still indicates that higher average valence has a favorable effect on the number of likes received per post the centers make.

There is a correlation between minimum- and maximum valence ($r = .541$, $p < .001$). The reason for the correlation between the two is that posts tend to include both negative and positive words together, e.g. “We understand that you are a victim of abuse and violence, but we assure you that the bright days are to come, and you’ll have a beautiful life soon.”

We can see that minimum positive extremity has a significant correlation with minimum valence (r = .442, p < .001). What this tells us is that posts with a minimal amount of positive extremity will have a higher minimal valence score. This suggests a relationship in which more generally positive sentiments are linked to minimally extreme positive sentiments.

Additionally, there is a strong association (r = .536, p < .001) between average valence and average positive extremity. The average valence has a reasonably strong trend to rise along with an increase in average positive extremity, suggesting that posts with higher positive extremity levels are viewed as more positive.

The strong negative correlation between the minimum negative extremity and minimum valence (r = -.674, p < .001), although containing only 39 cases (N = 39), shows that posts with the least extremes in their negativity tend to be more positive in their overall sentiment.

Maximum positive extremity displays a perfect positive correlation with maximum valence (r = 1.000, p < .001). This means that when the maximum levels of positive extremity increase, so does the maximum valence in a completely proportionate manner. This implies that the most extreme positive sentiments expressed in the posts are perfectly aligned with the positive valence peaks. Words like “Spectacular” and “Incredible” are two examples of positive extreme sentiments.

The only perfect negative correlation we find lies between minimum valence and minimum negative extremity (r = -1.000, p < .001), simply meaning that every increase in minimum valence leads to a proportional decrease in the minimum negative extremity. Words associated with negative extremity can be “Disastrous” and “Catastrophic.

4.3.2 Extremity And Emotionality

Variables with extensive discrepancies regarding N cases will be overlooked as there may be bias in the values, e.g. maximum positive extremity, and minimum negative extremity (N = 22), as these cases may not be representative of the general population and lead to a Type II error (false negatives) (Smith, 2012).

		number of likes	extremity_min	extremity_max	extremity_avg	extremity_min_pos	extremity_max_pos	extremity_avg_pos	extremity_min_neg	extremity_max_neg	extremity_avg_neg	emotionality_min	emotionality_max	emotionality_avg	emotionality_min_pos	emotionality_max_pos	emotionality_avg_pos	emotionality_min_neg	emotionality_max_neg	emotionality_avg_neg
number of likes	Pearson Correlation	1	0,038	0,077	0,061	0,086	0,138	0,134	0,092	0,050	0,074	-0,025	-0,065	-0,039	-0,084	-0,062	-0,064	0,118	0,000	0,046
	Sig. (2-tailed)		0,699	0,424	0,525	0,415	0,191	0,203	0,580	0,763	0,655	0,796	0,505	0,690	0,425	0,557	0,543	0,474	0,998	0,779
	N	164	109	109	109	92	92	92	39	39	39	109	109	109	92	92	92	39	39	39
extremity_min	Pearson Correlation	0,038	1	.368**	.832**	.755**	.389**	.673**	.845**	.533**	.753**	.403**	-0,080	0,174	0,081	-0,109	-0,022	.489**	0,238	.382*
	Sig. (2-tailed)	0,699		0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,407	0,070	0,443	0,302	0,838	0,002	0,145	0,016
	N	109	109	109	109	92	92	92	39	39	39	109	109	109	92	92	92	39	39	39
extremity_max	Pearson Correlation	0,077	.368**	1	.797**	.305**	.740**	.579**	.525**	.826**	.735**	-0,009	.419**	.257**	-0,154	0,176	0,002	.448**	.599**	.573**
	Sig. (2-tailed)	0,424	0,000		0,000	0,003	0,000	0,000	0,001	0,000	0,000	0,922	0,000	0,007	0,144	0,094	0,982	0,004	0,000	0,000
	N	109	109	109	109	92	92	92	39	39	39	109	109	109	92	92	92	39	39	39
extremity_avg	Pearson Correlation	0,061	.832**	.797**	1	.744**	.706**	.847**	.782**	.822**	.877**	.241*	.197*	.265**	-0,036	0,007	-0,028	.564**	.537**	.601**
	Sig. (2-tailed)	0,525	0,000	0,000		0,000	0,000	0,000	0,000	0,000	0,000	0,012	0,041	0,005	0,730	0,945	0,793	0,000	0,000	0,000
	N	109	109	109	109	92	92	92	39	39	39	109	109	109	92	92	92	39	39	39
extremity_min_pos	Pearson Correlation	0,086	.755**	.305**	.744**	1	.502**	.887**	-0,086	-0,157	-0,096	0,181	-0,101	0,031	0,197	-0,048	0,078	-0,147	-0,307	-0,165
	Sig. (2-tailed)	0,415	0,000	0,003	0,000		0,000	0,000	0,703	0,486	0,672	0,084	0,336	0,772	0,059	0,648	0,457	0,515	0,165	0,462
	N	92	92	92	92	92	92	92	22	22	22	92	92	92	92	92	92	22	22	22
extremity_max_pos	Pearson Correlation	0,138	.389**	.740**	.706**	.502**	1	.829**	-0,075	-0,050	-0,068	-0,066	0,144	0,011	-0,023	.224*	0,089	-0,171	-0,126	-0,120
	Sig. (2-tailed)	0,191	0,000	0,000	0,000	0,000		0,000	0,740	0,825	0,763	0,533	0,171	0,917	0,830	0,032	0,399	0,447	0,575	0,593
	N	92	92	92	92	92	92	92	22	22	22	92	92	92	92	92	92	22	22	22
extremity_avg_pos	Pearson Correlation	0,134	.673**	.579**	.847**	.887**	.829**	1	-0,077	-0,097	-0,074	0,071	0,018	0,025	0,096	0,091	0,092	-0,177	-0,208	-0,144
	Sig. (2-tailed)	0,203	0,000	0,000	0,000	0,000	0,000		0,734	0,668	0,742	0,504	0,863	0,811	0,362	0,387	0,384	0,431	0,352	0,522
	N	92	92	92	92	92	92	92	22	22	22	92	92	92	92	92	92	22	22	22
extremity_min_neg	Pearson Correlation	0,092	.845**	.525**	.782**	-0,086	-0,075	-0,077	1	.675**	.909**	.433**	0,092	.360*	-0,350	-0,171	-0,307	.686**	.418**	.568**
	Sig. (2-tailed)	0,580	0,000	0,001	0,000	0,703	0,740	0,734		0,000	0,000	0,006	0,577	0,024	0,111	0,446	0,164	0,000	0,008	0,000
	N	39	39	39	39	22	22	22	39	39	39	39	39	39	22	22	22	39	39	39
extremity_max_neg	Pearson Correlation	0,050	.533**	.826**	.822**	-0,157	-0,050	-0,097	.675**	1	.917**	0,288	.479**	.561**	-0,387	-0,126	-0,296	.593**	.750**	.737**
	Sig. (2-tailed)	0,763	0,000	0,000	0,000	0,486	0,825	0,668	0,000		0,000	0,075	0,002	0,000	0,076	0,575	0,182	0,000	0,000	0,000
	N	39	39	39	39	22	22	22	39	39	39	39	39	39	22	22	22	39	39	39
extremity_avg_neg	Pearson Correlation	0,074	.753**	.735**	.877**	-0,096	-0,068	-0,074	.909**	.917**	1	.398*	0,311	.511**	-0,390	-0,194	-0,343	.701**	.644**	.724**
	Sig. (2-tailed)	0,655	0,000	0,000	0,000	0,672	0,763	0,742	0,000	0,000		0,012	0,054	0,001	0,072	0,388	0,118	0,000	0,000	0,000
	N	39	39	39	39	22	22	22	39	39	39	39	39	39	22	22	22	39	39	39
emotionality_min	Pearson Correlation	-0,025	.403**	-0,009	.241*	0,181	-0,066	0,071	.433**	0,288	.398*	1	.443**	.836**	.826**	.454**	.727**	.671**	.490**	.610**
	Sig. (2-tailed)	0,796	0,000	0,922	0,012	0,084	0,533	0,504	0,006	0,075	0,012		0,000	0,000	0,000	0,000	0,000	0,000	0,002	0,000
	N	109	109	109	109	92	92	92	39	39	39	109	109	109	92	92	92	39	39	39
emotionality_max	Pearson Correlation	-0,065	-0,080	.419**	.197*	-0,101	0,144	0,018	0,092	.479**	0,311	.443**	1	.836**	.519**	.907**	.780**	.351*	.681**	.581**
	Sig. (2-tailed)	0,505	0,407	0,000	0,041	0,336	0,171	0,863	0,577	0,002	0,054	0,000		0,000	0,000	0,000	0,000	0,029	0,000	0,000
	N	109	109	109	109	92	92	92	39	39	39	109	109	109	92	92	92	39	39	39
emotionality_avg	Pearson Correlation	-0,039	0,174	.257**	.265**	0,031	0,011	0,025	.360*	.561**	.511**	.836**	.836**	1	.797**	.769**	.881**	.695**	.821**	.828**
	Sig. (2-tailed)	0,690	0,070	0,007	0,005	0,772	0,917	0,811	0,024	0,000	0,001	0,000	0,000		0,000	0,000	0,000	0,000	0,000	0,000
	N	109	109	109	109	92	92	92	39	39	39	109	109	109	92	92	92	39	39	39
emotionality_min_pos	Pearson Correlation	-0,084	0,081	-0,154	-0,036	0,197	-0,023	0,096	-0,350	-0,387	-0,390	.826**	.519**	.797**	1	.597**	.902**	-0,393	-0,240	-0,279
	Sig. (2-tailed)	0,425	0,443	0,144	0,730	0,059	0,830	0,362	0,111	0,076	0,072	0,000	0,000	0,000		0,000	0,000	0,070	0,282	0,209
	N	92	92	92	92	92	92	92	22	22	22	92	92	92	92	92	92	22	22	22
emotionality_max_pos	Pearson Correlation	-0,062	-0,109	0,176	0,007	-0,048	.224*	0,091	-0,171	-0,126	-0,194	.454**	.907**	.769**	.597**	1	.872**	-.426*	-0,051	-0,244
	Sig. (2-tailed)	0,557	0,302	0,094	0,945	0,648	0,032	0,387	0,446	0,575	0,388	0,000	0,000	0,000	0,000		0,000	0,048	0,821	0,274
	N	92	92	92	92	92	92	92	22	22	22	92	92	92	92	92	92	22	22	22
emotionality_avg_pos	Pearson Correlation	-0,064	-0,022	0,002	-0,028	0,078	0,089	0,092	-0,307	-0,296	-0,343	.727**	.780**	.881**	.902**	.872**	1	-.481*	-0,180	-0,321
	Sig. (2-tailed)	0,543	0,838	0,982	0,793	0,457	0,399	0,384	0,164	0,182	0,118	0,000	0,000	0,000	0,000	0,000		0,023	0,423	0,146
	N	92	92	92	92	92	92	92	22	22	22	92	92	92	92	92	92	22	22	22
emotionality_min_neg	Pearson Correlation	0,118	.489**	.448**	.564**	-0,147	-0,171	-0,177	.686**	.593**	.701**	.671**	.351*	.695**	-0,393	-.426*	-.481*	1	.722**	.896**
	Sig. (2-tailed)	0,474	0,002	0,004	0,000	0,515	0,447	0,431	0,000	0,000	0,000	0,000	0,029	0,000	0,070	0,048	0,023		0,000	0,000
	N	39	39	39	39	22	22	22	39	39	39	39	39	39	22	22	22	39	39	39
emotionality_max_neg	Pearson Correlation	0,000	0,238	.599**	.537**	-0,307	-0,126	-0,208	.418**	.750**	.644**	.490**	.681**	.821**	-0,240	-0,051	-0,180	.722**	1	.945**
	Sig. (2-tailed)	0,998	0,145	0,000	0,000	0,165	0,575	0,352	0,008	0,000	0,000	0,002	0,000	0,000	0,282	0,821	0,423	0,000		0,000
	N	39	39	39	39	22	22	22	39	39	39	39	39	39	22	22	22	39	39	39
emotionality_avg_neg	Pearson Correlation	0,046	.382*	.573**	.601**	-0,165	-0,120	-0,144	.568**	.737**	.724**	.610**	.581**	.828**	-0,279	-0,244	-0,321	.896**	.945**	1
	Sig. (2-tailed)	0,779	0,016	0,000	0,000	0,462	0,593	0,522	0,000	0,000	0,000	0,000	0,000	0,000	0,209	0,274	0,146	0,000	0,000	
	N	39	39	39	39	22	22	22	39	39	39	39	39	39	22	22	22	39	39	39

It is instantly apparent that there is no meaningful association between the number of likes on the posts and the correlation between the extreme and emotional variables. These findings suggest that the number of likes the centers gain on their posts may not be strongly correlated with the usage of extreme and emotional language.

In the table showcasing correlations between the extremity- and emotionality variables we can see that there is a significant correlation between minimum extremity and minimum emotionality (r = .403, p < .001), suggesting that a minimal level of intensity has a moderate to strong positive correlation. This specifically means that as there is an increase in the minimum level of strong language, we also see an increase in the lowest level of emotionality.

Another significant result is the correlation between the minimum extremity and minimum negative emotionality ($r = .489$, $p = .002$), displaying a moderate to strong association in these two variables where an increase of the least intense sentiments used in posts also prompts an uptick in the lowest amount of negative emotional content.

Maximum extremity correlates with maximum emotionality ($r = .419$, $p < .001$), indicating that the most extreme negative or positive words used in the text reflect the most positive or negative emotional words used. Maximum extremity also correlates with minimum and maximum negative emotional words ($r = .448$, $p = .004$ and $r = .599$, $p < .001$), displaying a moderate to strong correlation where maximum negative emotionality shows the strongest correlation.

The average extremity shows a significant correlation with the average emotionality ($r = .265$, $p = .005$), implying that the overall intensity of the sentiments alongside the average emotional tone increases with a weak positive correlation. Another correlation displayed in the average extremity variable is with the minimum negative emotionality ($r = .564$, $p < .001$), which indicates that there is a strong increase in the average intensity as the lowest negative emotional tone in the posts rises. We can see almost the same correlation when comparing the average extremity to both the maximum negative emotionality ($r = .537$, $p < .001$), and the average negative emotionality ($r = .601$, $p < .001$). Simply put, as with the correlation between the average extremity and minimum negative emotionality, there is a positive increase for both the maximum negative emotionality and the average negative emotionality when compared to the average extremity.

The last effect we see is between the average negative extremity and all three negative emotionality variables (minimum negative emotionality ($r = .701$, $p < .001$), maximum negative emotionality ($r = .644$, $p < .001$), and average negative emotionality ($r = .724$, $p < .001$)). It must be mentioned that these cases also only contain 39 observations (N = 39), and the risk of making a Type II error is higher than those correlating with a higher number of observations, e.g. N = 109. This looks to be the case for every correlation regarding the extremity- and negative emotionality variables.

4.3.3 Certainty:

		number of likes	valence_min	valence_max	valence_avg	extremity_min	extremity_max	extremity_avg	y_min_pos	extremity_max_pos	y_avg_pos	extremity_min_neg
certainty_min	Pearson Correlation	0,125	0,220	0,044	0,188	.322**	0,128	.259*	.479**	.396**	.486**	0,046
	Sig. (2-tailed)	0,202	0,050	0,701	0,094	0,004	0,258	0,021	0,000	0,001	0,000	0,782
	N	105	80	80	80	80	80	80	64	64	64	38
certainty_max	Pearson Correlation	0,090	-.342**	0,071	-0,158	-0,165	0,115	-0,031	0,016	0,194	0,100	-0,047
	Sig. (2-tailed)	0,361	0,002	0,529	0,162	0,144	0,310	0,782	0,902	0,125	0,431	0,778
	N	105	80	80	80	80	80	80	64	64	64	38
certainty_avg	Pearson Correlation	0,120	-0,002	0,082	0,070	0,138	0,170	0,155	.289*	.321**	.339**	0,082
	Sig. (2-tailed)	0,224	0,985	0,467	0,534	0,223	0,132	0,170	0,021	0,010	0,006	0,626
	N	105	80	80	80	80	80	80	64	64	64	38

		_max_neg	y_avg_neg	emotionality_min	emotionality_max	emotionality_avg	emotionality_min_pos	emotionality_max_pos	emotionality_avg_pos	emotionality_min_neg	emotionality_max_neg	emotionality_avg_neg	certainty_min	certainty_max	certainty_avg
certainty_min	Pearson Correlation	-0,257	-0,088	-0,079	-.237*	-0,220	-0,164	-0,208	-0,220	0,010	-0,301	-0,138	1	0,109	.786**
	Sig. (2-tailed)	0,119	0,599	0,486	0,035	0,050	0,197	0,099	0,080	0,951	0,067	0,410		0,266	0,000
	N	38	38	80	80	80	64	64	64	38	38	38	105	105	105
certainty_max	Pearson Correlation	-0,215	-0,156	-0,215	0,111	-0,052	0,004	0,148	0,087	-0,114	-0,312	-0,250	0,109	1	.623**
	Sig. (2-tailed)	0,194	0,350	0,055	0,327	0,647	0,975	0,245	0,497	0,496	0,056	0,130	0,266		0,000
	N	38	38	80	80	80	64	64	64	38	38	38	105	105	105
certainty_avg	Pearson Correlation	-0,277	-0,100	-0,162	-0,116	-0,182	-0,148	-0,063	-0,118	-0,043	-.387*	-0,251	.786**	.623**	1
	Sig. (2-tailed)	0,092	0,549	0,152	0,308	0,105	0,245	0,623	0,353	0,796	0,016	0,128	0,000	0,000	
	N	38	38	80	80	80	64	64	64	38	38	38	105	105	105

Under this section too, we notice that correlations between the certainty variables and the number of likes is not significant. These findings suggest that the number of likes the centers gain on their posts may not be strongly correlated with the usage of certain languages.

Between minimum certainty and minimum extremity ($r = .322$, $p = .004$) we notice a slightly positive correlation showing that posts with higher levels of minimal certainty also typically have higher minimal extremes. This may imply that even the most subdued posts are made with a certain amount of intensity.

In minimum certainty and minimum positive extremity ($r = .479$, $p < .001$), we find a greater correlation implying that posts are significantly associated with higher levels of minimal positive extremity when there is a higher baseline certainty. What this means is that at the minimal level of certainty in posts, we see a moderate increase in the minimum levels of the minimum positive extremity, framing the content more positively.

The correlation between minimum certainty and maximum positive extremity ($r = .396$, $p = .001$) shows us that the minimum level of certainty is associated with a higher level of maximum positive extremity, implying that posts with an indefinite tone can reach high levels of positive sentiment.

For the last minimum variable of certainty, we find a correlation with the average positive extremity ($r = .486$, $p < .001$), which tells us that the average positive extremity increases when we see a more determined language used in their posts.

In the maximum certainty variable, we only find one correlation, which is with minimum valence ($r = -.342$, $p = .002$). This moderate negative correlation suggests that a higher level of certainty is associated with a lower level of minimum valence. Highly assertive content such as “surely” and “absolutely” could be perceived as less positive, which can be connected to the implementations from the correlation between minimum certainty and maximum positive extremity.

In the average certainty variable, we also find a few correlations. There is a moderate positive correlation between the average certainty and maximum positive extremity (r = .321, p = .010), suggesting that a consistent level of certainty shows more extreme positive words. We also see the same moderate correlation between a consistent certainty level with the average positive extremity in posts (r = .339, p = .006).

For the last variables in this correlation model, we look at how the average certainty behaves in correlation with the minimum levels of certainty (r = .786, p < .001). There is quite a strong positive correlation that tells us the general level of certainty does not drop below a certain threshold. We also get a strong positive correlation regarding the maximum certainty levels (r = .623, p < .001), which then tells us that the posts seem to maintain a somewhat consistent degree of certainty.

4.4 Poisson Regression

"Poisson regression is used to predict a dependent variable that consists of "count data" given one or more independent variables" (laerd statistics, n.d.). The Poisson regression analysis uses a dependent variable and predictors. The dependent variable in this case is the number of likes. The predictors contain the 3 centers as factors and chosen variables from LS as covariates. Bodø Crisis Center is set to 0 because it serves as a reference and provides a comparison for other groups. Bodø Crisis Center helps us understand the starting point before any covariates are considered. Only then is it possible to see how the covariates behave.

Some of the variables with extensive discrepancies regarding N cases didn't work in the Poisson regression analysis. Some variables have only 22 observations, e.g. maximum positive extremity. By including variables with only 22 observations, the analysis excluded 142 out of 164 cases, therefore we needed to exclude these variables to lower the likelihood of a type II error. After excluding the discrepancies, we ended up with 80 cases. The 80 cases are distributed with 30 cases in Stavanger Crisis Center, 18 cases in Molde Crisis Center, and 32 cases in Bodø Crisis Center.

Case Processing Summary

	N	Percent
Included	80	48.8%
Excluded	84	51.2%
Total	164	100.0%

Categorical Variable Information

			N	Percent
Factor	center_groups	1.00	30	37.5%
		2.00	18	22.5%
		3.00	32	40.0%
		Total	80	100.0%

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.396	.4336	.546	2.245	10.359	1	.001
[center_groups=1.00]	-.102	.0754	-.250	.046	1.838	1	.175
[center_groups=2.00]	-.182	.0847	-.348	-.016	4.602	1	.032
[center_groups=3.00]	0[a]	.	.	.	.	.	.
valence_min	-.078	.0258	-.129	-.027	9.118	1	.003
valence_max	.064	.0485	-.031	.159	1.768	1	.184
valence_avg	.146	.0615	.025	.266	5.632	1	.018
extremity_min	.135	.1123	-.085	.355	1.454	1	.228
extremity_max	.081	.1430	-.199	.361	.321	1	.571
extremity_avg	-.235	.2345	-.695	.224	1.007	1	.316
emotionality_min	-.084	.0672	-.216	.048	1.563	1	.211
emotionality_max	-.212	.0615	-.333	-.092	11.924	1	<.001
emotionality_avg	.338	.1142	.114	.562	8.775	1	.003
certainty_min	.166	.0639	.041	.291	6.746	1	.009
certainty_max	.172	.0784	.018	.326	4.808	1	.028
certainty_avg	-.247	.1468	-.535	.041	2.836	1	.092
(Scale)	1[b]						

Minimum valence negatively affects the number of likes received ($\beta = -.078$, $p = .003$). E.g. words like “Failure” and “Bad” are negative valence. The statistical reliability of the relationship is indicated by the significance level; however, the impact is not very strong.

The average valence shows a positive effect ($\beta = .146$, $p = .018$), indicating that the overall valence in posts results in more likes received. Words such as “Book” capture a neutral tone and go under average valence.

Maximum emotionality has a negative impact on likes received ($\beta = -.212$, $p < .001$), albeit with a somewhat low effect size. Strong emotional words in this context show evidence of a lower number of likes received on posts. Highly emotional words are words like “Devastating”, “Passionate”, and “Heartwarming” and can be both negative and positive.

The average emotionality affects in a positive way ($\beta = .338$, $p = .003$), with a more impactful effect size. This implies that a more overall emotional tone in posts tends to bring in more likes.

Minimum certainty affects positively ($\beta = .166$, $p = .009$), revealing that less certain language in posts affects the number of likes received positively. Low-certainty words are “Maybe” and “Possibly”. Maximum certainty shows a positive effect as well ($\beta = .172$, $p = .028$), which tells us that a more certain language in their posts results in more likes received. We also see that the relation between likes received, and the average certainty is negative ($\beta = -.247$, $p = .092$), but with a p-value indicating insignificance. This could potentially mean that posts attract more likes when using minimal certainty and maximum certainty, but less in the context of the overall levels. This will be words like “definitely” as a certain word and “maybe” as an uncertain word.

“Yesterday we had a nice visit from Hege and Ane who work in the crisis center Secretariat in Oslo. They were given a tour of the crisis centers, met the full-time staff, and were served lunch. Furthermore, they got to meet some of our partners such as PBL, Statens Barnehus, Family Violence Coordinator in the Nordland police district and the Abuse Center in Bodø
We continue today - then they will get a full day's introduction to how the Bodø Crisis Center works and all our projects!! So just hang in there - there's a lot of exciting things we're doing here in Bodø, not to mention all our projects! We are passionate about the work we do.”

This is a good example from one of the posts from Bodø Crisis Center. With a total of 5 certainty words, it scores both high on maximum certainty and minimum certainty. Examples of the words used here can be “continue” and “passionate” as a certain word and “not” and “hang” as uncertain words. In addition, it has a high count of the number of likes, proving that the relation between uncertain and certain language results in more likes.

The extremity variables proved to generally not have any significant effect in this Poisson regression, which can indicate that extremity scores have less influence on the number of likes received.

5. Conclusion

“*The effect of sentiment analysis in social media*”

In this dissertation, we have looked at the effect that sentiment analysis has on social media. We utilized the text analysis tool, The Lexical Suite, to obtain sentiment variables from 164 Instagram posts made from three crisis centers in Norway. The crisis centers are in Stavanger, Molde, and Bodø. We interviewed our contact person, a staff member at Stavanger Crisis Center, to get a more detailed insight into the daily work occurring at these institutions.

To further examine the effects sentiment brings to social media and increased engagement, we used SPSS which is a statistical software suite, to conduct ANOVA, correlation tests, and Poisson regression. Through these tests, we were able to conclude how these sentiment variables correlated, how much variation they consisted of across the three centers, and how they impacted one another.

Key findings in our research show that the order in which the highest number of likes are received is as follows: Bodø Crisis Center, Molde Crisis Center, and Stavanger Crisis Center. This aligns with the initial observations as well as an indication made by their fanbase, where the order from highest to low remains the same. The difference in the number of likes they receive may be attributed to having a larger following on the respective accounts. However, we did find multiple significant results that would suggest sentiment affects how users engage with posts.

In Tukey's HSD test run for the valence variables, there is an indication that Bodø Crisis Center utilizes more positive sentiments in their communications. With this in consideration, the maximum valence correlated positively with the number of likes, which would suggest that using a higher level of positive sentiment is an effective way of gaining better engagement. The evidence of the mean differences in likes between the centers shows this effect as the center in Bodø is the main engagement attractor.

Another variable that indicates the same effect of a higher number of likes received is average valence, which is a neutral tone in the words expressed. Bodø Crisis Center maintains a more neutral language compared to the Stavanger Crisis Center.

The minimum valence variable shows a negative correlation with the number of likes received. Stavanger Crisis Center usually expresses a lower level of minimum valence in their posts in comparison to both the crisis centers in Molde and Bodø. Through ANOVA we find Stavanger Crisis Center to receive the fewest likes, which indicates that more negative sentiments are linked to less engagement from Instagram users.

Maintaining a consistent level of emotionality in posts will lead to an increase in the number of likes, as shown through Poisson regression. We again see that the cause for Stavanger Crisis Center's engagement levels could be indicated by their sentiments. They have a more inconsistent level of emotions throughout their posts, which indicated by the differences in likes between the center in Stavanger and Molde in ANOVA, may be attributed to the positive correlation between the number of likes and average emotionality.

In the correlation test for certainty in we found that highly assertive words such as "Surely" and "Absolutely" are perceived as less positive, while a more indefinite tone can correlate with high levels of positive sentiment. Linking these findings to the Poisson regression, we found on the other hand, that the regression analysis shows us a significance in maximum certainty having a positive effect on likes, but not as significant as the positive effect minimum certainty variable has on likes. Words that express less certainty in the language could be "Maybe" and "Possibly".

By bringing in the last certainty variable, average certainty, from Poisson regression, we can see that it has a negative significant effect on the number of likes. For certainty in general, this could potentially mean that posts attract more likes when using both minimal certainty and maximum certainty, but less in the context of the average certainty levels.

"Which variable has the most influence on the number of likes?"

The sentiment variables that would suggest the strongest influence on the number of likes received are the maximum- and average valence levels. They both show a positive, highly significant correlation with the engagement that posts receive from Instagram users. The minimum level for valence, however, did not reveal any indication of correlation in this regard. The other sentiment variables such as extremity, emotionality, and certainty did not indicate any significant impact on the number of likes received.

"Are there any significant differences between the centers' engagement strategies?"

Through the ANOVA analyses, we can conclude that there certainly are strategic differences between the three centers. As stated by our contact person at Stavanger Crisis Center, they must handle all social media communications themselves. We were made aware that there was no set capacity for actively using social media to create engagement. According to the statements made by our contact person Stavanger Crisis Center does not try to strategically plan their posts for maximum engagement levels. We do not know if this applies to the centers in Molde and Bodø, but the scores found through the analyses show differences in how they all express minimum emotionality, minimum valence, maximum valence, average valence, and average emotionality. These are all variables that have shown a direct correlation to the number of likes received on posts.

“What causes the biggest extremes from the valence?”

The rating for valence ranges from 0 to 9, meaning that scores close to 0 and 9 indicate a large extreme from the valence. By using two posts as examples the biggest extremes from valence can be more easily projected:

“'The TRUST study is a research project under the auspices of the National Knowledge Center on Violence and Traumatic Stress (NKVTS). We need more knowledge to improve the health and quality of life of victims of sexual abuse, and to prevent long-term damage. More knowledge gives us the opportunity to help vulnerable people in a better way.

Have you experienced sexual abuse during the past year? By participating in the TRUST study, you help others in the same situation.”

The word “Abuse” consistently lands a score of 0.54 rating on the minimum valence scale, which captures the emotional tone of the least favorable word used. This applies to a multitude of posts where they reuse the word. Since it is close to 0, it is counted as an extreme from the valence in a negative direction. On the other hand, it is difficult for a crisis center not to mention the word “Abuse” when they aim to spread awareness about these delicate matters.

“When we travel around with our school tour, we talk to the young people about myths. Myths that are passed down between generations, and that you may never come to terms with. We talk about whether myths are truths, or more assumptions. We meet so many thoughtful and beautiful young people - who understand that these myths do not correspond to reality.”

The two words thoughtful and beautiful land an especially high score on valence, which reflects the tone of the most favorable word used, with an 8.4. Since the words give a valence score of almost 9 it is counted as an extreme from the valence in the positive direction. Words that rank a high score on valence prove to contribute to more engagement through likes.

“How should a crisis center utilize the results from the analyses?”

For a crisis center that is looking to improve its engagement levels on social media, there is a clear emphasis on maintaining positive sentiments in posts. Engagement through likes shows a significant correlation with how positive posts are portrayed. If the messages within the posts contain a low level of minimum valence, they resonate worse with Instagram users. Being able to maintain a consistent level of emotion shows a positive impact on viewer engagement, whereas a high level of emotionality acts in contrast.

Focusing on keeping a steadier emotional sentiment in posts, in addition to a more overall positive balance, should be prioritized by centers willing to improve engagement levels. Knowing that crisis centers sometimes have to make use of extreme and emotionally negative words such as “Abuse”, they can focus on putting some positively connected words into the same post to keep a positive level of valence.

6. Research Limitations

There were a few limitations we met during our research phase. The data collection had to be manually executed by gathering posts from each of the three centers’ Instagram accounts. The number of likes of the posts of these centers was manually counted, as the count of likes had been semi-anonymized. The method of data collection resulted in a smaller sample size than we optimally would have liked.

As a result of the small sample size, The Lexical Suite, would show multiple missing values for certain variables containing the negative/positive values such as minimum negative extremity. The discrepancies found in this regard could potentially lead to making a Type II error.

The number of comments each post had was significantly fewer than the number of likes, which can be expected from an account concerning the matters of domestic abuse. We had originally planned to also use the number of comments as a variable, but there were simply too few to get any reliable results from.

Another limitation was not being able to interview with both Bodø- and Molde Crisis Center in addition to the one we were granted with our contact person at Stavanger Crisis Center. Through the interview with our contact person, we were provided with information that changed our perspective regarding how they conducted communications through social media. We believe that it would have been beneficial to examine how the other two centers engage in their social media communications in comparison to that of Stavanger Crisis Center.

7. Future Research

This thesis develops multiple directions for further research on the topic of sentiment analysis. The need for sentiment analysis is constantly growing and new ways to implement it in research are being done.

For future research, the idea of conducting more interviews and going in a more qualitative direction can be explored. This is something we saw as a limitation in our research, and we could have drawn more conclusions from the information they could have brought us.

It can be interesting to see the reaction through engagement if a crisis center chooses to exclude words that are connected to negative valence, for instance, “Violence” and “Abuse”. Would the engagement go up, but the awareness of domestic violence go down?

One direction can be to look at how changes in sentiment over time influence engagement on social media platforms for crisis centers. Does consistent positive or negative sentiment impact long-term follower behavior or perception?

Seeing broader than just a crisis center, it would be interesting to look at the results if the sentiment analysis were exploring a non-crisis organization instead of a crisis center on social media. Are the engagement drivers fundamentally different, and how can these differences be leveraged?

Are there particular sentiments that resonate more effectively with specific age groups, genders, or other demographic segments? Using stricter boundaries for future research and dividing the population into specific groups trying to point out which groups react and gives more engagement.

Lastly, it would be interesting to see the results from our conclusion if the crisis centers chose to implement them into their social media strategies. Through a comparison, seeing in the long-term how the engagement differs from before and after our research.

8. Problems Within The Research

The Lexical Suite is made so that it won't output a variable when it comes across a word that isn't in the lexicon. It was during our Poisson regression analysis that we became aware of this. We encountered multiple posts where some of them didn’t contain words conducted into Lexical suits’ lexicon, so we had to rule out several factors that we were interested in researching more.

Another problem we see with our research is that we only interviewed one of the three crisis centers, which told us that Stavanger Crisis Center did not actively engage in a high level of social media outreach. By interviewing the other 2 centers we could have possibly gotten more information about their strategies and thoughts regarding their social media presence.

Most of the time, in online reviews or any other online text source, the presence of more positive words does not necessarily make the review positive or vice versa. In most cases, it is impossible to use the same lexicon for scoring documents of different domains. To address this, a new set of sentiment lexicons should be prepared based on the nature of the target domain. There has been some research work done to build domain-specific sentiment lexicons for specific target domains by bootstrapping from an initial smaller lexicon (Kannan et al., 2016).

9. Final Words

In hindsight, there are a few things we could have done more efficiently. We had originally planned to use RStudio for the analysis section of our research, which proved to be too time-consuming. Making the switch to SPSS alleviated our work on the analyses, making it easier to conduct the tests and view results. This should have been done from the start to save valuable time.

As we conclude this part of our academic career, we express our gratitude to our tutor, Elham Ghazimatin, for her valuable help and insights. We also want to thank Stavanger Crisis Center for their willingness to provide us with the resources needed to complete our research.

We believe that further studies could examine how excluding negative sentiments affects the engagement received. Since this study only focused on the quantitative side of engagement effects in sentiments through social media, we believe that a more qualitative approach could be desirable. We gathered this from the interview we held with our contact person at the Stavanger Crisis Center.

The work committed to this thesis has proved to be incredibly educational for us both academically and personally.

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Attachments

Table 1: Summary of words generated and selection for The Evaluative Lexicon 2.0 (Rocklage et al., 2018)

	Initial Number of Words	Number of Words Added/Removed	Details of Addition/Removal
Initial wordlist	6.2 million	− 6.18 million	Extracted the 10,000 most frequently used words from each of the five sources
Refinement of the wordlist, Part 1			
Initial word assessment (Step 1)	21,189	− 16,691	Removed words unknown by a majority of judges and those judged unlikely to be indicative of an evaluative reaction
Seed-word propagation (Step 2)	1,359	+ 1,766	Propagated synonyms for those words judged likely to be indicative of an evaluative reaction. Added unique synonyms to main wordlist
Further word assessment (Step 3)	6,264	− 3,291	Removed words unknown by a majority of judges and those judged unlikely to be indicative of an evaluative reaction
Quantification of each word	2,973	− 137	Removed words unknown by a majority of judges
Refinement of the wordlist, Part 2	2,836	− 1,295	Removed words not used consistently across topics
EL 2.0	1,541		

Numbers in the "Initial Number of Words" column represent the number of starting words for that step and not necessarily the overall number of words obtained up to that step.

Table. 2: Summary of words generated in The Certainty Lexicon. (Rocklage et al., 2023)

	Number of Words/Phrases	Details of Addition/Removal
Phase I: Generating Candidate Word List		
Initial word list (Steps 1–3)	1,425	Generated through two empirical studies and existing word lists
N-gram propagation (Step 4)	+35,193	Propagated synonymous words and phrases for each n-gram in the initial word list
Resulting word list	36,618	
Phase II: Initial Filtering		
Based on real-world frequency (Step 1)	−15,512	Removed n-grams that occurred with low frequency in news articles and Reddit data
Based on human assessment (Step 2)	−16,002	Removed n-grams judged as unknown or unlikely to be indicative of certainty
Resulting word list	5,104	
Phase III: Quantifying Certainty		
Based on human assessment	−1	Removed one n-gram that raters judged as unknown
Resulting word list	5,103	
Phase IV: Final Refinement		
Based on real-world prediction	−1,618	Removed n-grams where the normative score and regression coefficient were not directionally consistent
Final CL word list	3,485	

Automated reports from Stavanger Crisis Center:

Attachment 1. Adult residents.

DEL 1
Øverst kommer en oppsummerende del. Man **må ha besvart spørsmål 4** om bruker ønsker å reservere seg mot registreringen.

Her vises:
- Totalt antall skjema.
- Totalt antall overnattingsdøgn.
- Kjønnsfordeling med antall og prosent.

Totalt antall skjema: **213**
Totalt antall overnattingsdøgn: **3 270**

Antall døgn kvinner: **2 941**
Antall døgn menn: **329**

2. Hva er beboerens kjønn?

	Prosent	Respondenter
Kvinne	88,3%	188
Mann	11,7%	25
Annen kjønnsidentitet	0,0%	0
I alt	100,0%	213

UNIKE BEBOERE. Med det menes førstegangsopphold i 2023. Ved å telle førstegangsopphold, teller vi i praksis de enkeltindivid som har bodd på senteret i løpet av året. Man **må ha besvart spørsmål 4** om bruker ønsker å reservere seg mot registreringen.

Her vises:
- Antall førstegangsopphold i 2023.
- Kjønnsfordeling for førstegangsopphold.

Antall førstegangsopphold 2023: **169**

UNIKE BEBOERE: 2. Hva er beboerens kjønn?

	Prosent	Respondenter
Kvinne	85,8%	145
Mann	14,2%	24
Annen kjønnsidentitet	0,0%	0
I alt	100,0%	169

Del 3
Under listes svarene på spørsmål 3 til 36 opp.

Attachment 2. Day visits and one-on-one phone calls.

1008 - Krisesenteret i Stavanger

Autorapport dagsbesøk og enesamtaler på telefon 2023
1008 - Krisesenteret i Stavanger

Øverst vises noen hovedtall for registreringer i 2023.

Først en del med alle skjema som er registrert:
- Antall skjema som er registrert. For å regnes med her må spørsmål om brukeren ønsker å reservere seg mot registrering være besvart.
- Antall registrerte dagsbesøk og enesamtaler på tlf
- Brukerens kjønn for alle registreringer

Antall skjema registrert totalt: **1 596**

2. Dagsbesøk eller enesamtale på telefon:

	Prosent	Respondenter
Dagsbesøk	60,5%	965
Enesamtale på telefon	39,5%	631
I alt	100,0%	1 596

3. Brukerens kjønn?Krysset med: 2. Dagsbesøk eller enesamtale på telefon:

	Dagsbesøk	Enesamtale på telefon
Kvinne	906	561
Mann	56	69
Annen kjønnsidentitet	0	0
I alt	962	630

Dagsbesøk pr mnd:Krysset med: 3. Brukerens kjønn?

	Kvinne	Mann	Annen kjønnsidentitet	I alt
Januar	53	7	0	60
Februar	58	2	0	60
Mars	85	7	0	92
April	46	4	0	50
Mai	67	1	0	68
Juni	100	11	0	111
Juli	50	2	0	52
August	95	5	0	100
September	92	4	0	96
Oktober	65	4	0	69
November	116	4	0	120
Desember	79	5	0	84

Attachment 3. Number of comments per post-bar graph using SPSS: