Emotions in Facebook:

Analysing Emotions' Distribution, Diffusion and Agenda Effect on VG's Facebook Page

Xiaojuan Hou

Master's Thesis in Nordic Media

Department of Media and Communication

UNIVERSITY OF OSLO

Spring 2020

2020

Emotions in Facebook: Analyzing Emotions' Distribution, Diffusion and Agenda Effect in VG's Facebook page

Xiaojuan Hou

http://www.duo.uio.no/

Trykk: Reprosentralen, Universitetet i Oslo

Acknowledgements

The writing process of this thesis is memorable and challenging for me. As an international student in the program of Nordic Media, this is my first experience studying in a country other than my motherland, and everything is exciting and challenging for me. Here, I would like to thank some people who provide huge help and inspirations to me during the carrying out process of this thesis, otherwise I couldn’t achieve this project.

First and foremost, I would like to express my heartfelt appreciation to my supervisor Charles Melvin Ess who has given me plenty of help during the past two years. Thank you for your patience on regular greetings about the progress of my thesis and whether I need more help. Thank you for your encouragement regarding my lack of confidence in writing the first non-native thesis. Thank you for your rich scholarship and guidance for every step of my thesis writing. Your feedbacks are always highly valuable for me in the project and I have learned and benefited a lot from you.

I also want to thank you to my husband, Qiang Wen, who always encourage me and gave lots of help regarding emotion detection skills in this project. Thank you also to my parents for their countless support.

Finally, I would like to thank my classmates in Nordic Media program, who made my studying life at University of Oslo more memorable.

Abstract

This study examined emotions of news and comments from a famous Norwegian newspaper called Verdens Gang's (VG) Facebook public page. The data set for analysis contains 84 news items and 7876 comments collected from the new posted on VG's Facebook page in the last three days in August 2018. Emotions of textual content (news titles and comments) were detected by Senpy which is automatic emotion detector and extract emotions in a detailed level (output specific types of emotion e.g.: happiness, sadness, fear, anger and disgust) rather than polarity level (positive, negative and neutral). After analysing the reactions expressed by public and emotions of comments and news titles, findings suggest that: the main emotion on VG's Facebook page is happiness, and the emotional strength (total number of emotions in comments of each news) is highly positive correlated with happiness. Findings also suggest that people are more likely to express happiness when the engagement of the news is large. News with the emotion of anger could reach the highest number of users, whereas news with the emotion of fear reach the smallest number of audiences and have the lowest intensity of diffusion. Moreover, anger news gets a comment faster and spread longer than news with other emotions, while happy news will take the longest time to get a feedback from public and has the shortest spreading time span. In addition, more than half part of the news' emotional agenda corresponds with the public's emotions; happiness and anger has a stronger agenda affect than fear and sadness.

Contents

List of Tables

List of Figures

Chapter 1 Introduction

1.1 Overview

Social media is becoming a vital space for people sharing thoughts, ideas, information and news (Lee & Ma, 2012; Kümpel, Karnowski & Keyling, 2015; Shearer & Matsa, 2018). Not only for individuals, media organizations also benefit a lot by posting contents and news on social media. Traditional media institutions etc. news providers have established their own social media presence on Facebook and Twitter to deliver news to obtain more traffic, article views, audiences and revenue. (Ju, Jeong & Chyi, 2014).

In addition to the traditional motivations that promote people sharing news on social media, such as status attainment (e.g., getting attention) (Kümpel, Karnowski & Keyling, 2015), establishing social relationships and reputations (Hsu & Lin, 2008; Park et al., 2009), and information seeking (Goh et al., 2009; Dunne et al., 2010), hashtag inclusion (e.g.: communication and organization) (Ames & Naaman, 2007), homophily (e.g., topics, profile) (Macskassy & Michelson, 2011) (cited in Lee & Ma, 2012, p.331), emotion is another important factor that drive information diffusion on social media platforms (Ferrara & Yang, 2015b; Stieglitz & Dang-Xuan, 2013; Burke & Develin, 2016; Zhao, Dong, Wu & Xu, 2012; Berger & Milkman, 2010; Tadic et al., 2013). Analysing emotions or sentiment on social media has become an important domain in social media studies.

Prior research figures out that social media content often conveys the author's emotional state, judgment or evaluation of a certain person or topic, or the author's intention to carry out emotional communication, and news' emotional state is connected with information diffusion on social media (Stieglitz & Dang-Xuan, 2013). Celli, et.al. (2016) point out that viral messages containing Ekman's (1982) six emotions (surprize, joy, sadness, anger, fear, and disgust) are connected with sharing behaviours in social media. Berger and Milkman (2010) argued that contents with emotions were more likely to be shared. Although the diffusion effect of emotion has been proved by scholars, the debates about whether there is a positive emotional bias (positivity bias) or negative emotional bias (negativity bias) in social media are never stop. Scholars who support the former one argue that there are more positive emotions in social media (Leung, 2013; Ferrara & Yang, 2015a; Yu & John-Baptiste, 2016). People who agree the latter one point out there are more negative emotion in social media, and to the diffusion effect level, information with negative emotions could get more comments and retweets than positive information (Stieglitz & Dang-Xuan, 2013). However, some researchers also hold opposite opinions on how different emotions affect news dissemination in social media. For instance, positive emotions could encourage people to continue to post more and longer comments (Joyce & Kraut, 2006). Nelson-Field, Riebe and Newstead (2011) point out that video on Facebook with positive emotions is more likely to be shared. In addition to the controversy between positivity bias and negativity bias, and the different opinions regarding which emotion has a stronger diffusion effect in social media, scholars also found out that different countries have different emotion tendency in social media platforms (Chu & Choi,2011; Stieglitz & Dang-Xuan, 2013; Xu, 2017), and people with different culture background express different types of emotions (Hyvärinen & Beck, 2018). Thus, examining emotions on Facebook in the context of Norway seems necessary because there is not much similar research has been conducted in Norway, especially focusing on specific emotions in news reports posted by newspapers on social media.

This study will take the Facebook page of a Norwegian newspaper which named Verdens Gang (VG) as the research object, analyse news and comments' emotions and emoji/reactions on the page, and answer the following research questions: RQ1. What is the main emotion on VG's Facebook page? RQ2. How do emotions affect public's engagement of the news and news diffusion on VG's Facebook page? RQ3. How do emotions of the news post on VG's Facebook site affect public's emotions which conveyed by news commentators? RQ4. Which emotion has a stronger agenda effect on the public? In order to answer these research questions, 84 news items and 7876 pieces of comments were collected from VG's Facebook page, and emotions in news and comments were detected by a tool called Senpy[1] (Sánchez-Rada et al., 2016). After a quantitative content analysis of all data (emotions in news titles, comments and emoji/reactions), findings show that the main emotion on VG's Facebook page is happiness, and public prefer to give a happy feedback to the news while the engagement is large. Angry news gets the largest number of engagement, comments, reactions and sharing, whereas news with an emotion of fear has the fewest number of engagement. Moreover, news with anger could get a comment much faster and spread longer than news with happiness, fear and sadness, while happy news takes the longest time to get a comment from public and has the shortest spreading time span. Furthermore, half part of news' emotional agenda

[1] https://senpy.readthedocs.io/en/latest/

corresponded with the public's emotions on VG's Facebook page, and emotions of anger and happiness both have stronger agenda effect than sadness and fear.

In the next part of this chapter, detailed research purposes, research questions and research gaps will be provided. Then I will briefly introduce the method applied to this study. After that, I will present the structure of this thesis which contains 6 chapters. The last section of this chapter refers to some basic definitions and background information which are introductions of social media and Facebook, and the state of news consumption on social media.

1.2 Research Purpose and Research Questions

This project will focus on the one of the most famous Norwegian newspapers Verdens Gang (VG)'s Facebook page and analyse the emoji/reactions expressed by public, and emotions of news titles and comments which detected by emotion detector, Senpy, in which there are five basic emotion categories: sadness, happiness, fear, disgust, and anger (without surprise compared to Ekman's six emotion). Then I try to find out the main emotion on VG's Facebook page by analysing emotions of news and comments given by audiences as well as emoji. I also want to figure out what's the relations between the engagement of the news and the emotions, and whether the diffusion of news is associated with emotions. Finally, I will examine how do emotions in news reports affect public's emotion on Facebook and what kind of emotion has a stronger agenda effect on the public on VG's Facebook site in the context of Norway.

Even though there are two worldwide used social media platforms—Facebook and Twitter, in this study, only Facebook will be focused because it has a much higher amount of monthly active users than Twitter. The monthly active users in Facebook and Twitter are 2.38 billion[2] and 330 million[3] respectively in the first quarter of 2019.

The reason for selecting VG as the research object will be presented following. VG is a Norwegian tabloid newspaper and started in 1945[4]. It is one of the largest amount of circulation newspapers in Norway, with 233000 readerships for print newspaper in 2018[5], and

2 https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/
3 https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/
4 https://no.wikipedia.org/wiki/VG
5 http://medienorge.uib.no/english/?cat=statistikk&page=avis&queryID=273

a number of 65403 circulations in 2018 which made VG as the second largest print newspaper in Norway (No.1 is Aftenposten, with a circulation 132 409)[6]. However, VG is the most reading online newspaper in Norway, with the largest readership (1974 000)[7] in 2017, whereas Aftenposten (816 000) got the third position. In addition, the number of VG's followers on its Facebook page has over 505 000 which is much larger than Aftenposten's followers which is less than 390 000 (by September 2019). Based on the largest number of audiences on Facebook, VG was identified as the research object in this study to examine the following research questions:

RQ 1. What is the main emotion on VG's Facebook page?
a) What is the distributions of emotions on VG's Facebook page?
b) What is the mean of the proportion of each emotion in each news' comments and emoji/reactions?
c) How does the number of emotions rank in the comments and emoji/reactions of each news?
d) Is there a main emotion tendency in the comments and emoji/reactions of each news?

RQ 2. How do emotions affect public's engagement of the news and news diffusion on VG's Facebook page?
a) What is the relationship between emotions and emotional strength which is measured according to the number of emotional votes each news receives (reactions/emoji) and the frequency of emotions in comments?
b) What is the relationship between the emotions and engagement of the news which is the sum of the numbers of comments, sharing times and emoji/reaction?
c) What is the relationship between emotion of the news and the speed of comments given by audiences and the news spreading time span on VG's Facebook page?

RQ 3. How do emotions of news posted on VG's Facebook page affect public's emotions which conveyed by news commentators? RQ 4. Which emotion has a stronger agenda effect on the public?

[6] http://medienorge.uib.no/english/?cat=statistikk&page=avis&queryID=353
[7] http://medienorge.uib.no/english/?cat=statistikk&page=avis&queryID=253

1.3 Research Gaps

As mentioned in the first section of this chapter, the debate between positivity bias and negativity bias on emotions in social media has long existed. Scholars argue that there are more negative messages than positive ones on social media (Robertson et al., 2013), and there is also a negativity bias in social media based on the diffusion effect of emotions which is that information with negative emotion could get more comments and be shared easier (Stieglitz & Dang-Xuan ,2013). However, other researchers argue that there are more positive emotions than negative emotions in social media (Sas et al., 2009, p.120; Reinecke & Trepte, 2014), Ferrara and Yang argue that the positive massages reach larger number of readers than negative news, what is called positivity bias (Ferrara &Yang, 2015b, p.9). And some argue that positive emotion also could get more comments (Joyce & Kraut, 2006) and easier to be shared (Nelson-Field, Riebe & Newstead, 2011). These opposite arguments indicate that there is no agreement not only on the topic whether there is more positive emotion or more negative emotion on social media, but also which emotion could be shared easier. Moreover, emotions in social media have different distributions in different countries. For instance, Yu and John-Baptiste (2016) conducted a research in UK and found out there are more positive emotions both in Facebook and Twitter. However, in China, negative emotions or events on Weibo (Twitter liked platform in China) and Tianya BBS account for 75.6% and 95.8% respectively (Xu, 2017, p.78. My translation). Xu (2017) also argue that there is a significant "angry" bias to the feedback of online social news. In Norway, there is not much similar research has been carried out. Studies mentioned above which state different opinions on positivity bias or negativity bias, the differences of emotion distributions in different cultural backgrounds and the research gaps in Norway give a good chance for this study to examine emotions distributions and mediate effect on social media in the context of Norway.

Despite significant theoretical information relates to sentiment or emotion analysis on social media, the majority studies are related to the polarity level of sentiment analysis which only figures out whether the textual content is positive or negative (Yu & John-Baptiste, 2016; Almashraee, et al., 2016; Reinecke & Trepte, 2014). However, Almashraee, et al. (2016) argued that the emotion polarity is insufficient because "sentiment polarity does not convey the affective meaning that writers give to an object or to any of its related features" (Almashraee, et al., 2016, p.2). Therefore, a more fine-grained method compared with polarity emotion detection is needed, which could extract the specific emotions (e.g., happiness, sadness, anger, fear) from the textual content in social media. This project will use the emotion detection tool Senpy and extract emotions of news and comments posted on VG's Facebook page as the following emotion categories: happiness, sadness, fear, anger and disgust.

Furthermore, previous studies related to sentiment analysis on social media were more likely to focus on personal updates which referring some specific events (e.g., political election) or self-presentation (Panger, 2017) and found out people's emotional expression (Bazarova, 2015; Utz, 2011; Forest and Wood, 2012; Qiu, Lin, Leung, and Tov, 2012; Tsugawa & Ohsaki, 2015; Utz, 2015; Pfitzner, Garas, & Schweitzer, 2012; Kramer, Guillory, & Hancock, 2014). But very few people focus on media's public pages on social media and users' emotions in news and comments. This study will analyse audiences' emotions to the news, comments and emoji/reactions and the emotion of the news posted on VG's Facebook page, and find out the main emotions on the page, relationships between emotions and news diffusion, and further figure out the emotional agenda effect in Facebook which is also a domain that not many people have reached.

1.4 Methodological Approaches

The primary data for this study are collected from VG's Facebook page in September 2018, which contains 401 news items and 45 977 comments. Due to the huge amount of the dataset, which couldn't be handled by myself in this project, I randomly choose the data from the last three days (29/08-31/08) in August 2018 as a sample which contains 84 pieces of news and 9157 pieces of comments. After a filtering process which deleting some items such as unrecognizable information (e.g., "kkkkk", "Nääääąj"), messy codes, people's names without emoticons (hardly detect emotions), punctuations, blanks and some comments written in forms of links, a sample dataset with 84 news items and 7876 comments is done. Then all the news titles and comments will be translated from Norwegian to English by Google Translate because the emotion analysis service Senpy (Sánchez-Rada et al., 2016) is English and Spanish only. Senpy is an automatic emotion detection tool and could detect emotions from textual content (news titles and comments) based on five emotion categories: anger, fear, disgust, happiness, sadness (there is no "surprise" compared to Ekman's six emotion categories). After the emotion detection process, all results will be checked and modified. When the final dataset is ready, quantitative content analysis will be applied to this study to figure out all the three research questions.

1.5 Structure

The first chapter will provide an introduction of the outline, research gaps and research questions of this thesis. Methods used to conduct this study and simple backgrounds also provided in this chapter. Chapter 2 presents previous literature related to this project. Firstly, definitions of sentiment analysis and its applications from computer science to media studies are introduced. Then, differences between terms: sentiment, emotion, affect, mood are examined, but in this project, they could be used interchangeably. After that, definitions of emotion and different types of emotions defined by different theorists as well as the introduction of emotions in different detection tools will be presented. In the later part of chapter 2, state of emotions in social media, and emotion's diffusion effect, agenda effect will be compared and discussed. Chapter 3 provides the methodology of this research relating to big data analysing, sampling, coding, quantitative content analysis, limitations and ethical considerations. Chapter 4 gives out findings of this study: The main emotion on VG's Facebook page is happiness, and people more likely to give a happy feedback to news when the engagement of the news is large. News with an emotion of anger could reach the largest number of Facebook users (largest number of engagement, comments, reactions and sharing times), while fearful news reaches the smallest number people. Angry news gets a comments 8 times faster and spread 3 times longer than happy ones which has the fewest engagement and shortest spreading period. Moreover, over half part of news's emotion corresponded with the dominate emotions in comments and reactions, and emotions of anger and happiness have strong agenda effect. Chapter 5 discusses how all findings align with previous research, and presents limitations and generalizability of this study as well as the possibility for further research. Chapter 6 provides a brief conclusion of this thesis.

After providing the outline of this thesis, some basic backgrounds regarding definitions and characteristics of social media and Facebook as well as the state of news consumption on social media will be presented, which are the premise information of the literature review part. Hence, these kinds of background are listed separately from the literature review chapter and will be introduced next.

1.6 Backgrounds

1.6.1 Social Media

To-date, social media, such as Facebook, Twitter, YouTube and some other platforms in different countries, plays an important role in people's daily life. On social media platforms, people not only could share opinions, insights, experiences with each other, they could also get instant information and news from worldwide, contact with friends and family, even in some countries people could use social media platforms to pay bills and shopping. Statistics shows that internet users averagely spend 136 minutes on social media per day in 2018[8].

As the rapid growth of social media users, the public discourse and communication patterns in society have changed. Before that, people had to invest a lot of money and manpower to spread information to a large number of people in a community (Stieglitz & Dang-Xuan, 2013). Now, the emergence and application of social media have changed the physical barriers of information communication (Stieglitz & Dang-Xuan, 2013), which makes people easier to share and spread information. Information spreading on social media has become an important content for people browsing the Internet, which not only creates hot topics which promote people to discuss in their social life, but also attracts the competition of traditional media to follow up (Ju, Jeong & Chyi, 2014).

In the academic area, social media was defined as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content" (Kaplan & Haenlein, 2010, p.61). Another widely cited definition was made by boyd and Ellison, they define that social network sites as "web-based services that allow individuals to construct a public or semi-public profile within a bounded system, articulate a list of other users with whom they share a connection, and view and traverse their list of connections and those made by others within the system" (boyd & Ellison, 2007, p.211). boyd argue that there are "four types of features that play a salient role in constructing social network sites as networked publics – profiles, Friends lists, public commenting tools, and stream-based updates" (boyd, 2010, p. 43). Beyond these features, social media platforms vary greatly in their features and user base. Some have photo-sharing or video-sharing capabilities (boyd & Ellison, 2007), like Instagram and YouTube; some could be used to share opinions with limitation of characters, like Twitter; some are available for public based on the default setting, like Facebook etc.; but some are designed as private community and just open to friends, like WeChat (a Chinese social media platform).

The concept of *affordance* couldn't be ignored in the context of social media, which makes collective activities easier to organize and happen (Tufekci, 2017), information easier to be

[8] https://www.statista.com/statistics/433871/daily-social-media-usage-worldwide/

seen, found, spread and persisted (boyd, 2014). It was originally generated in ecological psychology by James Gibson (1979) to refer to a specific kind of relationship between animal and the environment. In the social media field, Bucher and Helmond (2017) developed affordance as an important term for understanding and analysing relations between technology (platform itself) and publics (social media users). boyd (2014) describes four affordances that shape our social media platforms and affect what we do in our online networks: persistence, visibility, spreadability and searchability. The last two were considered the unique affordances of social media, which implicate "how one's digital records are easily searchable by other people/entities and how certain contents on social media become viral and spread through the network quickly" (Johnson, Lee, Cionea & Massey, 2018, p.175).

In sum, it is precisely because of these characteristics of social media that it becomes a public sphere (Fuchs, 2014) where people can express their opinions and emotions, and engage social discussion freely. As mentioned in the front part of this section, there are many types of social media platforms, but in this study, I only focus on Facebook, and the related background will be provided next.

1.6.2 Facebook

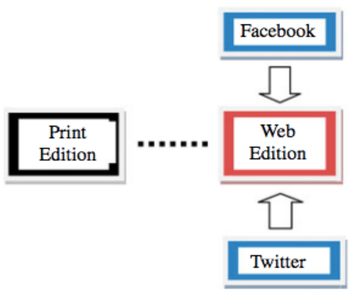
Facebook started in 2004, and at that time, it was just a Web-based directory for students at colleges and universities, where people could create a personal profile and browse the information of others (Panger, 2017). After development and improvement for many years, Facebook has changed lot and it becomes the biggest social network worldwide (Statista, 2019). Unlike the original simple functions, Facebook nowadays can be accessed on different internet connected devices such as computers, tablets, smartphones etc. After registering, users can create a customized profile presenting information about themselves. People also could send a request to other users to add them as friends. If the other users confirm the request, their "friendship" on Facebook is established (boyd, 2006; cited in Ju, Jeong & Chyi, 2014, p.2). People can post all kinds of messages without character limitation to express their thought, feeling and share current activities, photos, multimedia and links of other interesting information with their friends and also could see friends' activities on Facebook. When users read information from their news feed on Facebook, they can click emoji/reactions such as "Like", "Love", "Haha", "Wow", "Angry" or "Sad" to express their emotions to the postings, or give comments and share the information. Unlike Twitter, Facebook has an attribute of "friends and family come first", and has been revising the algorithms system since many year ago in order to prioritize users' friends' and families' posting come first (Mosseri, 2016).

There are three dominate sections on Facebook: personal networks, groups and public pages. Public pages were originally envisioned as “distinct, customized profiles designed for businesses, bands, celebrities, etc. to represent themselves on Facebook” (Sun et al., 2009, p.147). Public pages on Facebook can’t be friends with individual users, but people can “like” or follow the pages (Ju, Jeong & Chyi, 2014). Ju, Jeong and Chyi (2014) point out that lots of companies and traditional media institutions use Facebook for marketing purposes. For instance, newspapers take Facebook as a new channel in order to get more traffic and attention for their official website and brand marketing, which will be detailed in the next section regarding news consumption on social media (Ju, Jeong & Chyi, 2014).

1.6.3 News Consumption on Social Media

Social media nowadays have become a vital news resource in the world, and it is changing the way customers consuming and sharing news (Lee & Ma, 2012; Ju, Jeong & Chyi, 2014; Shearer & Matsa, 2018). News could be distributed across countries and discussed by people around the world within minutes via social media platforms. People get news via social media has increased by over 50% since 2009 in America (Weeks & Holbert, 2013). An investigation by asking 4581 American adults was made by Pew Research Centre. Results show that about two-thirds of American adults (68%) at least occasionally get news on social media. There are two factors determine public choose which social media platforms to obtain news, which are the overall popularity the social media and the extent to which people see news on the site (Shearer & Matsa, 2018). In Norway, 85 % of people use Internet every day to get news, and more than half of Norwegian use social media to meet their needs for information (Johannessen, 2015).

Figure 1.1Multiplatform newspaper: print, Web, and social media (Ju, Jeong & Chyi, 2014, p.4)



Ju, Jeong and Chyi argue (2014) that news organizations such as newspapers are becoming multiplatform enterprises. They explained that newspapers provide news not only through the original print products and websites, they also open their own accounts on social medias and spread information. Figure1.1 illustrates the relationships among the three platforms of newspapers discussed above.

If people want to get news from news institutions on social media, they can "Like" or follow their public pages which update news reports all the time, and this kind of "relationship can be viewed as a form of subscription" (Ju, Jeong & Chyi, 2014, p.4). Nowadays, almost all the news organization have opened their public pages on social media for news spreading by textual content, pictures, videos, or links to their official websites in order to attract more traffic to some extent (Ju, Jeong & Chyi, 2014). Grzywinska and Borden (2012) also argue that social media and traditional media are in a "symbiotic relationship where traditional media extends its user base through sharing in social media" (Grzywinska & Borden, 2012; cited in Johannessen, 2015, p.19).

The way people read news on social media is different from the way they get news in traditional media. Readers could customize news topics and discuss or interact with other audiences (Chung, 2008; cited in Lee & Ma, 2012, p.332) when they read news on social media, whereas readers can only unilaterally access news transmitted by traditional media (Lee & Ma, 2012). These kinds of interactivities include giving comments and reactions, making conversations and debating or discussing with other readers about the news or sharing news to others, which is a process that "users actively participate in agenda-setting process" (Goode, 2009; cited in Lee & Ma, 2012, p.332). Users' motivations for these interactivities are also diverse. Besides the traditional motivations mentioned in the first section of this chapter, for instance, status attainment (e.g., getting attention), establishing social relationships and reputations, and information seeking (Lee & Ma, 2012, p.331), emotion is another important element that trigger public to discuss or spread news in social media platforms (Stieglitz & Dang-Xuan, 2013; Weeks & Holbert, 2013; Ferrara &Yang, 2015b; Xu, 2017), which is the key point of this study regarding emotion/sentiment analysis in social media. Previous literature related to emotion/sentiment analysis in media studies, the theory of emotions, and emotion research in terms of news diffusion on social media will be provided in the next chapter in a detailed way.

Chapter 2 Literature Review

Sentiment analysis has grown rapidly with the development of social media platforms, and applied from nature science to social science (Liu, 2015). The traditional task in sentiment analysis is classifying the emotional polarity of textual information and found out whether these texts could express positive, negative, or neutral sentiment (Satapathy, Cambria & Hussain, 2018). However, polarity level of sentiment analysis can't reveal the specific emotions of information, which results in the appearance of emotional level sentiment analysis by which researchers extract sentiments from texts in terms of emotions such as "angry", "sad", and "happy" (Almashraee, et al., 2016). Indeed, emotion analysis is the key concept in this study.

In this chapter, I will present the key concepts that provide the theoretical framework for this project and analyse their application in previous research. This chapter is divided into five sections. Firstly, I will introduce the definitions of sentiment analysis, and its applications extended from computer science to management and social science. Then the classification of sentiment analysis will be presented, especially the emotional level of sentiment analysis. In the last part of this section, sentiment analysis applying in social media data will be analysed. Secondly, I will examine the different understanding of terms: Sentiment, emotion, affect, mood in psychology, but in the domain of emotion analysis in social media they could be used interchangeably. Thirdly, definitions of emotion from mental state to physiological response, the form of cognition and behaviour tendency will be discussed. Then different categories of emotion from different scholars will be presented as well. Fourthly, I will explore the state of emotion in social media regarding the debate between positivity bias and negativity bias. There is no agreement on the state of emotions in social media, as some researchers agree that there are more positive emotions in social media (Lin & Utz, 2015; Golder & Macy, 2011; Tsugawa & Ohsaki, 2015; Utz, 2015), whereas some argue that there is a negativity bias in social media based on the argument that news with negative emotion could evoke people to give more comments and share the news (Stieglitz & Dang-Xuan, 2013). Researchers also found that different countries had different emotion tendency on social media (Chu & Choi,2011; Stieglitz & Dang-Xuan, 2013; Xu, 2017), and there is very little similar research has carried out in Norway which makes this study necessary in the context of social media in Norway. Moreover, scholars found a media effect in emotion, which is that information with emotions could be diffused wider than neutral news in social media (Kramer,2012; Rimé, 2009; Celli, et.al., 2016; Pfitzner et al., 2012). Researchers also argue that different emotions have different spread effects (Zhao, Dong, Wu & Xu, 2012; Berger & Milkman, 2010; Tadic et al., 2013; Joyce & Kraut, 2006). However, there is still no agreement regarding which emotion in news could be spread easier. Finally, the last section of this chapter turns to emotional agenda-setting theory which proved by researchers that media's emotion corresponds with public's emotion (Coleman & Wu, 2010), which provides theoretical support for this study.

2.1 Sentiment analysis

2.1.1 What is Sentiment Analysis

Sentiment analysis which firstly started by Nasukawa and Yi (2003, citied in Liu, 2015, p.1) is a field of research that aims to "analyze people's opinions, sentiments, appraisals, attitudes, and emotions toward entities and their attributes expressed in written text" (Liu, 2015, p.1). Many similar names, for instance, sentiment analysis, opinion mining, opinion extraction, affect analysis and emotion analysis are now all under the category of sentiment analysis (Ibid).

At the beginning, sentiment analysis derived from the analysis with emotional words. For example, "good" is a good word, but "ugly" is a derogatory word (Hatzivassiloglou & McKeown, 1997). Later, Jeonghee Yi (2003) started to use Sentiment Analyzer (SA) to extract sentiment from online text documents. He pointed out this kind of analysis use two linguistic resources: the sentiment lexicon and the sentiment pattern database.

With the emergence of a large number of emotional and subjective text online and social media platforms, researchers have gradually transited the simple analysis of the emotional words study to more complex emotions and emotional textual research (Liu, 2015). According to the processing of text granularity, sentiment analysis can be divided into document, sentences and discourse level (Liu, 2015). Based on the difference of the text category, it can be divided into the base of news commentary sentiment analysis (Ku, Liang, & Chen, 2006) and sentiment analysis in product reviews (Turney, 2002; Pang et al., 2002; Lee, 2005; Wilson et al., 2006; Yao et al., 2006; Pang & Lee, 2008). The former mainly deals with news comments, such as the emotional sentence "He believes that Trump is the best president in the world.", which indicates the viewpoint and emotions of writer's position on the issue of American politics. The latter mainly deals with product review texts, such as "iPhone's appearance is very fashionable", which indicates that the evaluation of "iPhone's appearance" is "fashion".

Although there is no perfect algorithm to solve the problem of emotion analysis (Liu, 2015), emotion analysis plays an important role in practical applications, which presented as follows:

-Product assessment. The application of sentiment analysis on product assessment largely used by companies. When companies launch some new products to the market, it's hardly possible for them to review all of the comments to those new products from customers and analyse those information by hand. In this situation, sentiment analysis is a good way to solve this problem. Firstly, people can use tools to collect all of the comments information automatically, and dig up the main product attributes and evaluation of words. Then THE company could provide users with the product attributes evaluation opinions through the statistics and inductive reasoning. At present, there are many research institutions, according to the specific needs in real life, which have developed sentiment analysis systems in many areas to help users analyse massive amounts of information and decision-making. For instance, Pang and Lee (2008) developed a system called Opinion Observer could handle online customer product evaluation and compare the overall quality of products; Wilson et al. (2006) developed Opinion Finder system which could automatically identify subjective sentences and extract sentiment in sentences. Yao et al. (2006) has developed an emotion analysis system for Chinese automotive BBS, mining and summarizing people's comments and opinions on various automobile brands.

-Prediction. With the rapid development of the Internet, the impact of network information on people's life has become more and more important. A new event occurs or the buzz of an event on the network to a great extent, affect the people's thinking and action. Sentiment analysis is not only implemented on product assessment but can also help people predict the future situation by analysing news, posts and other information sources on the Internet (Yu et al., 2013; Hagenau et al., 2013; Maks & Vossen, 2012). For example, in the financial market, a hot discussion on a certain stock on the Internet influences the behaviour of financial practitioners and further influences the trend of stock market (Nguyen, Shirai & Velcin, 2015). Devitt and Ahmad (2007) made predictions on the future financial trend by identifying the sentiment polarity of financial comment texts. Moreover, in the political elections, many candidates hope to predict whether they will be elected or not by summarizing the online comments made by voters. Kim& Hovy (2007) predicted the result of the U.S. election by a large number of online news comments during the U.S. election. Lin et al. (2006) constructed an “Israeli Palestinian war” comment analysis system to distinguish whether a comment is “supporting Palestine” or “supporting Israel”.

2.1.2 Sentiment Analysis Classification

In the field of computer science, sentiment analysis normally is classified to three different levels based on the types of text: document-level, sentence-level and aspect/feature-level (Liu, 2015). Here, a brief introduction of these three levels of sentiment analysis will be presented.

Document level. Extracting a positive or negative sentiment from a document or report in where the data unit is considered an entire archive (Pang et al., 2002; Turney, 2002; Chopra & Bhatia, 2016; cited in Liu, 2015, p.9). For instance, the mobile phone company Huawei has launched a new product to the market, and the company collects all of the comments to the new mobile phone from the customers on one of the online stores. Then the analysis system will determine whether all of the comments express an overall positive or negative sentiment or emotion about the product.

Sentence level is determining “whether each sentence expresses a positive, negative, or neutral opinion” (Liu, 2015, p.9). According to Liu’s statement, this level of analysis is closely related to subjectivity classification (Ibid), which distinguishes whether the sentence is subjective or objective. For instance, “I love apple” is a subjective sentence, which express subjective views. “Apple is a kind of fruit” is an objective sentence, which describe factual information. However, it’s not true that all of the subjective sentence could express emotion or sentiment, for instance, “I think she will go to work after breakfast.” However, objective sentence may express positive or negative sentiment, for example, “He bought this camera last week, but the lens has broken.”

Aspect/feature level analysis directly “looks at opinion and its target” (Liu, 2015, p.9), which was started by Singh and Piryani (2013). They analysed the textual reviews of a movie and examined the sentiment label on different aspect. An aspect or feature is an attribute or a factor of an object, such as the lens of a camera, the quality of the bed or service in a hotel. The advantage of aspect level sentiment analysis is to figure out the subtle differences about the entities, and different aspects can arouse unalike emotional response, for instance, a car could have good exterior, but bad quality (Cataldi et al., 2013).

Researchers have designed different kinds of algorithms to extract sentiments or emotions based on different types of textual content, even different languages (Liu, 2015). Here, I'm not going to explore too much about how does the sentiment analysis system work in terms of different level of the content, which is a part of computer science. What I'm going to focus in this study is that how does the result will be presented after sentiment analysis, and try to find the specific emotion, such as happiness, sadness, anger etc. in textual content in Social media by sentiment analysis. Actually, the basic task in sentiment analysis is classifying the emotional polarity of a textual content, whether these texts could express positive, negative, or neutral sentiment (Satapathy, Cambria & Hussain, 2018). Scholars have applied different ways to extract the polarity (positive or negative) of product reviews (Turney, 2002) and movie comments (Pang et al., 2002; cited in Satapathy, Cambria & Hussain, 2018, p.5).

However, Almashraee, et al. (2016) argued that the sentiment polarity is insufficient to detect the precise sentiment or emotion of the text's writers. That is because "sentiment polarity does not convey the affective meaning that writers give to an object or to any of its related features" (Almashraee, et al., 2016, p.2). Therefore, a stronger and more effective and detailed emotion detection method is needed, which can detect writer's true emotions in terms of "happiness", "sadness", "anger" etc. towards the content on the emotional level, what is this thesis really wants to figure out. Seyeditabari et al. (2018) argued that emotion analysis can be considered as "a natural evolution of sentiment analysis and its more fine-grained model" (Seyeditabari et al., 2018, p.1). As mentioned above, sentiment analysis could be applied in many areas, but emotional level of sentiment analysis could gain more useful information. For instance, the two emotions "fear" and "anger", both are negative sentiments which express people's opinions to someone or something, but anger is "more relevant in marketing or socio-political monitoring of the public sentiment" compared with fear (Seyeditabari et al., 2018, p.1). Study show that people who are fearful usually have a pessimistic view compared with angry people who are more likely to have an optimistic view (Seyeditabari et al., 2018, p.1). Researchers have focused on the role of the two emotions (anger and anxiety) in politics, and they found out that anger and anxiety are correlated with different political attitudes and behaviors (Hasell & Weeks, 2016). In media studies, scholars have found out that different emotions have different arousing effect on the audiences. For instance, an emotion of happiness could encourage people to keep a continual conversation in forum (Joyce & Kraut, 2006), and online news with anger and anxiety emotions could be shared more than other emotional information (Hasell & Weeks, 2016). More detailed information relate to emotion analysis in media studies and emotions diffusion effect will be presented in section 2.4.

2.1.3 Sentiment Analysis on Social Networks

Since the beginning of 2000, sentiment analysis has become one of the most active research topic in the field of natural language processing (Liu, 2015). Although there is no perfect algorithm for sentiment analysis, it has become increasingly popular and extended from computer science to management and social science (Liu, 2015). Sentiment analysis also has grown rapidly with the rising of social media platforms, such as Facebook, Twitter etc. In these social media platforms, researchers could access to the largest datasets of opinion ever. These kinds of social media data can help researchers in order to discover and mine useful information in terms of human's activities, relationships between media and public through these data existing in social media, Liu (2015) argue that sentiment analysis is a "necessary technology" (p.3).

In business domain, Nguyen, Shirai and Velcin (2015) build a model to predict stock price movement using automatic emotion detection tools to extract emotions from social media texts in the light of Zhang, Fuehres, and Gloor's (2011) research that analysing the correlations between emotions and stock market indicators. They found that emotional tweets' percentage significantly negatively correlated with Down Jones, NASDAQ and S&P 500, but had significant positive correlation to VIX (cited in Nguyen, Shirai & Velcin, 2015, p.9604). Not only for predicting, researchers in media studies found that sentiments or emotions could spread via social media (Kramer, Guillory & Hancock, 2014), information with emotions will be spread faster than neutral messages (Nelson-Field, Riebe & Newstead, 2011; Weeks & Holbert, 2013; Stieglitz & Dang-Xuan, 2012; Lai & Tang, 2016), and different types of emotion have different diffusion effects (Berger & Milkman, 2010; Tadic et al., 2013; Jalonen, 2014; Ferrara & Yang, 2015b; Valenzuela, Piña & Ramírez, 2017). For instance, news with an emotion of anger could spread easier than information with other types of emotion, while news with sadness is less likely to be disseminated (Zhao, Dong, Wu & Xu, 2012). More literature related to this topic will be detailed in section 2.4.

Actually, the main purpose of people publishing information in social media platforms is to express their opinions, even emotions. Therefore, user-generated content in social media contains a large amount of valuable information, such as patterns of human activities, which gives plenty of resources for scholars focusing on the domain of sentiment analysis. This section is just a brief introduction regarding the definition, application and classification of sentiment analysis which is generated in computer science, and also provides a short review of the application of sentiments analysis moving from computer science to social science and media studies. Before moving to the literature reviews referring to emotion analysis in social media, which is the main part of this thesis, some similar concepts regarding sentiment, emotion, affect, mood will be interpreted in the next sections.

2.2 Sentiment, Emotion, Affect, Mood

In this thesis, many terms such as sentiment, emotion, affect and mood will be related, and these concepts have been widely studied in psychology, philosophy and sociology (Liu, 2015). Liu argue that even though these concepts have been studied in many different fields, it is still confusing to understand all of them because they are interchangeable in some contexts, and different researchers have different definition for them, even they totally can't agree with each other about the definition and categories of emotion, sentiment, affect and mood. For instance, researchers have presented from two to twenty basic human emotions regarding the term of emotion (Ortony & Turner, 1990; cited in Liu, 2015, p.31). McDougall (1926) proposed that people have 7 types of emotion, which are anger, disgust, elation, fear, subjection, tender emotion, wonder. Mowrer (1960) argued that there are two types of basic emotion which are pain, pleasure. Ekman et al. (1982) proposed that there are 6 types of emotion: anger, disgust, fear, joy, sadness and surprise, which has been applied broadly. Munezero et al. (2014) argue that inconsistent using of these terms may lead confusion in different context. This section will present the different definitions and understanding of these terms and provide evidence why they could be used interchangeably in this study.

2.2.1 Sentiment, Emotion, Affect and Mood in Psychology

In order to figure out the differences between emotion, sentiment, affect and mood, definitions from dictionary and their synonyms will be presented firstly in Table 2.1. The repetition of these terms' definition and synonyms provided in Table 2.1, which confirms Batson, Shaw, and Oleson's (1992) argument: "most often, the terms affect, mood, and emotion are used interchangeably, without any attempt at conceptual differentiation" in general psychology (p.295).

However, in the field of psychology, definitions of these terms are different. Detailed interpretation will be presented as fowllows.

Affect. This term is defined as a "neurophysiological state consciously accessible as a simple primitive non-reflective feeling most evident in mood and emotion but always available to consciousness" (Russell & Feldman Barrett, 2009, p.104). Munezero et al. (2014) state that within the psychological literature, affect has been treated as an umbrella term, which covers emotions, feelings, and sentiments. Batson et al. (1992) found that "affect is present in the yelp of a dog and in the coo or cry of an infant" (p.298). Here is the example from Liu what explains how affect differs with feeling and emotion in the mental process when people experience something:

> *You are watching a scary movie. If you are affected, it moves you and you experience a feeling of being scared. Your mind further processes this feeling and expresses it to yourself and the world around you. The feeling is then displayed as an emotion, such as crying, shock, and screaming. (Liu, 2015,32)*

Table 2.1 Definitions from Oxford Online dictionary.

Term	*Definition*	*Synonyms*
Emotion	*Excitement; the affective aspect of consciousness; a state of feeling; a conscious mental reaction (as anger or fear) subjectively experienced as strong feeling usually directed toward a specific object and typically accompanied by physiological and behavioural changes in the body*	*Feeling; Sentiment*
Sentiment	*An attitude, thought, or judgement prompted by feeling; a specific view or notion*	*Feeling; Emotion*
Affect	*The conscious subjective aspect of an emotion considered apart from bodily changes; also, a set of observable manifestations of a subjectively experienced emotion*	*Feeling*
Mood	*A temporary state of mind or feeling*	*Feeling*
Feeling	*An emotion state or reaction; often unreasoned opinion or belief*	*Sentiment; Emotion*

Note: cited in (Munezero et al. 2014, p.2).

Emotion. There are many different kinds of definitions about emotion. In 1981, Kleinginna and Kleinginna listed 92 different definitions of emotion, plus their three own, and nine sceptical statements compiled from literatures on emotion (Kleinginna & Kleinginna, 1981). They suggested a formal definition of emotion as "a complex set of interactions among subjective and objective factors, mediated by neural and hormonal systems, which can a) give rise to affective experiences such as feelings of arousal, pleasure and displeasure; b) generate cognitive processes such as emotionally relevant perceptual affect, appraisals, labelling processes; c) active widespread physiological adjustments to the arousing conditions; and d) lead to behaviour that is often, but not always expressive, goal-directed and adaptive."(p.355). Shouse argue that emotion is the expression of affect and/or feelings (Shouse, 2005), it concerns with a specific object such as an event, a person or a thing and lasts a short period of time (Ekkekakis, 2012; Munezero et al. 2014; Liu, 2015). There are many types of emotion, such as anger, happiness, surprise, disgust, sadness, fear and so on, which will be presented more in section 2.3.2.

Mood. Mood is "the appropriate designation for affective states that are about nothing specific or about everything-about the world in general" (Frijda, 2009, p.258). One distinguishing feature of mood is that it typically lasts longer than emotion (Ekkekakis, 2012). Furthermore, mood is less specific, less intense than emotion (Liu, 2015). For instance, people could be very angry because of a specific thing, person or event, but mood could be caused by many things, and sometimes it's hard to find the exactly reasons (Ekkekakis, 2012, p.332). People could be very angry pretty fast but they couldn't keep this anger emotion for a long time, whereas they may stay in an irritable mood for a whole day (Liu, 2015, p.32).

Sentiment. Cattell defined sentiment as "an acquired and relatively permanent major neuropsychic disposition to react emotionally, cognitively, and conatively toward a certain object (or situation) in a certain stable fashion, with awareness of the object and the manner of reacting" (Cattell, 1940, p.16). Sentiment involves "combinations of bodily sensations, gestures, and cultural meanings that we learn in enduring social relationships" (Gordon, 1981, p.563). Thoits (1989) gave examples of sentiments which include "romantic love, parental love, loyalty, friendship, patriotism, hate, as well as more transient, acute emotional responses, to social losses (sorrow, envy) and gains (pride, gratitude)" (cited in Munezero et al. 2014, p.103). Munezero et al. (2014) and Liu (2015) point out that sentiment and emotion normally could be used interchangeably. That is mostly because both emotions and sentiments refer to "experiences that result from the combined influences of the biological, the cognitive, and the social" (Stets, 2006, p.310). However, there are still some differences between them. Compared with emotions, sentiments could be formed and kept longer, and it is more stable and dispositional (Munezero et al., 2014). For instance, a person may have a sentiment of, for example, love when he or she does not actually have an occurring state of love (Ibid).

2.2.2 Sentiment, Emotion, Affect and Mood in Social Media Study

Discussions about emotion, affect, mood, sentiment etc. terms focus on people's mental state and the differences between these terms in psychology field. In sentiment analysis, Liu (2015) argue that researcher should figure out how those emotions, affects etc. mental states expressed by language and how they can be recognized. He pointed out that detecting affect in text is hard to take into research in sentiment analysis as affect is a "primitive response with no target", and written in text or other forms of expressions almost has change into emotion and mood (Liu, 2015, p.36).

In this thesis, I'm not going to discuss the differences of the algorithms regarding sentiment analysis. I will use the existing tool to extract emotions from the comments and news posted on VG's Facebook page. Actually, in media studies, social media content often contains all kinds of opinions, comments, attitudes, and emotions toward people, events. For instance, a piece of information posted on social media may express the author's emotional state or his/her judgment or evaluation of a certain person or topic (Dang-Xuan et al., 2013). Public's emotional states expressed in social media referring to those different concepts mentioned above are mostly subsumed under the term of sentiment (Pang & Lee 2008; Liu 2011; Dang-Xuan et al., 2013). As Munezero et al said, in most cases, subjectivity terms such as sentiment, emotion, affect and mood are treated as synonymous, and all four terms sometimes could be used interchangeably (Munezero et al. 2014). Liu (2015) proposed that people don't need to be too much focus on the differences between those terms in sentiment analysis, "we can pick up and use whatever emotion or mood states suitable for the applications at hand" (Liu, 2015, p.31). Therefore, in the later part of literature review, terms about affect, emotion, mood etc. will appear frequently, and all of them are expressing the meaning of emotion. As the key term of this thesis, emotion definitely should be presented in a separate section, and detailed definitions and types of emotions will be provided in the next part along with an introduction of the emotion detection tool with different types of emotions.

2.3 What is emotion

2.3.1 Definitions

As mentioned in section 2.2.1, there is no consensus for definitions of emotion, and Kleinginna and Kleinginna (1981) listed almost 100 different definitions from different theorists, and also provided a formal definition to emotion regarding four dimensions: mental state (feeling of arousal), physiological adjustments, generating cognitive processes and leading to behaviours. Discussions about definitions of emotion will go with these four factors.

Nabi (1999) argued that emotions are "internal, mental states representing evaluative, valanced reactions to events, agents, or objects that vary in intensity…they are generally short-lived, intense, and directed at some external stimuli" (Nabi, 1999, p.295). In addition to this statement which referring to that emotion is a kind of mental state, other scholars point out that emotion is also a kind of physiological response. Panksepp (1994, p.86) stated that emotions "reflect the intense arousal of brain systems that strongly encourage the organism to act impulsively". Dolan (2002) believed that from a physiological perspective, emotions are "embodied, that is we experience emotions not just as mental events that are in our heads but also as full-body experiences" (p.1191). However, Cabanac (2002) still believes that "emotion is a mental state, even when somatic signals participate in this mental experience" (Cabanac, 2002, p.70).

In addition, cognition is also a vital component of emotion. In 1962, Schachter and Singer (1962) define emotion as "a state of physiological arousal and of cognition appropriate to this state of arousal" (p.380). Those who hold this view believe that people must firstly be cognized by objects, then emotions will be aroused (Turner, 2009, p.342). Turner further explained if these objects are deemed to be beneficial to the achievement of the goal, positive emotions will be stimulated. However, if these objects are considered to be harmful to the achievement of the goal, then this evaluation will cause negative emotions (Turner, 2009, p.342). Another example, before people experience the emotion of fear, they may recognize that they are in a dangerous situation and reaction such as sweating, muscle tension will appear in their body[9]. Scherer (1993) argue that all cognition participates more or less in emotion, and Griffiths (1997) considers emotion as an "irruptive motivational complex in higher cognition" (p.243; cited in Cabanac, 2002). Izard (2010) revealed that theorists focus on "conceptualizing emotion show moderate to high agreement on the structures and functions of emotion, agreeing that there are rapid, automatic, and unconscious connections among emotion, cognition, and action" (p.366). Moreover, emotion is also associated with behavioural tendency and will lead to some behaviour directly (Kleinginna & Kleinginna, 1981; Baumeister et al. 2010), which is proved by the most common example that when

[9] https://en.wikipedia.org/wiki/Emotion

people experience the emotion of fear, they will consciously escape immediately (Baumeister et al., 2010).

Emotions are complex. Thoits (1990) listed a series of interrelated factors, in which emotion was considered as a complex of causal relationships “among situational cues, physiological changes, emotional labels and expressive gestures” (cited in Tuner 2009, p.341). Emotions are a combination which may contain elements of feelings, physiological changes, behaviour and motivation, and these components are not emotions, and emotions are not the entities that cause these elements. (Barrett & Russell, 2014).

Turner (2009) argued that the definitional problem refers to emotion is that “emotions operate at many different levels of reality—biological and neurological, behavioural, cultural, structural, and situational” (p.341), and depending on which aspect of emotions the researchers focus on, which leads to a different definition of emotion (Turner, 2009). He detailed that “if the neurological aspects of emotions are emphasized, then emotions are the arousal of body systems; if culture is seen as important, then the ideologies, rules, and vocabularies of emotions are seen as critical; if cognitive aspects of emotions are considered critical, then conscious feelings along some certain dimensions will be part of the definition” (Turner, 2009, p.341).

2.3.2 How many emotions are there?

In addition to the various definitions of emotion, types of basic emotions also have been grouped into many categories by scholars. The classification of specific emotions includes Ekman’s six (anger, disgust, fear, happiness, sadness, and surprise; 1982), Weiner and Graham’s two (happiness and sadness; 1984) and Izard’s ten (anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, surprise; 1977). Bollen et al. (2009) analysed the amount of variation of emotion on Twitter between 1st August and 20th in December 2008. They extended the Profile of Mood States (POMS) and classified the extracted emotions into six categories: tension, depression, anger, vigour, fatigue and confusion. Table 2.2 (Liu, 2015, p.33) provides different types of basic emotions from different theorist in where indicates that there is still no agreement among them.

However, Turner (2009) claimed that the number of basic emotions is quite small, and the majority research proved that there are at least four basic emotions that people experienced: anger, fear, sadness, and happiness, but disgust, surprise and expectancy are also should be added to this list. Turner (2009) also point out that most of scholars agree that "there are low, medium, and high intensity variants of the four to seven primary emotions, with their behavioural expression converging across cultures" (Turner, 2009, p.342).

In media studies, scholars argue that different types of emotions also correlated with different audience behaviours and different information dissemination effects (Ferrara & Yang, 2015b; Stieglitz & Dang-Xuan, 2013; Burke & Develin, 2016; Zhao, Dong, Wu & Xu, 2012; Berger & Milkman, 2010; Tadic et al., 2013; Joyce & Kraut, 2006; Berger & Milkman, 2010; Hansen et. al. 2011; Valenzuela, Piña & Ramírez, 2017), which will be detailed in section 2.4. Before moving to that section, an introduction of various emotion types associated with different emotion detection tools will be provided in next part.

Table 2.2 Basic emotions from different theorists.

Source	*Basic emotions*
Arnold (1960)	*Anger, aversion, courage, dejection, desire, despair, fear, hate, hope, love, sadness;*
Ekman et al. (1982)	*Anger, disgust, fear, joy, sadness, surprise*
Gray (1982)	*Anxiety, joy, rage, terror,*
Izard (1971)	*Anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, surprise*
James (1884)	*Fear, grief, love, rage*
McDougall (1926)	*Anger, disgust, elation, fear, subjection, tender emotion, wonder*
Mowrer (1960)	*Pain, pleasure*
Oatley and Jobnson-Laird (1987)	*Anger, disgust, anxiety, happiness, sadness*
Panksepp (1982)	*Expectancy, fear, rage, panic*
Plutchik (1980)	*Trust, anger, anticipation, disgust, joy, fear, sadness, surprise*
Tomkins (1984)	*Anger, interest, contempt, disgust, distress, fear, joy, shame, surprise*
Watson (1930)	*Fear, love, rage*
Weiner and Graham (1984)	*Happiness, sadness*
Parrott (2001)	*Anger, fear, joy, love, sadness, surprise*

Note: cited in (Liu, 2015, p.33).

2.3.3 Emotion Types and Emotion Analysis Tools

What I'm going to do in this study is to use automatic emotion detector to extract emotions in terms of happiness, sadness, fear etc. from textual content (news reports posted in VG's Facebook page and comments given by audiences to the news). The working principle of the emotion detection tool is analysing the input text content and outputting specific emotion categories, and it is an easier method for researchers who has no computer science background working on the field of emotion analysis. Here, previous literature relating to emotion analysis tools will be provided.

In computer science, researchers developed huge numbers of algorithms (Yang et al., 2007; Liu, 2015), emotion or sentiment detectors (Denis, Cruz-Lara, & Bellalem, 2013; Sánchez-Rada et al., 2016), emotion lexicons (Bradley & Lang, 1999; Strapparava & Valitutti, 2004; Mohammad, Kiritchenko & Zhu, 2013; Staiano & Guerini, 2014) to detect emotions from textual content. Denis, Cruz-Lara and Bellalem (2013) stated that researchers usually use different emotion analysis tools in different fields, but all detection tools face three common problems: the dependence of algorithms in different fields, the representativeness of emotion types, and language issues. As Liu (2015) argued that, up to now, there is no perfect algorithm for emotion analysis, but lots of algorithms of emotion detection tools are combined with emotion lexicon which is a list of words and phrases (e.g. bad, good, beautiful, amazing, horrible) that people often use to express specific emotions (Liu, 2015). These kinds of tools could extract key words from sentences or paragraphs to analyse the specific emotion based on emotional words or phrases included in the emotion lexicons. Actually, there are many types of emotion lexicon, such as ANEW (Bradley & Lang, 1999), WordNet (Strapparava & Valitutti, 2004), NRC (Mohammad, Kiritchenko & Zhu, 2013), DepecheMood (Staiano & Guerini, 2014).

Emotion detection tools with emotion lexicon is highly used in the field of media studies for researchers detecting emotions in social media. For instance, Farnadi et al. (2014) used NRC hash-tag emotion lexicon to detect emotions from almost 1million Facebook posts, and found that almost 60% of status updates contain at least one type of emotion expression. According to the huge types and different opinions of emotions among researchers (see Table 2.3), various detection tools follows different classification of emotions which summarized by different theorist. Moreover, tools also have unalike requirements regarding languages. For instance, some tools are only English available, but some of them are available for many kinds of languages (Denis, Cruz-Lara & Bellalem, 2013).

Here, I just simply display some emotion detection tools which based on unlike emotion lexicons with different classification of emotion types (Table 2.3). Senpy is the tool I chose to use in this project, and more detailed literature regarding emotion lexicon and emotion detector related to this study, and the reason why I choose Senpy to conduct this study by comparing with other tools will be analysed and discussed in section 3.2.2 and 3.3.2 in the Methodology chapter.

Table 2.3 Emotion detection tools with different emotion lexicons, emotions types and languages.

Tools	Lexicon	Emotions	Languages
Senpy[10]	ANEW	Happiness, sadness, fear, anger, disgust, neutral (Ekman et al., 1982, without surprise)	English; Spainish
	WordNet	Anger, fear, disgust, joy, sadness, neutral (Ekman et al., 1982, without surprise)	English
	DepecheMood	Fear, sadness, awe, joy, indifference, annoyance, anger, amusement	English; Italian
SATI API[11]	Unknown	Anger, disgust, fear, joy, sadness, surprise (Ekman et al., 1982)	English; non-english based on Google Tranlstion
TwinWord[12]	Unknown	Anger, disgust, fear, joy, sadness, surprise (Ekman et al., 1982)	English
Syuzhet[13]	NRC	Trust, anger, anticipation, disgust, joy, fear, sadness, surprise (Plutchik, 1980)	Global

Note: Syuzhet is not a simply automatic tool, but a package used in R language which is a programming language, mainly used for statistical analysis, drawing graphics and data mining[14].

So far, the theoretical review related to definitions and types of emotions which applied in different emotion detection tools is done. Next, I will turn to another main point of this study

[10] https://senpy.readthedocs.io/en/latest/
[11] http://talc2.loria.fr/empathic/ (It is inaccessible now. There is more information in p.53-54)
[12] https://www.twinword.com/api/emotion-analysis.php
[13] https://cran.r-project.org/web/packages/syuzhet/vignettes/syuzhet-vignette.html
[14] https://en.wikipedia.org/wiki/R_(programming language)

regarding the distribution of emotions and the impact of emotions on information dissemination in social media.

2.4 Emotions in Social Media

2.4.1 The State of Emotion in Social Media

This section will discuss the state of emotions in social media. The first part organized the statements from previous research referred to positivity bias (Garcia, Garas & Schweitzer, 2012). Although some researchers agree that there are more positive emotions in social media (Leung, 2013; Ferrara & Yang, 2015a; Yu & John-Baptiste, 2016; Ferrara & Yang, 2015b; Nelson-Field, Riebe & Newstead, 2011), the main emotion in social media varies depends on different countries and regions (Hyvärinen & Beck, 2018; Xu, 2017), which indicates that the positivity bias doesn't apply globally. Moreover, very little research regarding this topic has been carried out in Norway, which make this study conducted in the context of Norway necessarily. The second part presents an opposite argument that there is a negativity bias in social media (Stieglitz & Dang-Xuan, 2013; Park, 2015), and there are always lots of negative emotions even more than positive ones in social media (Jalonen, 2014). No matter from the amount of positive and negative emotions, the intensity of negative emotions' diffusion, the antisocial behavior in social media or characteristics of different social media platforms which may have different emotion preferences (Jalonen, 2014), all of which lead to an opinion that there is no agreement on positivity bias or negativity bias in social media, which give this study a good chance to disclose the state and distribution of emotions on VG's Facebook page.

Positivity Bias

Scholars found out that social media users will receive more reactions and positive feedbacks from their online friends when they post positive information on their social media platforms, while receive less feedback when they post sad or negative information (Bazarova, 2015; Utz, 2011; Forest & Wood, 2012; Qiu, Lin, Leung & Tov, 2012). Sas, Dix, Hart, and Su (2009) conducted a study and recruited 13 people aged between 21-29. They found out that social media users capitalized positive emotions both in private and public interactions on Facebook. Once people post positive information publicly on Facebook, they will get more positive feedbacks from others, which make them feel better than the information or event itself, which could be considered as an emotional benefit. Furthermore, their research shows that people's "most memorable experiences with Facebook are all about positive emotions, in particular those concerned with connectedness and entertainment" (Sas et al., 2009, p.120). Based on these prior studies, Reinecke and Trepte (2014) proposed a term "positivity bias in SNS communication" (p.98), which is also supported by Ferrara and Yang (2015b) who argue that public are more likely to share and prefer positive information which can target more people, what is the so-called positivity bias or pollyanna hypothesis (Garcia, Garas & Schweitzer, 2012; Boucher & Osgood,1969; cited in Ferrara & Yang, 2015b, p.1).

Majority studies by using different kinds of methods show that people convey more positive emotions than negative emotions in social media (Lin & Utz, 2015; Golder & Macy, 2011; Tsugawa & Ohsaki, 2015; Utz, 2015; Pfitzner, Garas, & Schweitzer, 2012; Kramer, Guillory, & Hancock, 2014; Bazarova et al., 2015; Burke & Develin, 2016. Cited in Panger, 2017, p.12). Lin and Utz (2015) launched an online questionnaire for active Facebook users in 2014. Almost all of the participants were Americans and they were asked to log in their Facebook accounts and browse the recent posts in news feed, then evaluate their emotions after reading each post. The result of this study showed that most of the posts on Facebook were positive and entertaining, and "positive emotions are more prevalent than negative emotions when browsing Facebook" (p.32). This finding is agreed by Leung (2013) who argues that Facebook is not the channel for people venting negative emotions due to the fact that Facebook is generally perceived as a platform for meeting friends, sharing updates about one's self or seeing updates about others, and it is not a place for a serious debate or a place for expressing conflicting views. Leung's study shows that people prefer to express negative feelings in forums and blogs.

Yu and John-Baptiste (2016) conducted a similar research to find out the characteristics of emotion expression on social media. They recruited 100 participants aged between 18-28 in UK and asked them to log in to their Facebook and Twitter accounts, and then browsed the latest 20 posts they posted. Participants were asked to count the number of positive and negative emotions they expressed in the posts. Results showed that 67.1% of the posts (the latest 20 messages) were positive.

Ferrara and Yang (2015a) observed 3800 active Twitter users in one week and measured the emotional valance of content the users are exposed to before posting their own tweets. They found out that, on average, "a negative post follows an over-exposure to 4.34% more negative content than baseline, while positive posts occur after an average over-exposure to 4.50%

more positive contents" (p.1). Ferrara and Yang suggested that the likelihood of Twitter users adopting positive emotions is much greater than that of negative emotions.

Ferrara and Yang (2015b) conducted another research by analysing 19,766,112 tweets which are English content and exclude URLs or media content (photos, videos, etc.). They identified four classes of Twitter conversation: anticipatory discussions, unexpected events, symmetric discussions and transient events (Ferrara &Yang, 2015b, p.7). Their findings show that the average proportions of positive sentiment in the dataset is 35.95%, negative is 21.59%. They concluded that individuals clearly tend to share and "prefer positive tweets, which are favorited as much as five times more than negative or neutral ones; the same holds true for the amounts of retweets collected by positive posts, which is up to 2.5 times more than negative or neutral ones" (Ferrara &Yang, 2015b, p.9). They also found out that negative information on social media spread faster than positive messages, but positive ones could attract a larger number of readers (Ibid). Nelson-Field, Riebe and Newstead (2011) observed that video with high arousal of positive emotions was more likely to be shared than video with high arousal of negative emotions on Facebook.

Based on the literature reviews, all the studies seem to be that most of social media users prefer to post and share information with positive emotions, and it is not necessary to continue this research in the context of Norway. However, researchers found out that different countries may have different emotions online (Hyvärinen & Beck, 2018; Lim, 2016), and people from different countries may prefer different social media platforms (Chu & Choi, 2011; Jalonen, 2014). By comparing social media users in America and China, Chu and Choi (2011) found out that American users preferred to use loose social networks, while Chinese users preferred "tightly knit networks with close ties" (cited in Jalonen, 2014, p.130). The prior research mentioned above were conducted in English countries or data were chosen in English, results of these studies show that social media have a positive emotional bias. However, in China, according to the 2011 annual report of China online public opinion index, negative events on social media account for more than 80% of the total topics on average, while negative events on Weibo (Twitter liked platform in China) and Tianya BBS account for 75.6% and 95.8% respectively (Xu, 2017, p.78. My translation). Xu (2017) also stated that there is a significant "angry" bias to the feedback of online social news. Stieglitz and Dang-Xuan (2013) conducted a study in Germany, and find out that information with negative emotions in social could get more attention and comments. These research projects show that positivity bias on social media doesn't apply globally. And Hyvärinen and Beck (2018) people with different culture background may have distinct way to express different emotions (Hyvärinen & Beck, 2018). The phenomenon that different countries have unalike emotion patterns in social media, gives an opportunity to figure out the emotion patterns in social media of Norway because very little similar research has been done here, especially referring to emotions on Facebook public news report page.

Furthermore, most studied were conducted in a limited period, and there may be something special happening at that time, such as political elections, cultural or celebrity events, which definitely will affect the public's emotions. Bollen et al. (2011) have found a relationship between public emotion and social, economic and other major events. They found that "social, political, cultural and economic events have a significant and immediate effect on the various dimensions of public mood" (p.450). Thus, the argument that there is a positivity bias on social media is not universal.

Negativity Bias and Negative Emotion

Even though the positivity bias is supported by so many scholars, there are also various researchers argue that social media is always full of "bad news" (Park, 2015; Rainie et al., 2013), and there are more negative messages than positive ones in social media (Robertson et al., 2013). Actually, the debate about positivity bias or negativity bias in social media never stops. Prior research points out that there is a negativity bias on social media, which was extended by Park (2015). He examined how negative emotions triggered by negative news in Twitter, and argued that negative news could make reader feel angrier and more disgusted (Park, 2015, p.353). Stieglitz and Dang-Xuan also support this argument that there is a negativity bias based on emotions' diffusion effect of in social media, what is that negative emotion posts will get more comments and retweets than positive messages (Stieglitz & Dang-Xuan, 2013, p.224). Here, I'm not going to discuss too much about negativity bias regarding the intensity of diffusion influenced by emotions, which will be detailed in section 2.4.3. In the following part of this section, I will focus on previous studies on patterns of negative emotions in social media.

Web-based communication was traditionally thought to be less control due to the characteristics of "anonymity, greater expressive control and little in the way of synchronous or nonverbal feedback from interaction partners" (Panger, 2017, p.14). Panger argues that anonymity gives people chances to reduce the risk what we do online will have an impact on people's offline identity. And the risk may lead to some negative behaviors such as flaming, cyberbullying etc. in email, forum, and live chats, and it also might lead people to express negative emotions in an unrestricted manner that they would never do in face to face interactions (Yu & John-Baptiste, 2016). NCH (2005) surveyed 770 young people aged 11 to 19 years; 20 percent reported ever having been cyberbullied (14 percent by text message, 5 percent through chat rooms, 4 percent by email); 28 percent of victims told no one they had been bullied. A study conducted by Pew Research Center shows that, 86 percent of adult internet users have taken steps from time to time to avoid surveillance by other people or organizations when they were using the internet (Rainie et al., 2013). However, 21 percent of online adults have had an email or social media account hijacked and 11% have had vital information like Social Security numbers, bank account data, or credit cards stolen (Rainie et al., 2013)[15]. In 2017, 41 percent of Americans have been personally subjected to harassing behaviour online, and an even larger share (66 percent has witnessed these behaviours directed at others (Duggan, 2017).

However, in the context of American's social media platforms, anonymity is less common because platform provider prohibits it, such as Facebook, and it is more typical today to connect with people we know offline, "the most common use cases of social media continue to offer greater expressive control and to lack the synchronous or subtle nonverbal feedback of face-to-face interactions (though arguably things like emoji have helped some)" (Panger, 2017, p.15). So, one similarity between social media and traditional web-based communication is the persistence of flaming, harassment on social media platforms such as Twitter and Facebook (Panger, 2017). Whittaker and Kowalski (2015) conducted a research by surveying 169 females and 75 male undergraduate students aged from 18 to 25 in US. Their results show that 22 percent of the participants indicated they had been cyberbullied at least once within the last year. 14 percent stated they had cyberbullied others at least once within the past year. They also found out that the most common social media venues by which people reported becoming victims of cyberbullying were Twitter (12.0 percent) and Facebook (11.4 percent).

In sum, based on the controversy between positivity bias and negativity bias in social media, there is no definite answer about the state of emotion distribution on social media. In addition, very little research regarding emotions of news reports and comments given by public has been conducted in Norway. These debates and gaps provide an opportunity for this study to

[15] https://www.pewresearch.org/internet/2013/09/05/anonymity-privacy-and-security-online/

examine emotions patterns on VG's Facebook page. In addition to distribution of emotions, mediating and diffusion effect influenced by emotion is also a vital part of emotion analysis in social media, which will be discussed in the next section.

2.4.2 The Media Effect and Diffusion Effect of Emotion

Research shows that information's diffusion is quite related to the fact that whether the information itself contains emotion or not. Forgas (2006) argued that emotions "appear to influence what we notice, what we learn, what we remember, and ultimately the kinds of judgments and decisions we make" (p.273). As mentioned in previous sections, emotional words could generate "cognitive processes such as emotionally relevant perceptual affect, appraisals, labelling processes" (Kleinginna and Kleinginna, 1981, p.355) and attention (Bayer, Sommer, & Schacht, 2012). Stieglitz and Dang-Xuan presented detailed literature regarding the relationship between cognitive caused by emotions and information sharing:

> *An increased level of cognitive involvement may in turn lead to a higher likelihood of behavioural response to emotional stimuli in terms information sharing. Furthermore, attentional processes are also shown to have an impact on emotional contagion, which is the spread of mood and affect through populations by simple exposure. Research on emotional contagion has shown that emotions might spread through different kinds of social networks in various contexts, such as between people in frequent close contact such as families, during workplace interactions, or in leadership situations. Emotional contagion may in turn have an influence on individual and group-level communication behaviour in terms of information coordination and sharing. (Stieglitz and Dang-Xuan, 2013, p. 222-223)*

These empirical observations prove that emotions have great influence on information diffusion and sharing in daily life. Applying to social media area, scholar also found out that emotions of information could affect sharing behaviours. Fowler and Christak (2008) analysed the emotional infection and its diffusion in social networks by followed 4739 individuals from 1983 to 2003. They studied the dynamic spread of happiness in large social networks and found that the relationship between people's happiness extends up to three degrees of separation, and people who are surrounded by many happy people and those who are central in the network are more likely to become happy in the future. Kramer (2012) analysed emotion transmission by examining status updates posted on Facebook. Results indicate that emotion could transmitted through text-only communication, social networks and indirect communications media.

Emotions could be spread in social media, while information with emotions are more likely to be shared and spread. Researchers discovered that viral messages which containing the six primary emotions (surprize, joy, sadness, anger, fear, and disgust) are correlated with the content of the information being spread, and the person who share the message have no influence on the sharing behaviour (Celli, et.al. 2016). Rimé (2009) argued that there is a positive correlation between the intensity of emotion evoked by emotional events and the extent to which events are shared. Liu (2012) constructed a model using comments, sharing and retweeting on the social media to identify the emotion of the content, and the amount of the retweeting rely on the content's emotion. Nelson-Field, Riebe and Newstead (2011) examined the relationship between video's emotional arousal and the shared rate on Facebook, and found that video with high emotional arousal was more likely to be shared. Lai and Tang (2016) the analyzed the influence of information's emotions on network rumor's diffusion. Result shows that the audiences in the emotional rumor group have a higher willingness to retweet information than those in the non-emotional rumor group, which proves that emotional rumor has a greater impact on the sharing behavior of the audience.

Recent studies have also examined how emotional information diffused in social media has impact on certain political purpose (Weeks & Holbert, 2013). Stieglitz and Dang-Xuan (2012) put together emotion and information spread based on a data set of 64,431 tweets, and found out a positive relationship between the words' affective dimensions (including positive and negative emotions) related to political parties and politicians in a tweet and its retweet rate, and emotional tweets could be retweeted more often and more quickly than the neutral tweets. They also conducted a researched in 2013 and got the same result based on two databases of more than 165,000 tweets in total during the political election period (Stieglitz and Dang-Xuan, 2013).

Pfitzner et al. (2012) studied whether the expression of emotion in Twitter will influence the subsequent distribution. They found out that emotional divergence indeed affected the sharing of tweets, hence affecting the dissemination of information. They explained "highly emotional diverse tweets can have up to almost five times higher chances of being retweeted" (Pfitzner, Garas & Schweitzer, 2012, p.543). Hill et al. proved that information with positive and negative emotions both could spread longer than neutral ones in social media (Hill et al., 2010).

Based on these reviews, it's easy to find out that expression of emotions in social media will attract more attention and arousal, and emotions in information could affect the diffusion or sharing behaviour in social media, which provides strong theoretical support for the second research question of this thesis: *how do emotions affect public's engagement of the news and news diffusion on VG's Facebook page?*

2.4.3 Different Emotions Have Different Diffusion Effects.

Last section has provided the literature regarding that information with emotions (both positive and negative) is more likely to be shared and diffused than neutral ones in social media, which indicates that emotions are not just passive and hidden objects in media, but active forms (Xu, 2017). As discussed in section 2.3.2, there are various types of emotions according different theorists, and these emotions are totally different. It is necessary to explore whether different emotion types have different dissemination effects, which could make a better understanding of emotions' diffusion effects in social media. Prior research has found out that different emotions have different diffusion effect. For instance, for social information on social media, negative emotion spread faster (Ferrara & Yang, 2015b) and got more comments and feedbacks (Stieglitz & Dang-Xuan, 2013; Burke & Develin, 2016) than positive ones. The negative emotion anger is more likely to be spread in social networks, while sad is less likely to be spread (Zhao, Dong, Wu & Xu, 2012; Berger & Milkman, 2010). However, some argue that positive information could get more attention (Tadic et al., 2013) and reach larger reader (Ferrara & Yang, 2015b). The controversy about whether negative emotion or positive emotion is easier to be share not only existing normal postings but also existed in news reports in social media. Most researchers argue that news with negative emotions could attract more attention and is more likely to be shared (Sui & Li, 2012; Hansen et. al. 2011). However, scholars hold the opposite opinion that news with negative emotion social media could be less viral because people post messages on social media is to show and maintain a better personal image, and posting negative emotions is not conducive to this purpose, which may reduce the possibility of news with negative emotions to be spread in Facebook (Valenzuela, Piña & Ramírez, 2017). Therefore, I want to figure out the diffusion effect of different types of emotions on VG's Facebook page. Detailed literatures regarding emotion's diffusion effect will be presented following.

According to Sui and Li (2012), negative emotions can be spread more easily than positive ones, and negative information is always the transmission direction, both in traditional media and new media. Ferrara and Yang (2015b) found out that information with negative emotions spread faster than positive ones in Twitter. Stieglitz and Dang-Xuan (2013) argued that negative emotion posts will get more comments and retweets than positive messages.

Burke & Develin (2016) found out that people prefer to share both positive and negative emotions when their social networks are smaller and denser. They further explained that when people share bad thing or troubles on Facebook will receive more and longer emotional comments which support the postings. Zhao, Dong, Wu & Xu (2012) analysed emotions on Weibo which is a Twitter liked Chinese social media platform. They classified 95 emoticons into four categories of emotions: anger, disgust, joy and sadness. Results show that anger is more likely to be spread in social networks, while sad is less likely to be spread.

Tadic et al. (2013) quantified collective emotions through fractal analysis of social networks, they found that “the dominance of messages with negative emotion valance on Blogs leads to the occurrence of large avalanches” (p.5090). Social media enabled people get access to all kind of information and make conversation to other people, which could “increase the rate of emotional burst” and “multiplies the ability to express negative experiences” (Jalonen, 2014, p.6). Jalonen explained that avalanches result from numerous interactions between interconnected users that lead to a series of nonlinear progression events. “From the perspective of negative emotions, the significance of interactions promoted by social media lies in that they enable the multiplication of small influential changes” (Jalonen, 2014, p.6).

However, some scholars have different empirical findings on the diffusion effect of negative emotions, and they suggest that contents with positive emotions could get more attention. In a study of newsgroup participation, Joyce and Kraut (2006) figured whether there is a relationship between the emotions of the messages people posted in an online community and the continuity of conversation. Results show that messages with positive emotions could encourage participation to continue to post more information (e.g. longer comments), whereas negative emotions will result in insulting interactions (Joyce & Kraut, 2006). Research suggested that content conveying positive emotions could trigger higher levels of arousal (Berger, 2011, cited in Stieglitz & Dang-Xuan, 2013, p.218) which can further affect feedback and social sharing behaviour (Berger & Milkman, 2012, cited in Stieglitz & Dang-Xuan, 2013, p.218), for instance, posts with positive emotions could attract more readers than negative emotions in social media (Ferrara & Yang, 2015b, p.1).

In the news field, news relate to politics can result in fear, hope, and often anger, and news of the hometown team's triumph can be joy and happiness, all the while reports of a health threat may spur anxiety (Myrick & Wojdynski, 2016). Berger and Milkman (2010) examined how emotion shapes virality by analysing 6956 online articles which were published on *New York Times* in three months. Results show that contents with positive emotions (i.e., awe) is more likely to be shared, while contents with negative emotions (i.e., anger or anxiety) also have a great possibility to be shared, but online news with the emotion of sadness is less likely to be viral. They suggested that online news with high arousal were much easier to be shared. Hansen et al. (2011) conducted a further research which studied the influence of emotion on information retweeting on twitter and the complex correlation between them. According to the data base, they found that positive emotions could promote the retweeting for social messages, but for news content, negative emotion promote retweeting, which just in the domain of news-----"if you want to be cited: Sweet talk your friends or serve bad news to the public" (Hansen et. al. 2011, p.34).

Conflict news which tend to be negatively valance, could increase the virality of the news (Valenzuela, Piña & Ramírez, 2017), and this kind of news is more likely to be chosen by readers or editors than neutral or positive news (Zillmann, Chen, Knobloch, & Callison, 2004; cited in Valenzuela, Piña & Ramírez, 2017, p.806). Researchers further find out that conflict news could get more comments by the same user groups, and could be shared more on social media (Weber, 2014; Trilling et al., 2017; cited in Valenzuela, Piña & Ramírez, 2017 p.807).

However, argument presented above is not universal, and researchers found out that negative news or news with negative emotion couldn't be spread so broadly (Burke & Develin, 2016). Social media is considered as a front stage for public present themselves, maintain good images or receive more supports from friends (Hogan, 2010; Bazarova, 2015; Utz, 2011; Forest & Wood, 2012, which motivate people post and share more positive emotion and reduce the possibility for sharing and spreading negative news in social media platforms (Leung, 2013; Valenzuela, Piña & Ramírez, 2017). Burke and Develin (2016) also argue that "social media users may also perceive a proscriptive norm against sharing negative emotions" (p.1464) because, as Valenzuela, Piña and Ramírez said, people are generally "hesitant to share negative news on social media, they do not want to be perceived as a Cassandra, always predicting bad news" (Valenzuela, Piña & Ramírez, 2017, p.807). Thus, in the case of this study, it is necessary to figure out how do emotions of news affect news diffusion on VG's Facebook page according to these contradictory arguments mentioned above.

In sum, based on previous research, section 2.4 have mainly discussed the state of emotions on social media regarding positivity bias or negativity bias, presented emotion's media effect referring to that emotional information could be spread and shared easier than neutral information, and analysed emotion's diffusion effect according to emotion types. These previous studies provide a lot of theoretical support for the formulation of research questions 1 and 2: *RQ 1. What is the main emotion on VG's Facebook page? RQ 2. how do emotions affect public's engagement of the news and news diffusion on VG's Facebook page?* Studies also provide research gaps for this thesis, which makes this study valuable to figure out the main emotions and emotions diffusion effect in Facebook in the context of that there are not many such studies have been done in Norway. After that, literature review will turn to the third and fourth research questions (*How do emotions of the news post on VG's Facebook page affect public's emotions which conveyed by news commentators? which emotion has a stronger agenda affect to public?*) regarding emotion agenda effect, which will be discussed next.

2.5 Emotional Agenda Setting

"Agenda-Setting" theory was defined by McCombs and Shaw (1972, p.177) as the "ability of the news media to influence the importance placed on the topics of the public agenda". In other words, media's agenda sets the public's agenda, and tells the public which story is important, what kinds of people, communities, event and issues are important, hence to influence public's thought and views. There are two levels of agenda setting. The first-level agenda setting focuses on "the amount of coverage of an issue, exploring the media role in deciding what issues the public will be aware of; the second-level agenda setting focuses on how the issue is defined, or how the media also convey affective attributes of issues" (Coleman & Wu, 2010, p.315). Balmas and Sheafer (2010) argued that the focus at the first level agenda-setting emphasizing media's role in telling us "what to think about" is shifted to media's function of telling us "how to think about" at the second level agenda-setting. For instance, Wanta, Golan and Lee (2004) analysed if coverage of foreign countries had an agenda-setting influence by examining network newscasts in US. They found out that the more often the country is reported, the more audiences thought this country is important, which is support the first level of agenda setting theory. If media gives more negative reports to one country, audiences will think that country negatively, which supports the second level of agenda setting theory. However, they found that positive coverage of a countries has no influence on public's view (cited in Coleman & Wu, 2010, p.318).

Actually, emotions are always existed in news reports, and news media always have emotional elements (Hasell & Weeks, 2016) which has a great attention-attracting function (Doveling, von Scheve, Konijn, 2010). Doveling, von Scheve and Konijn point out that by reporting crime, war, disasters, triumphs and successes etc. events, the news inherently elicits emotional responses from viewers and readers. Furthermore, "emotions motivate people to focus their attention on distinctive information or objects and, because people are limited in their capacity to process information, emotions are helpful to selectively direct attention to parts of a media message (e.g., tears on a victim's face), subsequently affecting memory for specific information only" (Lang 2000; cited in Doveling, von Scheve & Konijn, 2010, p.49). As the development of technologies which expanded the media market and increase the competitions for a smaller share of the audiences, which result that news media prefer to report emotional stories and report news in emotional ways in order to retain or attract more audiences and subscribers (Hasell & Weeks, 2016). News consumers also tend to prefer and select emotional news. Trussler and Soroka (2014) found out that news content with negative emotions will have a broader coverage (cited in Hasell & Weeks, 2016, 643). People feel more anger and disgusted if they exposed to highly negative news stories in social media, and they are more willingly seek more information about these stories (Park, 2015). Goodall et al. (2013) found that the emotion of anger can be elicited through news media if the news blames the individuals, and fear can be evoked if news contains a perceived threat to individual's personal safety. The emotion of anger also could be elicited by news stories "when the stories threats audiences' identity or worldview" (Arpan & Nabi, 2011) or "when the news focuses on conflict rather than substance" (Gross & Brewer, 2007; cited in Hasell & Weeks, 2016, p. 643).

To emotional level, scholars have examined the agenda setting theory in TV news. Coleman and Wu (2010) argued that the "second, or affective, level" has included an important element of affect-emotions experienced by publics including anger, fear, sadness, happiness and so on. They analysed all the newscasts were recorded in the twelve weeks between Labor Day and election day 2004 from six mainstream media in America. Their results show that audiences' emotional attitude is indeed correlated with media's emotional agenda. Moreover, negative emotions for political candidates showed the only significant agenda-setting effect even the news is not a negative issue, but positive emotions of assessment of character traits showed no agenda-setting effect.

According to the emotional level of agenda setting theory which has changed news media's role from tell public "what to think" to "how to think" by setting content or emotions (Balmas & Sheafer, 2010). Most research regarding the second level of agenda setting focused on the traditional media, and very few analysed emotions agenda effects of news on social media platforms. Thus, one of the most important task of this thesis is to examine emotional agenda effect to public on VG's Facebook page, and also try to find out which kind of emotion has a stronger agenda effect in the context of Norwegian social media platforms. So far, all the literature related to this study have been reviewed and discussed, and the detail of methodological approaches and analysing process will be explained in the next chapter.

Chapter 3 Methodology

This chapter describes the related literature of methodology for conducting this study. In the beginning of this chapter, previous research regarding big data analysis will be provided. Then I present the method for data collection from VG's Facebook page and the process for sampling and filtering of dataset due to the huge amount of the original dataset collected. After that, literature regarding emotion lexicons aligned with emotion detection tools will be discussed, and the methods used to detect emotions from textual news titles and comments will be introduced. In this section, I will also describe how I translate all the Norwegian textual content (news titles and comments) to English, code emoji to emotions, and confirm and check the accuracy of the emotions detected from tools and adjust the wrong emotions to the proper ones. Since the data which is ready to be analysed, content of this chapter turns to the third section referring prior research about quantitative content analysis, and introduces the reliability and validity of this research in terms of processing of data collection, sampling and emotion detection (reasons for why I choose Senpy as the tool by comparing with other tool presented in section 2.3.3). At the end of this chapter, I describe limitations of methods used in this study and the ethical considerations in this research.

3.1 Data Collection

3.1.1 Big Data Analysis

As scholars increasingly paying attention to the public's emotional expression on social media, the huge number of updates, postings, tweets, comments and other "big data" played important roles in the research of human's behaviours in media studies. Normally, these data were generated by Internet services and could be collected by computer-based applications, and then take a deep insight into people's activities and find the relations (Panger, 2017). By comparing with traditional sociological methods, these kinds of datasets could be obtained from platform providers or collected independently with relatively less effort and time (Tufekci, 2014). Kitchin (2013) further argues that big data "holds the promise of a data deluge – of rich, detailed, interrelated, timely and low-cost data – that can provide much more sophisticated, wider scale, finer grained understandings of societies and the world we live in", and offers the possibility of shifting from "data-scarce to data-rich studies; static snapshots to dynamic unfoldings; coarse aggregations to high resolutions; relatively simple hypotheses and models to more complex, sophisticated simulations and theories" (p.263).

Fan et al. (2014) stated two advantages of using big data analysis: (1) “exploring the hidden structures of each subpopulation of the data, which is traditionally not feasible and might even be treated as ‘outliers’ when the sample size is small; (2) extracting important common features across many subpopulations even when there are large individual variations” (Fan, Han & Liu, 2014, p. 294). However, there are also challenges of analysing big data: (1) “high dimensionality brings noise accumulation, spurious correlations and incidental homogeneity; (2) high dimensionality combined with large sample size creates issues such as heavy computational cost and algorithmic instability; (3) the massive samples in big data are typically aggregated from multiple sources at different time points using different technologies” (Fan, Han & Liu, 2014, p.294).

To the application of big data in social media, Chen, Mao and Liu (2014) state that the analysis of big data from social media uses analytical method “provided for understanding relations in the human society by virtue of theories and methods, which involves mathematics, informatics, sociology, and management science, etc., from three dimensions including network structure, group interaction, and information spreading” (Chen, Mao & Liu, 2014, p. 199). They further argue that the application of big data analysis based on social media platforms includes “network public opinion analysis, network intelligence collection and analysis, socialized marketing, government decision-making support, and online education, etc.” (Ibid).

Actually, there are lots of studies have been conducted through big data analysis to explore the rules of human’s activities on social media platforms in many domains. In financial area, Skuza and Romanowski (2015) used Twitter Streaming API[16] to retrieve Twitter messages which contain name of the specific company or hashtag of that name in three months to predict stock price by using two different data bases. In media studies, Viswanath, Mislove and Gummadi (2009) collected 838,092 updates and examined the evolution of activity between users in Facebook. They found that links in active networks are more likely to come and go quickly, and the intensity of connections shows a general trend of decreasing activity as the age of social network links grows. They pointed out that only 30% of Facebook user interact consistently in two months (Viswanath, Mislove & Gummadi, 2009).

[16] APIs as objects of research for new media scholars are only slowly coming into view, despite their importance for the Web as data ecosystem (Rieder, 2013). However, Facebook has already shutdown and adjust the existing API service for access permissions according to The Cambridge Analytica scandal which disclosed on 17 March 2018 and is a great challenge for privacy protection on social media (Bruns, 2019).

In the emotion/sentiment analysis domain, the Pew Research Center (2015) collected more than 1.2 million tweets in English, French, and German in May 2014 to the EU elections, they found that there was more negative information than positive ones on Twitter. Moreover, almost all research activities mentioned in previous chapter (see section 2.4 and 2.5) have collected big data from social media platforms examining state of emotions, relationships between emotions of information and public's engagement and sharing behaviours. Therefore, literature regarding emotion analysis in social media will not be repeat again here.

In this thesis, in order to examine the main emotions on VG's Facebook page, and find out how do emotions affect public's engagement and news diffusion, and emotion's agenda effect, a huge number of data will be collected and analysed by online applications and internet services, which will be detailed in next.

3.1.2 Data Collecting

In order to make the dataset representative, at the beginning, I planned to create a big dataset and collect all the data posted in one month. Then I randomly chose all the news titles and comments posted on VG's Facebook page in August 2018. The scraping tool I used for collecting data was Netvizz[17] which allows researchers to "generate data files in standard formats for different sections of the Facebook social networking service without having to resort to manual collecting or custom programming" (Rieder, 2013, p.346). This application was widely used in research, and could extract data from three different sections of the Facebook platform: personal networks, groups, and pages (Rieder, 2013). In this project, data form VG's Facebook page will be collected. Due to the huge amount of the data in one month, Netvizz couldn't collect all of them one time. Then I divided data in one month into 4 periods for collecting: 1st - 11th, 12th -18th, 19th - 25th and 26th - 31st August 2018. After that, I got a total number of 401 news items in the selected month, and in each period, the number of news was 53, 19, 167, 162 respectively. And the amount of comments was 45 977 totally, and in each period, there were 7 823, 2 209, 19 757, 16 188 respectively.

After the scraping process, three files have been outputted in each period. One of the file contains all the comments and posts links, post-date. Another one contains all news titles, links and numbers of sharing, comments, engagement, reactions etc. of each news. The third

[17] https://wiki.digitalmethods.net/Dmi/ToolNetvizz . It is a API service, and not available right now due to the privacy protection on Facebook (see footnote in the previous page p.42).

file contains the statistical information per day in terms of total number of posts, "Like", reactions, comments and shares.

Figure 3.1 Interface of news posted on VG's Facebook page.

In addition to the news titles and comments, another important element of the dataset should be mentioned separately, which is the reaction/emoji. There are six types of reactions in each post on Facebook: "Likes", "Love", "Haha", "Wow", "Sad", "Angry", and public could choose and express a reaction after they read a piece of news to express their emotions according to the content (see Figure 3.1 which shows the interface of posting, comments and reactions). Actually, reactions are elements that could directly convey public's emotions to the news, which don't need any coding or detecting process, and the data collected relating to reactions could be used in the analysis process directly. But before moving to the analysing process, dataset need to be sampled and cleaned.

3.1.3 Sampling

Due to the huge amount of the dataset, which couldn't be handled by myself in this project. I randomly chose the data from the last three days (29/08-31/08) in August 2018 as sample which contains 84 pieces of news and 9157 pieces of comments. Even though these data are still huge for me to handle this study, the analytical result from the data just could illustrate the emotional reactions and tendency on VG's Facebook page in three days and could not represent the whole. But this is still an effective attempt to analyse the main emotions on VG's Facebook page, and find out relations between emotions and emotional strength which is measured according to the number of reaction/emoji and the frequency of emotions in comments, engagement of the news which is the sum of the number of comments, sharing and emoji, speed of feedbacks and spreading time span of the news, and also figure out the emotional agenda effect in the context of Norwegian social media.

3.1.4 Filtering: Creating a Clean Dataset

Even though the sample for this study has been set and confirmed, data for analysing still need to be cleaned for textual content in the dataset. For the comments part, I reviewed all the pieces and delete some useless items such as unrecognizable information (e.g., “kkkkk”, “Näääääj”), messy codes, people’s names without emoticons (hardly detect emotions), punctuations, blanks and some comments written in the form of links. Also, I have to change some words to right forms (e.g., “Ofc” to “Of course”, “f-a-s-h-i-o-n” to “fashion”, “Roooooosenborg” to “Rosenborg” and so on) for emotion detection. After all these works, the dataset has a total number of 7876 pieces of comments. For the news title part, I checked all 84 news items which would be analysed and found 14 pieces of news titles should be revised. Actually, these 14 news titles were posted in two lines on Facebook, but the scraping tool, Netvizz, just could get the first line of the title, which couldn’t express the full meaning and emotions of the news. For instance, in the news title of “SISTE: Falt 100 meter fra Trollveggen”, just “SISTE” was collected. In that case, I have to find the original link of the news from the database, and fill the file with whole title in dataset (see Table 3.1). When the database is clean and readable, the emotion detection process could be conducted.

Table 3.1 Examples of news titles changed manually in the dataset.

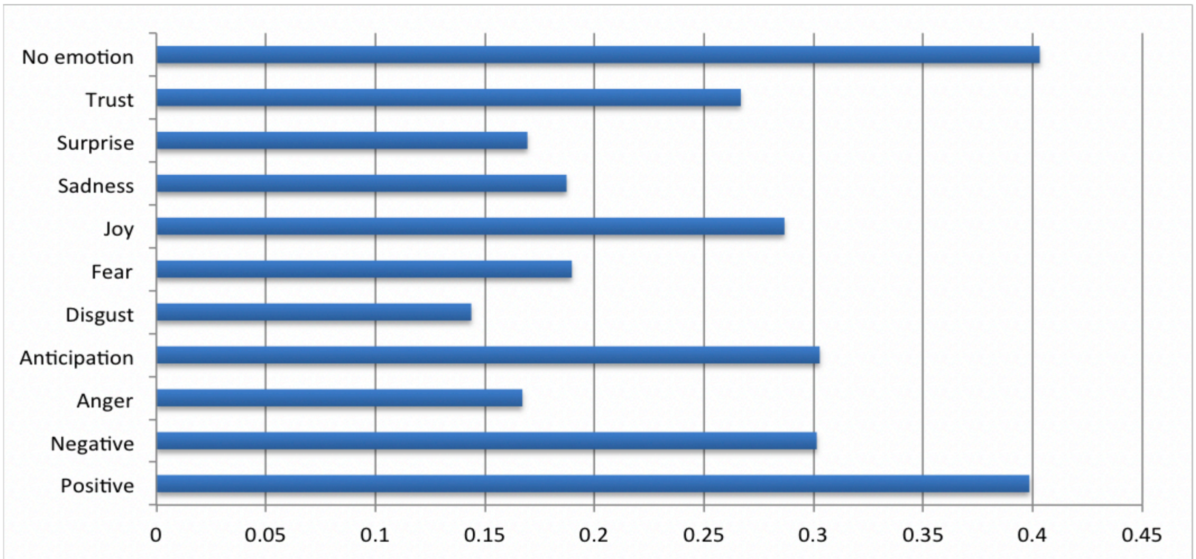
Original form	Final form
SISTE:	SISTE: Skudd mot bil i Oslo.
SISTE:	SISTE: Falt 100 meter fra Trollveggen.
Pinlig:	Pinlig: Ber Sivilforsvaret skaffe utstyr fra Finn.no.
🏝☀:	🏝☀: Her vil nordmenn kjøpe fritidsbolig i utlandet.
💪💪💪:	💪💪💪: Camilla Herrem scoret igjen 7 uker etter fødselen.
Men nå er Filip Ingebrigtsen (25) klar igjen 💪.	Men nå er Filip Ingebrigtsen (25) klar igjen 💪. Fikk alvorlig reaksjon på medisin.

3.2 Data Processing and Analysis

3.2.1 Emotion Lexicon Analysis

Before detecting emotions of the data, the theory of the detector which based on emotion lexicon will be presented (also mentioned in section 2.3.3). An emotion lexicon is a list of words and phrases (e.g. bad, good, beautiful, amazing, horrible) that people often use to express specific emotions (Liu, 2015), and lexicon consists of "finer-grained affective lexica based on emotional categories" (Pozzi et al., 2016, p.35), and Ekman's six emotion: anger, fear, joy, sadness, and disgust (Ekman, 1982) always be considered as the basic emotions. Researchers proposed algorithms to extract key high-frequency words from sentences or paragraphs to determine the specific emotions expressed by specific words (Liu, 2015). For instance, "beautiful" indicates "joy", "bad" indicates "anger", "disgust", "fear" and "sadness" in different context (Mohammad, Kiritchenko & Zhu, 2013). Yang et al. (2007) firstly constructed an emotion lexicon and performed emotion classification at the sentence level (cited in Liu, 2015, p.87). Liu stated that Yang et al. proposed the algorithm for designing the emotion lexicon by using sentences with emoji, and it "computes an association strength of the word with each emoticon using a measure similar to pointwise mutual information (PMI)" (p. 87).

Figure 3.2 Emotions' frequency in Facebook status updates.



(Note: Almost 60% of the status updates express at least one kind of emotion from the NRC lexicon, and many posts convey more than one emotion. Cited in Farnadi et al., 2014, p.5)

There are many studies related to the construction of emotion lexicon, and researchers use different kinds of online text as resources. WordNet-Affect is an early established and widely used emotion lexicon, in which "resource was developed starting from WordNet through the selection and labelling of the synsets representing affective concepts" (Strapparava & Valitutti, 2004, p.1083). Yassine & Hajj (2010) used WordNet-Affect to extract the emotional content of texts in online social networks and observed 81% of Facebook comments as containing some sort of subjectivity. They affirmed that online social networks were highly emotionally-rich. Mohammad, Kiritchenko and Zhu (2013) collected a set of 775,000 tweets to generate a large word–emotion association lexicon called NRC. They found that hash tagged emotion words such as joy, sadness, angry, and surprised are good indicators that "the tweet as a whole (even without the hash-tagged emotion word) is expressing the same emotion" (Mohammad, Kiritchenko & Zhu, 2013, p.2). Farnadi et al. (2014) used NRC hash-tag emotion lexicon to detect emotions from almost 1million Facebook personal updates. They found that almost 60% of status updates contain at least one type of emotion expression (Figure 3.2). Staiano and Guerini, M. (2014) created "a high-coverage and high-precision" (p.1) lexicon of roughly 37 thousand terms annotated with emotion scores, called DepecheMood, based on a large number of online news articles.

In sum, there are many types of emotion lexicons based on different emotion categories from different researchers applied in emotion detection tools (see Table 2.3, p.26). Automatic emotion detector and emotion lexicon used in this study will be introduced next.

3.2.2 Emotion Detection

In this thesis, an online emotion analysis service called Senpy[18] (Sánchez-Rada et al., 2016) which is a framework for NLP (Nature Language Processing) services will be used to detect emotions from the data (news titles and comments). Senpy has complex functions in testing polarity sentiment and specific emotions. People can input text and it returns a single emotion or scores from different emotion categories formatted in Emotion "Markup Language (EmotionML) format" (Schröder, et.al., 2011, p.316). Denis et.al. (2013) explained that an emotion is defined by a set of descriptors, and each descriptor refers to an emotional vocabulary document. The syntax and vocabularies of EmotionML are available to "describe emotions in terms of categories, dimensions, appraisals and/or action tendencies" (Schröder, et.al., 2011, 316).

Senpy offers automatic emotion model conversion based on five basic emotion categories:

[18] https://senpy.readthedocs.io/en/latest/

“happiness”, “fear”, “disgust”, “anger” and “sadness” (there is no “surprise” compared with Ekman’s six emotion categories) and also “neutral” option by using emotion lexicon (Bradley & Lang, 1999). There are three emotion lexicons plugged in Senpy, which are: ANEW, WordNet-Affect and DepecheMood. But in this research, ANEW (Affective Norms for English Words) will be chosen as the resource of dictionary, which is developed to provide “a set of normative emotional ratings for a large number of words in the English language” (Bradley & Lang, 1999, p.1). By comparing with WordNet-Affect and DepecheMood, ANEW is also a widely used lexicon with “maximized precision” (Staiano & Guerini, 2014, p.2). Moreover, emotion types in ANEW based on the widely used categories, but DepecheMood output emotion types as “fear”, “sadness”, “awe”, “joy”, “indifference”, “annoyance”, “anger”, “amusement”, which can’t be traced back to find which theoretician classified them. Even though WordNet-Affect have the same emotion types with ANEW, it is particularly insensitive and can’t find emotions in many sentences. Therefore, ANEW lexicon dictionary plugged in Senpy has been chosen as the tool to analyse emotions in news titles and comments from VG’s Facebook page, which is the premise of figuring out the main emotion of VG’s Facebook page, finding how do emotions affect public’s engagement and news diffusion and spreading span, and examining emotions agenda effect on Facebook news page.

Table 3.2 Examples of emotions detected by Senpy from comments.

Comments	**Emotions**
EN: Remember that the Social Security Act was a driving force to get through, and there are more parties that helped build our welfare as we know it today. **NO**: *Husk at trygdeloven var Høyre en pådriver for å få gjennom, og det er jo flere partier som var med å bygge vår velferd slik vi kjenner den i dag.*	Happiness
EN: They probably just kill each other. **NO**: *De dreper nok bare hverandre.*	Sadness
EN: A wolf in sheep's clothing! **NO**: *En ulv i fåreklær!*	Fear

Furthermore, Senpy works by calculating VAD (valance-arousal-dominance) of the sentence and determines which emotion is closer to this value, then detects possible emotions: anger, fear, disgust, happiness, sadness or neutral (Sánchez-Rada et al., 2016). The category of “neutral” means that there are is no emotion in the content, but according to all the detecting results, there is no textual content give out a result of "neutral". Results detected by Senpy show that there is only one type of emotion for each piece of comment or news titles. Table 3.2 illustrates examples of detection results from Senpy.

Actually, before I decided to use Senpy as the finally emotion detector, I used one week to learn R language because I tried to use the R package called Syuzhet (Jockers, 2017) to detect emotions based on NRC-Lexicon. As mentioned before, NRC follows Plutchik's eight emotions: trust, anger, anticipation, disgust, joy, fear, sadness, surprise, which has more emotion types than ANEW. Results detected from Syuzhet could contain more than one type emotion in one pieces of comment or news titles, whereas Senpy could only output one type emotion, which indicates that Syuzhet could interpret emotions of content in a more fine-grained way. However, I found that this tool works on sentence-level emotion analysis, and there are plenty of comments contains more than one sentence. In that case, I could only analyse these 7876 comments one by one, otherwise I couldn't figure out emotions belong to which comments because I don't know where are the breaks of comments in the processing of Syuzhet package if I do multiple analysis. I tried a lot and still can't find a good solution to deal with it as I totally have no computer science background. Due to the large number of the comments, I gave up this method and chose Senpy to continue my study.

Moreover, as I mentioned in the Acknowledgement part in the Preface of this thesis, my husband helped me a lot for the data processing in this project. Actually, the emotion detection part was completed with his help, which saved lots of time. He wrote a Python script to call the Senpy Package, then input the Excel file with all comments and news titles. After that, all emotions of comments and news were output automatically as a new Excel file. Otherwise, I should detect emotions in these 7876 comments one by one. Except for this, all other analysis and data processing were done by myself.

3.2.3 Translating, Coding and Checking

Before starting emotion detection, all news titles and comments should be translated from Norwegian to English by Google Translate as Senpy with ANEW is only available for English and Spanish language. Moreover, this tool is text only, and can't detect emotions from emoticon/emoji. However, lots of comments collected are presented as the form of Emoji. Hence, I have to code manually from emoticon/emoji to emotions in comments according to Wood and Ruder's (2016, p.77) classification (see Figure 3.3).

Figure 3.3 Selected emoji and their emotions (Wood & Ruder, 2016, p.77).

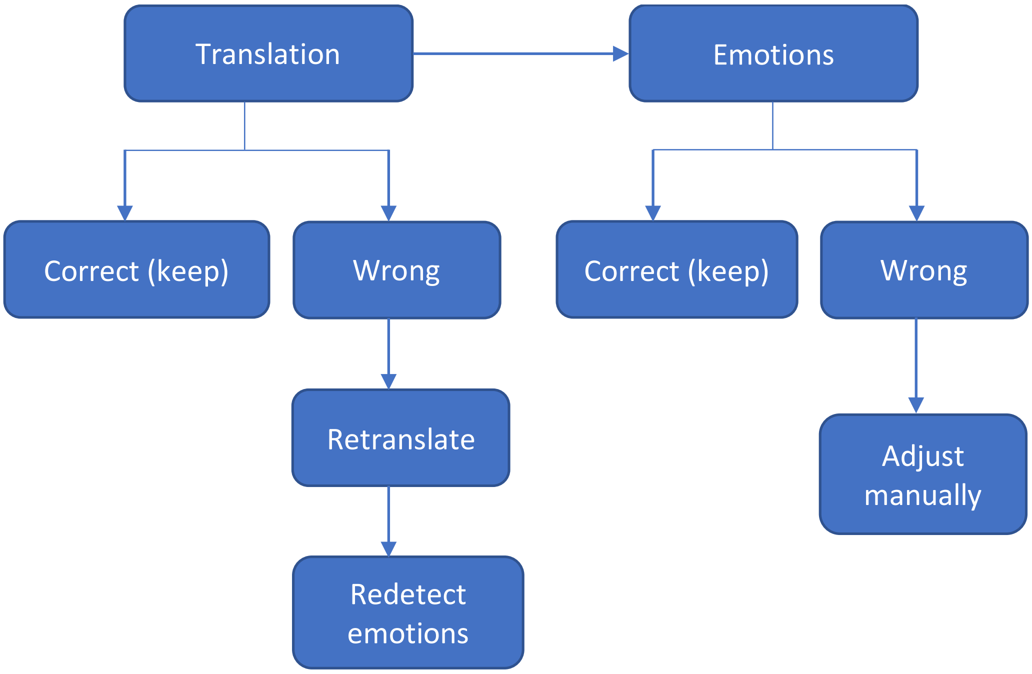
After detecting emotions of each news title and comment by Senpy, I have to check the accuracy of the results. Firstly, I checked all the translating and emotions of news titles (84 in total), and reviewed all the original news on Facebook based on the links collected by Netvizz. I retranslated some news titles again which looked weird by the work of Google Translate, and re-detected their emotions by Senpy. After that, I checked the emotions of each news title and found that the accuracy of Senpy was still over 85 percent as there were 12 news titles in all 84 with the wrong emotions. For instance, Senpy gave a result of sadness for news title "Finally, Friday!", which was absolute not correct in this context. Then I reviewed the main content of these 12 news items, and analysed and modified their emotions into right form based on the five emotion categories: anger, fear, disgust, happiness, sadness. The list of these 12 news titles and the main are presented in Table 3.3, which doesn't contain the Norwegian version.

For the comments part, I did the same checking process as the news title part (see Figure 3.4), and revised the emotions as well. For instance, there were two pieces of news related to the royal couples' golden wedding anniversary, and lots of readers gave a comment "congratulation", but emotion detected by Senpy was "sadness" which was totally wrong. Then I changed all of those emotions to "happiness". However, due to the huge number of comments which are 7876 pieces, I can't modify them as careful as the 84 pieces of news titles. But I reviewed them three times and modified the emotions in comment as best as I can, which definitely was a limitation of this research and will be introduced in the Limitation section (3.4).

Table 3.3 List of the 12 news titles which have been manually modified the emotions detected by Senpy.

News titles	Main content of the news	Senpy	Modified
Very excited!	Actors of the film «Skjelvet» walked the red carpet at the premiere.	sadness	happiness
Sylvi Listhaug on «Nytt på nytt» 😅	Sylvi Listhaug joked about her own visit to Rinkeby when she was a guest at «Nytt på nytt» at NRK.	sadness	happiness
Finally, Friday!	It's a recipe what tell people how to make pizza	sadness	happiness
Toxins are in many things we surround ourselves with and in a lot of the food we eat, unfortunately also in breast milk.	The Norwegian Scientific Committee for Food and the Environment has reviewed the research on environmental toxins in breast milk and concluded that the health benefits of breast milk far outweigh the potential negative effects of environmental toxins.	happiness	fear
A freezer stick that needs a seven-layer jacket? 😅	Are you a freezer stick? Then maybe this seven-layer Balenciaga jacket is for you, if you are not intimidated by the staggering 75,000kr price tag.	fear	happiness
I would love to do it, but there is no political basis for it in Parliament, says the fresh minister of affairs.	Jon Georg Dale (Frp) cannot promise that he will be the Minister of Transport of the Frp to end tolls, even though it was one of Frp's foremost election promises when they went to government.	happiness	sadness
Old picture creates Twitter wave 😅.	Halle Berry's "flirt" with Prince Harry is spread virally	fear	happiness
If Billie couldn't join me, I could never have done this.	Toddler mum Tone Damli brings both children and family / husband to Gran Canaria to record «Love Island»: - Couldn't Billie (her daughter) be there, I could never have done this here.	sadness	happiness
Aretha Franklin is buried today ❤.	Aretha Franklin is buried. Twenty artists will perform at the four-hour funeral for Aretha Franklin in Detroit this afternoon.	fear	sadness
What a criminal drama!	In Sarpsborg, Jørgen Halvorsens had secured Sarpsborg 08 a historic spot in the Europa League group stage.	fear	happiness
The cats threaten a popular bird 😱.	Nature conservationists in New Zealand believe cats are pests that threaten local species. The small village of Omaui will now ban the animals.	happiness	fear
Check if your bank provides this service. Now more access to Apple Pay.	In mid-June, Apple's payment solution Apple Pay was launched in Norway. Nordea Bank and Santander Bank were the first to offer the service to their customers, and now third parties also follow up: Sbanken (Skandiabanken).	sadness	happiness

Figure 3.4 The checking processes.



After all the checking processes, the total number of comments' emotions in each category under each news title will be counted. Then I checked that the total number of comments' emotions equals to the total number of comments which is 7876. After that, numbers of all types of emotions belong to each news will be added to the file which contains the emotions of the news title and the statistics of reactions and engagement of each news, then the final database for analysing is done.

Since the emotion categories of comments which detected by Senpy and reactions in emoji are not the same. So, emotions (happiness, sadness, anger, fear and disgust) in comments and emoji/reactions ("Love", "Haha", "Sad", "Angry", "Wow") will be analysed separately. And the final data set contains titles of 84 news items, links of the news resources, publishing time of the news, numbers of all types of emotions in comments of each news, number of all kinds of reactions, engagement, sharing etc. Then, the file is ready to go into the quantitative content analysis processing.

3.3 Quantitative Content Analysis

Before analysing all data in a quantitative way, literatures regarding quantitative content analysis will be provided. Then I will discuss the reliability and validity of the data collected and emotion detectors. The specific steps of data processing will not be discussed in detail here, but will be presented specifically when answering research questions in the Finding chapter.

3.3.1 Overview

Quantitative content analysis is a research method and defined as the "the systematic and replicable examination of symbols of communication, which have been assigned numeric values according to valid measurement rules, and the analysis of relationships involving those values using statistical methods, to describe the communication, draw inferences about its meaning, or infer from the communication to its context, both of production and consumption" (Riff, Lacy & Fico, 2014, p.19). Quantitative content analysis has been broadly used in a wide range of social science topics including gender and race, violence, media reporting and political communication, specially, it is widely employed in media communication (Coe & Scacco, 2017).

Riff, Lacy and Fico argue that the advantages of quantitative content analysis are numerous. Firstly, "it is a nonobtrusive, nonreactive measurement technique" (Riff, Lacy & Fico, 2014, p.30). They explain that all of the information collected is separate and apart from communicators and receivers, and the researcher can get conclusions from content evidence without having to contact with interviewees who may unable or don't want to be examined directly. Second, "because content often has a life beyond its production and consumption, longitudinal studies are possible using archived materials that may outlive the communicators, their audiences, or the events described in the communication content" (Riff, Lacy & Fico, 2014, p.30). Third, it is allowed to reduce the numbers of the messages or data during the quantification or measurement process, which is impossible for qualitative analysis (Riff, Lacy & Fico, 2014).

In order to conduct a successful quantitative content analysis, I followed Riff, Lacy and Fico's three process: conceptualization, design and analysis (Riff, Lacy & Fico, 2014, p.43). In the first stage, researchers have to identify the problems, research questions and hypotheses, then design what will be done to achieve research purpose, such as coding, sampling, pre-test etc. Finally, people should establish reliability and applying statistical method to analyse data.

In the case of this project, research questions and purpose have been done at the beginning of this thesis (see Chapter 1). The processing of data collecting and sampling also introduced in the former part of this chapter. Next, I will present the reliability and validity of the data and the analysis processing, then IBM SPSS and Excel etc. tools will be used to analyse data and answer the research questions.

3.3.2 Reliability and Validity

Reliability in content analysis is defined as “agreement among coders about categorizing content” (Riff, Lacy & Fico, 2014, p.94), while validity is what we want to measure (Neuendorf, 2016). Krippendorff (1980) emphasized “reliability and validity are what make replicative and valid inferences from data to their context” (p.21). In the case of this research, I try to ensure reliability and validity at every stage of data collecting, coding and analysis processing. In this section, I will introduce some steps and concerns related to the quality of this projects and how I ensure reliability and validity in some stages of data processing.

Data Collecting and Sampling

All the data was collected at the beginning of September 2018 by Netvizz. Results shows that data on Facebook which is closer to the scraping date can be more completely captured, while data that is farther from the scraping date can only be partially captured. Actually, before this data collecting action, I used another scraping API based on Python to scrape data from VG’s Facebook page in May 2018, and the results showed the same phenomenon. Take the final data as example. I collected data in four periods: 1st - 11th, 12th -18th, 19th - 25th and 26th - 31st August 2018. In the last two periods (19th-31st, 13 days), 329 pieces of news titles and 35945 comments were collected (25 per day on average), while just 53 news titles were collected during the first 11 days in August 2018, and there are only 5 items per day. Moreover, I manually counted the number of the news items VG posted on Facebook page in a week, and found out that the minimum number is around 20 pieces even at weekends. Hence, I argue that data that is far from the scraping date may be less representative and couldn’t be chosen as sample, which is the reason that why I chose the data in the last three days in August 2018. Furthermore, I aimed to choose a sample avoiding some special period or events (e.g.: political election, some big event or accident) which may lead to special emotions arousing and can’t represent the normal state of emotions on VG’s Facebook page.

Emotion Detector

The biggest challenge in this research is detecting emotions from textual content. Since I don’t have a background of computer science, I have to find some automatic online detectors and choose the best one to ensure the accuracy of the results. At the beginning, I found several online services for emotion detecting, such as SATI API, TwinWord, Senpy and even

R package Syuzhet (also see section 2.3.3). SATI API was used in the context of the Empathic Products ITEA2 project (11005) which was a European project “dedicated to the creation of applications that adapt to the intentional and emotional state of the users” (Denis, Cruz-Lara, & Bellalem, 2013, p.5). The emotion types in this tool follows Ekman’s six typically emotions: sadness, anger, surprise, fear, disgust, and joy. However, this API focus on tweets from Twitter, and there is no more academic information to explain how it works, either using emotion lexicon or sentiment pattern database (Jeonghee Yi, 2003). TwinWord is a commercial tool and could analyse all of the textual information, but is has the same problem as SATI API which lack academic explanation. In that case, Senpy is the best choice which with detailed academic explanation (Sánchez-Rada et al., 2016) and could ensure the accuracy to a large extent. The emotion lexicon I chose is ANEW which is also widely used and with “maximized precision” (Staiano & Guerini, 2014, p.2) by comparing with the other two emotion lexicons (WordNet-Affect and DepecheMood) plugged in Senpy.

3.4 Limitations

Although I attempted to ensure the reliability and validity during the research processing, the methodology applied in this study still has a few limitations. First, data collected may suffer from a self-selection bias. Even though I tried to ensure the data collected could be as normal as possible and avoid choosing the periods when specific events are happening, but it is not easy to ensure what is the exactly normal.

Second, all the data collected is only from three days, which is hardly to say that could represent the whole emotion tendency on VG’s Facebook page. Hence, the results only could explain the emotion situation and diffusion state in three days. Third, the data set is only based on a single page (VG) and single platform (Facebook). But this study demonstrated an empirical way to continue further studies on across platforms (e.g.: studying VG’s page both on Facebook and Twitter).

Finally, there will be some errors in the results detected by emotion detector which is based on Machine Learning and with unperfected algorithms (Liu (2015) argued that there is no perfect algorithm in emotion analysis right now). Moreover, languages in different context may lead to different meanings. All the original data are in Norwegian and should be translated to English by Google Translate, and the process of machine translation may also may produce errors. Even though I have checked translations and emotions in news titles, and result show that emotions detected by Senpy has an accuracy rate around 85 percent (see section 3.2.3), but there are also some errors. I could check these 84 news titles as careful as I can, but translations and emotions of these 7876 comments couldn't be checked one by one pretty carefully due to the huge amount. However, I reviewed emotions in comments detected by Senpy three times and tried to modify the wrong ones as best as I can, which still could not promise 100 percent accuracy of the results.

3.5 Research Ethic

The capacity to collect and analyse data from social media is growing exponentially. This scientific, social and technological trend toward "big data" has helped create a wealth of information that may challenge accepted social and ethical norms (Mittelstadt & Floridi, 2016). Mittelstadt and Floridi (2016) point out one of the most important areas referred to research ethic on social media is individual privacy, and privacy protecting is not only applied on personal information such name, age, location etc., but also emotional state according to the research guideline from Norway's Committee for Research Ethics in the Social Sciences and the Humanities (NESH, 2016, p.22). In the context of social media, emotions, preferences, "likes" and "comments" people give to news posted on social media are kinds of psychological privacy (Krämer & Haferkamp, 2011) which also should be protected.

The main goal of this study is to examine emotions of news and comments posted on VG's Facebook page, which directly present public's emotional state to the news, and all information regarding comments and reactions users gave to the news could be traced to specific person based on the content on Facebook page, which indicates that there are privacy issues in this study. However, the scrape tool, Netvizz, I used here is automatically anonymous to all Facebook users in groups and pages (Rieder, 2013). Hence, all the data collected from VG's Facebook page has anonymized users' personal information, which means that even I analyse emotions of people who write a comment on VG's Facebook page, I can't trace who is the exactly person. Moreover, Netvizz have no access to collect data from Facebook right now because Facebook announced more and more API restrictions to avoid research organizations scraping personal data in order to protect Facebook users' privacy due to The Cambridge Analytica scandal which disclosed on 17 March 2018 (Bruns, 2019). Moreover, I also contacted NSD (Norwegian Centre for Research Data) and uploaded my project description, and they answered that my project will not process data that can directly or indirectly identify individual persons, thus I does not need an assessment from them to continue my study.

After the introduction of the methodology for this study, findings from data analysis will be presented in next chapter.

Chapter 4 Findings

This chapter will introduce the findings of this research. Firstly, an overview of the data will be provided, which presents the number of news items, comments and reactions. Then the first research question will be answered in four sections, such as distribution of emotions on VG's Facebook page, mean of proportion of different emotions in each news, ranking position of each emotion in comments and emoji, and the concentration of emotions in news. Following this, I will solve the second research question and examine how do emotions affect public's engagement of the news and news diffusion on VG's Facebook page in three directions: examining relationship between emotions and emotional strength, engagement of news, speed of feedbacks given by audiences and the diffusion time span. After that, the third and fourth research questions relating to the emotional agenda setting affect will be addressed. In the last section of this chapter, a brief summary of the key findings will be presented.

4.1 Overview of Data

A sample data with a total of 84 pieces of news were analysed, and these data were collected from a Norwegian newspaper's Facebook page which called Verdens Gang (VG) and posted from 29th to 31st August in 2018. The descriptive statistics of the final dataset which was analysed by SPSS was showed in Table 4.1, from where we can see that there are 7876 pieces of comments after data cleaning (see section 3.1.4) and 28360 pieces of reactions (Emoji) which will be deeply analysed in later sections.

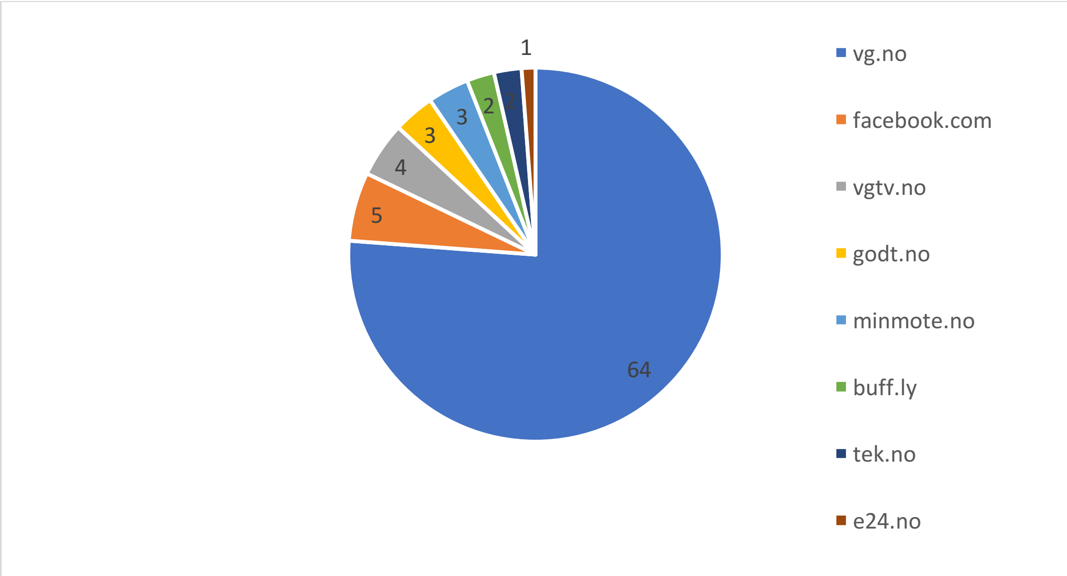
Table 4.1 The descriptive statistics of the dataset.

	Comments	Comments after cleaning	Reactions /emoji	Shares	Engagement
Mean	114.39	93.76	337.62	10.70	462.71
Std. Deviation	185.505	141.642	626.572	21.429	727.930
Minimum	0	0	5	0	10
Maximum	926	691	4287	147	4471
Sum	**9609**	**7876**	**28360**	**899**	**38868**

(Note: Reactions= "Like" + "Love" + "Wow" + "Haha" + "Sad" + "Angry"; Engagement= Comments count+ Reactions count+ Shares count.)

After analysing the resources of news posted on VG's Facebook page, data shows that 75% of news (63 out of 84) are directly linked to VG's official website *vg.no* (see Figure 4.1), which provides an evidence that traditional media institutions use social media as a channel to increase the traffic for their official website. The other resources, such as Facebook, VGTV etc., account for a very small proportion.

Figure 4.1 Resources of news posted on VG's Facebook page.



4.2 Research Question 1: Main Emotion on VG's Facebook Page

In this section, the first research question will be addressed: *What is the main emotion on VG's Facebook page?* In order to answer this question, the analysis was conducted in four parts (the four sub-RQs presented in section 1.2). Firstly, the distribution of emotions on VG's Facebook page will be presented, and results show that happiness is the emotion with the largest amount. For the purpose of avoiding extreme data which will affect the accuracy of the result from the first sub-question, the mean of the proportion of each emotion in comments and reactions of each news will be analysed. After that, the number of emotions in each news will be ranked from the first to the fifth in order to examine whether the frequency of the emotion which ranked No.1 supports the findings found from the last two parts. Finally, the top two dominant emotions will be analysed, and data suggests that there is an emotion tendency in comments and reactions even though there are many emotions existed in comments and emoji of each news.

4.2.1 Distributions of Emotions

The majority of content VG posted on its Facebook page have an emotion of happiness, and over half part of Facebook users give out happiness to the news when they review VG's Facebook page. For the news title part, Table 4.2 and Figure 4.2 show that 43 pieces of news titles (84 in total) are happiness (51.2 percent), 21 pieces are fear (25 percent), 18 pieces are sadness (21.4 percent) and only 2 pieces have an emotion of angry (2.4 percent). There is no news item in sample has an emotion of disgust.

Table 4.2 The descriptive statistics of emotions in news titles and comments.

	Title				Comments					
Emotions	Mean	Std. Dev	Number	PCT	Mean	Std. Dev	Min	Max	Number	PCT
Happiness	0,51	0.503	43	51.2%	47.95	96.670	0	563	4028	51.2%
Fear	0.25	0.436	21	25%	21.95	33.978	0	178	1844	23.4%
Sadness	0.21	0.413	18	21.4%	21.49	40.372	0	281	1805	22.9%
Anger	0.02	0.153	2	2.4%	1.99	5.412	0	43	167	2.1%
Disgust	0	0	0	0	0.38	1.307	0	9	32	0.4%

Figure 4.2 The frequency of emotions in news titles.

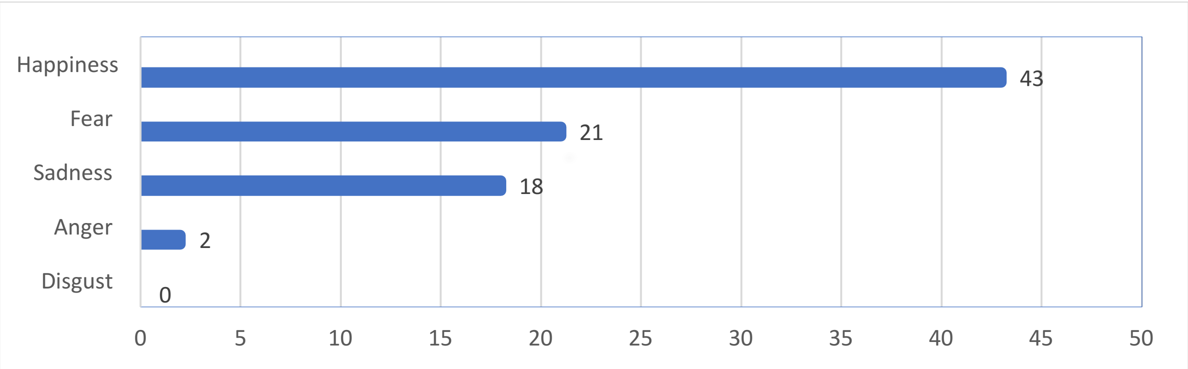
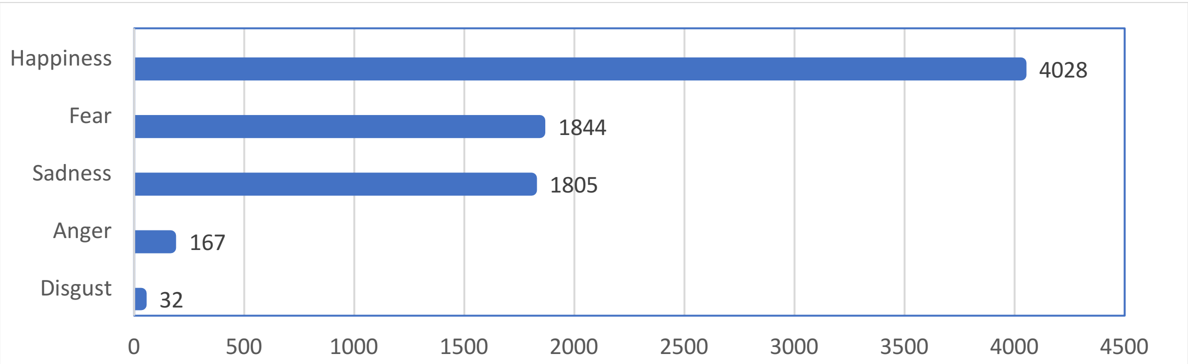


Figure 4.3 The frequency of emotions in comments.



The tendency of comments' emotions is basically the same as news title's emotions. The right part of Table 4.2 and Figure 4.3 shows the distribution of the comments' emotions. 4028 pieces of comments (7876 in total) have an emotion of happiness (51.2 percent, same as the titles' emotions), and 1844 pieces of comments are fear (23.4 percent). The number of the comments with sadness emotion is 1805 pieces (22.9 percent) which is only 39 fewer than fear. There are only 167 pieces of comments which have an emotion of anger with a proportion of 2.1%. The number of comments with disgust is 32, which contributes to the smallest scale (0.4 percent).

Descriptive statistics about numbers of emotions from news titles and comments seem show that happiness is the main emotion in VG's Facebook page, which has the largest proportion (over 50 percent) among all types of emotions. In other word, it also could be understood as that there are more positive emotions (happiness) than negative emotions (sadness, fear, disgust, anger) on VG's Facebook page. However, this finding could be largely influenced by extreme cases. To confirm this result, further analysis will be presented in the next section.

As described in Chapter 3, emotions of textual content such as comments and news titles detected by Senpy have happiness, sadness, anger, fear, disgust five types of emotions. However, results show that no item is neutral in the dataset. Thus, there are only five types of emotions existing in comments, and these five emotions are different with emotions in reactions/emoji which are: "Love", "Haha", "Sad", "Angry" and "Wow". Therefore, emotions in comments and emoji will be analysed separately. After analysing the numbers of emoji, the descriptive statistics support the results which analysed from news titles and comments.

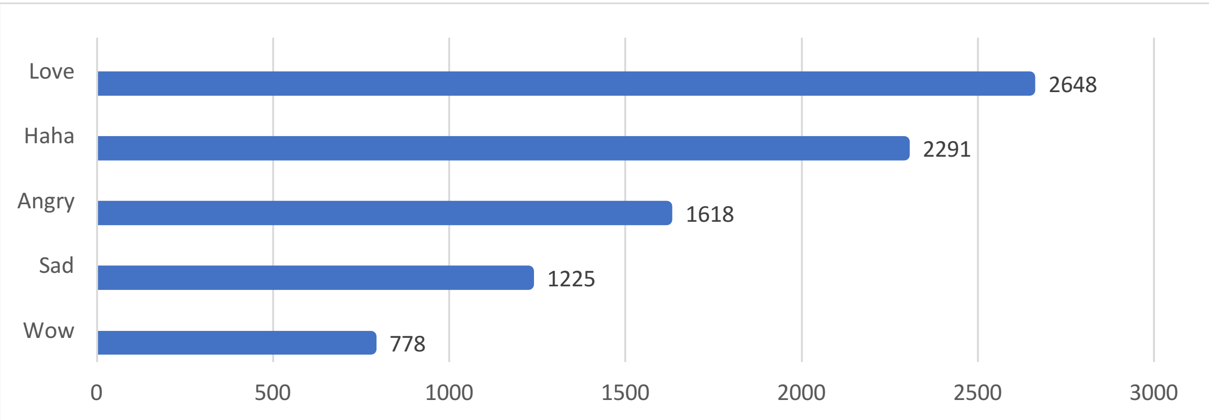
Table 4.3 and Figure 4.4 show that there are 19800 "Like" in total of collected data, and it accounts for the largest proportion which is 69.82 percent. Then followed by "Love" which has a total number of 2648 and a percentage of 9.34. "Haha" occupied the third position with a number of 2291 (8.08 percent). There were 1618 Facebook users gave out an "Angry" emoji in total (5.71 percent). The least two emoji are "Sad" and "Wow", which with a number of 1225 (4.32 percent) and 778 (2.74percent) respectively.

However, the emoji "Like" is hardly to be considered as an emotion according to Figure 3.3 in Chapter 3, which also shows that "Love" and "Haha" could be considered as an emotion of joy or happiness. Statistics without "Like" seems necessary, which are presented in the last row of Table 4.3, and results show that the trend of numbers of emoji follows the result that happiness which has a proportion of 57.69 percent (30.93 percent +26.76 percent) is the main emotion in VG's Facebook page.

Table 4.3 The descriptive statistics of Emoji (reactions).

	Mean	Std. Dev	Min	Max	Number	Percentage in total	Percentage without Like
Like	235.71	526.445	0	3746	19800	69,82 %	
Love	31.52	97.055	0	519	2648	9,34 %	30,93 %
Haha	27.27	82.218	0	573	2291	8,08 %	26,76 %
Angry	19.26	66.871	0	486	1618	5,71 %	18,90 %
Sad	14.58	32.974	0	226	1225	4,32 %	14,31 %
Wow	9.26	13.984	0	62	778	2,74 %	9,09 %

Figure 4.4 The frequency of reactions.



4.2.2 Mean of Proportion of Each Emotion

Even though emotion with the largest proportion on VG's Facebook page is happiness, which has already been found out from the last part, there may still be some statistical errors in the results, such as extreme cases. For instance, if one piece of news has an emotion of happiness in comments with a number of 2000, the result that the happiness is the main emotion in comments which based on that 4028 pieces of comments (7876 in total) are happiness is totally wrong. In order to further support the findings presented above and avoid the errors caused by extreme case, the mean of the proportion of each emotion in comments and reactions of every piece of news will be analysed in this part.

Dataset shows that there are many types of emotions existing in comments and reactions given by audiences for each news. Before analysing process, the number of all types of emotions and their proportion in comments and reactions of every piece of news is counted, then the mean of proportion of each emotion in will be calculated in SPSS. Results presented in Table 4.4 show that happiness accounts for an average of 44.72 percent in comments of each news, and the emotion that accounts for the least amount is disgust with an average proportion of 0.51 percent. The mean of proportion of fear which is 25.78 percent follows happiness, while the average proportion of sadness is the third largest which is 24.94 percent. The emotion of anger contributes a small scale (1.67 percent) in the average proportion of emotions in comments of each news. According to the average proportion of each emotions in comments, happiness takes up a much larger scale than other emotions on average and plays a prominent role in various emotions.

Table 4.5 shows the mean of proportion of emoji in each piece of news. The first two emoji, “Love” and “Haha”, account for an average of 25.32 percent and 24.22 percent respectively, then followed by “Sad” with a proportion of 19.19 percent. The average proportion of “Wow” is 16.25 percent which is the third largest amount, while the lowest scale of reaction is “Angry” which is 10.54 percent. Data shows that the emotion of happiness in emoji also has a larger scale than other emotions because “Love” and “Haha” could be considered as an emotion of happiness which mentioned above.

Table 4.4 The mean of proportion of comments’ emotions in each news.

	Happiness	Sadness	Fear	Anger	Disgust
Mean	44.72%	24.94%	25.78%	1.67%	0.51%
Std. Deviation	28.32%	21.79%	22.74%	4.54%	2.05%

Table 4.5 The mean of proportion of emoji in each news.

	Love	Haha	Wow	Sad	Angry
Mean	25.32%	24.22%	16.25%	19.19%	10.54%
Std. Deviation	34.64%	31.28%	22.47%	26.85%	20.58%

4.2.3 Ranking of Emotions

In this part, I will examine which emotion could come to the first place by ranking all types of emotions in comments and emoji of each news from the first to the fifth depends on its number, and figure out whether the result is still support that happiness is the main emotion on VG's Facebook page.

The ranking process is conducted in Excel by using the "Max" Function. However, I find some issues during the ranking process: if the total number of an emotion in comments or emoji of one piece of news is 0, the system will still rank the emotion; if there are more than two kinds of emotions with a number of 0, the system will only select the first emotion which has a total number of 0 and the later emotion also with a number of 0 will be ignored by Excel, which will influence the accuracy of the result. In order to avoid this issue, I modified the name of emotions which with a total number of 0 to 0 in the ranking list of the database, which means that these kinds of emotion will not be involved into ranking. If emotions have the same amount (except 0), they will be ranked in order. For instance, if one piece of new has 20 happiness, 20 sadness, 0 fear, 0 anger and 0 disgust in its comments, happiness will appear under the item of "No.1" and sadness will be selected in "No.2". Then, fear, anger and disgust will be marked as 0, otherwise fear will be selected by "No3", "No.4", "No.5" and the system will ignore anger and disgust here. These methods are also applied to the emoji ranking process.

Table 4.6 The number of news which have different types of emotions in comments ranked from the first to the fifth.

	No.1		No.2		No.3		No.4		No.5	
Happiness	48	57.14 %	21	25.00 %	7	8.33 %	1	1.19 %	0	0.00 %
Fear	20	23.81 %	23	27.38 %	19	22.62 %	1	1.19 %	0	0.00 %
Sadness	14	16.67 %	24	28.57 %	30	35.71 %	1	1.19 %	0	0.00 %
Anger	0	0.00 %	1	1.19 %	2	2.38 %	26	30.95 %	2	2.38 %
Disgust	0	0.00 %	0	0.00 %	0	0.00 %	7	8.33 %	9	10.71 %
Non-emotion	2	2.38 %	15	17.86 %	26	30.95 %	48	57.14 %	73	86.90 %

(Note: "Non-emotion" in the last row of this table means there are two news items have no emotion ranked in the first place.)

Comments

After ranking the total number of different emotions in comments of each news, Table 4.6 shows that there are only three types of emotions ranked No.1 in comments of new, which are happiness, sadness and fear, and numbers of disgust and anger never come to the first place in comments. In all 84 pieces of news, 48 news items (57.14 percent) have the emotion of happiness ranked No. 1 among five types emotions in comments. There are 21 pieces of news when the number of happiness in comments came to the second place, accounting for 25 percent of the total. The proportion of news which has happiness ranked No.1 and No. 2 is 82.14 percent of the total, which may suggest that happiness is the main emotion in comments.

Furthermore, by comparing of the sequence of the five emotions, in all 84 pieces of news, the average ranking position of happiness is 1.49, which is higher than all other types of emotions (smaller values indicate higher ranking, which means the emotion has more occurrences than other emotions). The ranking positions of other emotions are presented as follows: sadness is 2.26; fear is 2.33; anger is 4.16; disgust is 4.86. These analyses suggest that happiness in comments is the most frequent emotion in majority of news posted on VG's Facebook page. Moreover, happiness contributes to a proportion of 70 percent among all the emotions ranked in the first place in comments of each news.

Emoji

Table 4.7 shows results by analysing emoji. As mentioned before, "Love" and "Haha" could be considered as joy or happiness, so their statistics could be added together for analysis. According to Table 4.7, there are 48 news items out of 84 have "Love" or "Haha" coming to the first place, with a proportion of 57.14 percent. The amount of news which have "Love" and "Haha" with the second most of occurrences is 26, accounting for 30.96 percent, while the amount of news which have "Love" and "Haha" located at the third place to the fifth place is gradually decreasing. There are 74 news items have "Love" and "Haha" ranked No. 1 and No. 2, accounting for over 88 percent, which indicate that the emoji's emotional tendency follows comments' emotional tendency.

However, the average ranking of reactions in all 84 news items looks different with the ranking tendency of comments' emotion. As mentioned in the last paragraph of *Comments* part, the ranking value of happiness is much higher than other emotions, and the value of sadness and fear are very close to each other, while anger and disgust is much lower than other emotions. The result of the analysis of emoji shows that all these five emoji, "Love", "Haha", "Wow", "Sad" and "Angry", have very closed ranking values which respectively are 2.59, 2.15, 2.67, 2.72, 2.85. But "Love" and "Haha" still have the highest-ranking positions. Thus, I could argue that happiness is the main emotion in VG's Facebook page.

Table 4.7 The number of news which have different reactions ranked from the first to the fifth.

	No.1		No.2		No.3		No.4		No.5	
Love	24	28.57 %	11	13.10 %	10	11.90 %	12	14.29 %	10	11.90 %
Haha	24	28.57 %	15	17.86 %	9	10.71 %	6	7.14 %	4	4.76 %
Wow	11	13.10 %	26	30.95 %	15	17.86 %	4	4.76 %	11	13.10 %
Sad	13	15.48 %	17	20.24 %	14	16.67 %	3	3.57 %	12	14.29 %
Angry	9	10.71 %	5	5.95 %	9	10.71 %	4	4.76 %	7	8.33 %
Non-emoji	3	3.57 %	10	11.90 %	27	32.14 %	55	65.48 %	40	47.62 %

4.2.4 Emotion Tendency

In addition to analyze the ranking of happiness in comments and reactions of each news and the average ranking position of each emotion, it is also necessary to analyze the top two emotions of comments in each news in order to figure out whether emotions in comments and emoji/reactions are concentrated.

Comments

Table 4.6 shows that only three emotions in comments ranked No. 1 in total, which are happiness, fear and sadness. Of 84 pieces of news, 48 news (57.14 percent) have the emotion of happiness ranked number 1 among five types of emotions in comments, while 20 pieces of news (23.81 percent) have the emotion of fear as the most frequent emotion, and sadness has the largest number of occurrences in comments in 14 pieces of news (16.67 percent). There are two pieces of news received no emotion from comments.

Emotions ranked in the second place are also important, which still reflect the emotional tendency and audiences' feedback of the news. Moreover, there are some news items that have the same number of emotions and will be automatically ranked the first and the second. Table 4.6 shows that there are 24 pieces of news (out of 84) have sadness ranked in the second place, while 23 news items have the emotion of fear and 21 news items have happiness as the second largest number of occurrences in the second place. There are only one pieces of news has emotion of anger located in the second place, and no news has disgust ranked No.2. Moreover, there are 15 news items have no emotion in the second place, which may indicate that these 15 news items may have only one emotion in their comments. Even though the number of news has happiness ranked No. 2 is fewer than number of news has emotion of fear and sadness ranked No. 2, the number of news items are very close to each other which means that happiness is still an important emotion in the second place.

According to the last two least important emotions in comments of each news presented in the last two columns of Table 4.6, happiness, fear and sadness appear very infrequently. Inversely, anger and disgust which rarely appear in the first two place have more appearance in the last two places. Moreover, the last two cells in the last row of Table 4.6 show that there are 48 (57.14 percent) and 73 (86.9 percent) news items have no emotion ranked No. 4 and No. 5 respectively, which means that the majority of news have no emotions in comments ranked No.4 and No. 5, and majority of emotions in comments of these news items are mainly concentrated in the first three places.

The number of emotions in comments and emoji of each news have been ranked from the first to the fifth, then all the numbers of emotions in different position have been counted and presented in Table 4.8. Then bottom part of the Table presents the number of emotions in comments which come to the first place is 4509, accounting for 57.25 percent of the total. The number of the second most frequent emotions in comments is 1968, with a proportion of 24.99 percent. The proportion of the top two emotions in comments is 82.24 percent, and emotions located in the last three places have very low proportions. Thus, I can argue that emotions ranked in the first two places in news' comments can basically reflect public's emotional feedback to the news, and emotions in comments of each news have a certain concentration. According to the largest proportion of the first emotion in comments of news, the first emotion could be considered as the main or dominate emotion of comments.

Emoji

Numbers of news items which have different emoji/reactions ranked from the first to the fifth compared in Table 4.7, in where we can see that all reactions have chances to be ranked No.1. Among all 84 pieces of news, there are 48 news items have a most frequent of "Love" and "Haha", which made up 57.14 percent of the total. There are 13 news items have "Sad" to be the most frequent reaction, accounting for 15.48 percent, while "Wow" has the most frequent appearances in 11 news items and 9 pieces of news have "Angry" ranked No. 1. There are also 3 news items get no reaction from audiences.

In all 84 news items, 26 pieces of news have “Love” or “Haha” ranked No.2 with a scale of 30.95 percent which is the same as the proportion of news have “Wow” ranked No.2. Percentage of news have “Sad” and “Angry” ranked No. 2 are 20.24 and 5.95 respectively. There are also 10 pieces of news have no reaction ranked in the second place. These analyses suggest that “Love”, “Haha” and “Wow” are very important emotions in the list of No. 2. However, there are over 80 percent of news have “Love” and “Haha” ranked No.1 and No.2, which suggest that these two reactions are the major emotion.

Table 4.8 Total number of emotions ranked from the first to the fifth.

		No.1	No.2	No.3	No.4	No.5	Sum
Emoji	Numbers of emotions	6489	1438	407	166	60	8560
	Percentage	75.81 %	16.80 %	4.75 %	1.94 %	0.70 %	
Comments	Numbers of emotions	4509	1968	1208	174	17	7876
	Percentage	57.25 %	24.99 %	15.34 %	2.21 %	0.22 %	

Table 4.7 shows that number in the last two columns is fewer than the number of news have reactions ranked in the first two position. There are 55 and 40 pieces of news have no emoji ranked No. 4 and No. 5, accounting for 65.48 percent and 47.62 percent respectively. The top half part of Table 4.8 also shows that the total number of emoji which ranked No. 1 is 6489, accounting for 75.81 percent and the number of emoji located at the second place is 1438 (16.80 percent). The proportions of emoji located the third to the fifth place are 4.75 percent, 1.94 percent and 0.7 percent respectively, which are significantly lower than scales of emoji ranked No. 1 and No. 2. And the top two emoji in all news are made up 92.61 percent of the total. These analyses suggest that the large amount of the top two reactions indicate that emoji in each news also have a certain concentration. The first reaction with a proportion of 75.81 percent indicates that every piece of news has a main emotion tendency which is decided by the amount of the reactions which has the largest number and much higher than others.

4.2.5 Summary of Research Question 1

Hence, all findings presented above have answered the first research question: *What is the main emotion on VG’s Facebook page?* Findings show that the main emotion on VG’s Facebook page is happiness which existed in comments and reactions and news titles. This argument is supported by the four sub-questions.

a) What is the distributions of emotions on VG's Facebook page?

Happiness has the largest amount among all types of emotions either in comments, news titles or reactions. For the comment part, 51.2 percent of comments (7876 in total) have an emotion of happiness, 23.4 percent of comments have an emotion of fear, 22.9 percent are sadness and only 2.1 percent of comments are anger. The percentage of comments with emotion of disgust is 0.4 percent. In news titles, 51.2 percent of news are happiness, 25 percent are fear, 21.4 percent of news titles are sadness and only 2.4 percent of news titles have an emotion of anger. There is no news item in sample has an emotion of disgust. In reactions, "Love" and "Haha" which are considered as emotions of joy or happiness accounting for a proportion of 57.69 percent (30.93 percent +26.76 percent) in emoji. Unlike the emotion distributions in comments and news titles, "Angry" contributes to the second largest proportion,18,90 percent, while "Sad" has a percentage of 14,31. "Wow" accounted for 9,09 percent.

b) What is the mean of the proportion of each emotion in each news' comments and emoji/reactions?

The purpose of formulating this sub-question is to avoid impacts brought by extreme cases. Results show that the average proportion of happiness takes up the largest scale than all other emotions both in comments and reactions. Happiness accounted for an average of 44.72 percent in comments of each news, while "Love" and "Haha" account for an average of 25.32 percent and 24.22 percent respectively.

c) How does the number of emotions rank in the comments and emoji/reactions of each news?

Findings show that number of happiness has the most frequency to rank No.1 among all types of emotions. There are 57.14 percent news items have happiness as the most frequent emotion in comments. And the average ranking position of happiness in comments is 1.49, which is higher than all other types of emotions. 48 news items have a most frequent of "Love" or "Haha", which made up 57.14 percent of the total. The average ranking positions of "Love" and "Haha" are 2.59, 2.15 respectively, which still higher than positions of other emoji. Over 80 percent of news have "Love" and "Haha" in reactions and happiness in comments ranked No.1 and No.2, and happiness in all first emotions of comments contributes a proportion of over 70 percent, which may suggest that happiness is the main emotion in VG's Facebook page.

d) Is there a main emotion tendency in the comments and emoji/reactions of each news?

The top two emotions in comments and reactions of news have a proportion is 82.24 percent and 92.61 percent respectively, which indicates that emotions in comments and reactions have a certain concentration. And happiness also has the most frequency in the places of No.1 and No.2 both in comments and reaction among other emotions. Moreover, numbers of emotions in comments and emoji ranked No.1 exceed 50 percent, which indicates that each news has a main emotion which is decided by the type of the first emotion which has the largest number among all emotions in comments and reactions.

4.3 Research Question 2: Emotion and News Diffusion

This section will solve the RQ2 (*How do emotions affect public's engagement of the news and news diffusion on VG's Facebook page?)* in three parts. This section begins with the analysis of the relationship between emotions and emotional strength which is measured according to the number of emotional votes each news receives (emoji/reaction) and the frequency of emotions in comments. After that, relationships between emotions and engagements will be analyse. In the last part of this section, the relationship between emotion of the news titles and the speed of comments given by audiences, the time pan of news' diffusion on VG's Facebook page will be examined.

4.3.1 Emotion and Emotional Strength

This section will examine whether there is a correlation between the emotions and emotional strength which is measured according to the total number of reactions and the frequency of all emotions in comments (the larger the number of comments or reactions, the stronger of the emotional strength).

Comments

Table 4.9 presents the correlation matrix of emotions in comments of each news and emotional strength (total number of emotions in comments of each news). As showed in Table 4.9, happiness has the highest positive correlation with emotional strength among all types of emotions ($r = .879$, $p < 0.01$), then followed by sadness, fear, anger and disgust according to the Pearson's correlation coefficient, which also may indicate that the strength of emotional feedback given by audiences to the news (emotions in comments) is the greatest in relation to happiness, and the least in relation to the emotion of disgust. In other words, the stronger the news's emotional strength, the more happiness it may be in its comments; the more happiness in the news' comments, it is more likely to bring about a stronger emotional feedback strength.

Table 4.9 also shows that negative emotions, fear, sadness and anger are highly correlated: r (fear and sadness) = .694, $p < 0.01$; r (fear and anger) = .767, $p < 0.01$; r (anger and sadness) =.548, $p < 0.01$. These high coefficients show that these emotions, especially "fear + anger" and "fear + sadness" groups, were highly appeared together. The negative emotion disgust also has a weak but significant correlation with sadness ($r = .351$, $p < 0.01$), fear ($r = .500$, $p < 0.01$) and anger ($r = .273$, $p < 0.05$). Happiness also has a weak but significant positive correlation with sadness ($r = .377$, $p < 0.01$) and fear ($r = .335$, $p < 0.01$), but has no correlation with anger and disgust.

Table 4.9 Pearson's correlation matrix of emotions in comments of each news and emotional strength (the total number of emotions in comments of each news).

	Happiness	Sadness	Fear	Anger	Disgust	Total number of emotions in comments
Happiness	1					
Sadness	.377**	1				
Fear	.335**	.694**	1			
Anger	.191	.548**	.767**	1		
Disgust	.169	.351**	.500**	.273*	1	
Total number of emotions in comments	.879**	.733**	.701**	.511**	.355**	1

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

* Correlation is significant at the 0.05 level (2-tailed).

Emoji

Table 4.10 shows the correlation matrix of different reactions in each news and the total number of reactions. "Love" has the highest positive correlation ($r = .562$, $p < 0.001$) with emotional strength which measured by the total number of emoji of each news received. "Haha" has the second highest positive correlation with emotional strength, and the coefficient ($r =.559$, $p < 0.01$) is lightly lower than "Love". "Angry" also has strong and significant positive correlation with emotional strength ($r = .513$, $p < 0.01$). The last two emoji, "Wow" and "Sad", have weak but significant correlation with the total number of emoji of each news. These coefficients indicate that "Love", "Haha" and "Angry" have strong relations with emotional strength in emoji, but "Sad" has the weakest relation with emotional strength in reaction which is different with the result that shows in Table 4.9 that sadness in comments has a strong relation with the emotional strength. Reasons that lead to this difference may because of the imperfection of the emotion detector, Senpy, and also the types of emotions in Senpy and emoji in Facebook are different. However, results from the analysis of emoji are more reliable than result of emotional analysis in comments because reactions reflect emotions directly, while emotions in comments should be detected by tools which may produce errors.

Table 4.10 Correlation matrix of numbers of reactions in every piece of news and emotional strength (the total number of emoji of each news).

	Love	Wow	Haha	Sad	Angry	Total number of emoji/ reactions
Love	1					
Wow	-.011	1				
Haha	-.051	.328**	1			
Sad	-.067	.328**	.002	1		
Angry	-.072	.101	.050	.385**	1	
Total number of emoji/ reactions	.562**	.377**	.559**	.373**	.513**	1

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

Correlations between different reactions also can be found in Table 4.10. Negative reactions, “Angry” and “Sad” are positively correlated ($r = .385$, $p < 0.01$), which means that these two reactions were more likely to be used together. The positive reaction, “Wow” (Tran et. al, 2018) has the same correlation coefficient between positive emoji “Haha” and negative emoji “Sad” ($r = .328$, $p < 0.01$). However, the correlation between positive reactions (“Wow” and “Haha”) is weaker than negative emoji (“Angry” and “Sad”), which may suggest that negative reactions are more likely to be used together than positive reactions.

4.3.2 Emotions and Engagement

As presented in section 2.4.3 of Chapter 2, different emotions have different spreading effects (Stieglitz & Dang-Xuan, 2013; Burke & Develin, 2016; Zhao, Dong, Wu & Xu, 2012), and the types of emotions are correlated to the intensity of diffusion on media platforms. In this thesis, the intensity of diffusion will be measured by the amount of engagement which consist of numbers of comments, emoji/ reactions and sharing times, the larger the number of engagement, the stronger the intensity of diffusion of the news. In this section, the relationships between emotions and the degree of users' engagement on Facebook will be analysed in order to find out which emotion can make more people to engage the discourse of the news posted on VG's Facebook page.

Table 4.11 The correlation matrix of different emotions and engagement.

	Comments' emotion	Happiness	Sadness	Fear	Anger	Disgust
Engagement	Pearson Correlation	.623**	.302**	.268*	.223*	.122
	Sig. (2-tailed)	.000	.005	.014	.041	.271
	N	84	84	84	84	84
	Emoji	Love	Wow	Haha	Sad	Angry
Engagement	Pearson Correlation	.837**	.230*	.294**	.000	.142
	Sig. (2-tailed)	.000	.035	.007	1.000	.198
	N	84	84	84	84	84

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

* Correlation is significant at the 0.05 level (2-tailed).

The correlations between different types of reactions/emoji and engagement presented in Table 4.11. These analyses show that the emotion of happiness ($r = .623$, $p < 0.01$) and emoji of "Love" ($r = .837$, $p < 0.01$) have the strongest correlation with the amount of engagement compared with other types of emotions and emoji, which may suggest that the larger amount of engagement, the more likely it's to be happiness in comments and reactions, and with the increasing of happy feedbacks received by news, the number of engagement of the news will be higher.

However, the emotion of sadness in comments and the reaction of "Sad" have totally different correlation with engagement. Table 4.11 shows that sadness in comments has a weak but significant correlation with engagement, and the coefficient ($r = .302$, $p < 0.01$) is only lower than happiness but higher than fear, anger and disgust. But the reaction, "Sad", has no correlation with engagement. The reason that lead to the difference is same as mentioned in the last section that the emotion detector, Senpy, is not a perfect tool that guarantees 100 percent accuracy of emotions analysed from textual content, and types of emotions in Senpy are different from the emoji reactions in Facebook. However, there is a common result that happiness is always the most important emotion either in comments or reaction.

Emotions in Comments and engagement

Table 4.11 only presents the correlation of the emotions and engagement, and the detailed relationship of emotions and engagement showed in Table 4.12. As analysed in section 4.2.4, every piece of news has a main emotion tendency, and the number of the emotion is not only the largest, but much higher than other types emotions. In order to find out which emotion can evoke more people join the conversation of news on Facebook, the average number of engagement is analysed according to the first emotions in comments of each news, and the results are presented in Table 4.12. Analysis shows that news with happiness ranked No. 1 in comments have the largest number of engagement in average, which may suggest that if there are more happiness in comments, the engagement of the news could be larger. In other words, the higher the news engagement, audience is more inclined to give happy comments to the news. News with the most occurrence of emotion of sadness in comments has the smallest average number of engagement.

Table 4.12 The statistical numbers of engagement of each news when different emotions ranked No.1 in comments.

Emotions	Engagement		
	Mean	Min	Max
fear	354.05	19	1365
happiness	581.67	20	4471
sadness	272.14	10	1249

(Note: section 4.2.3 has already presented that there are only three emotions, happiness, fear and sadness ranked number 1 in comments)

Emoji and Engagement

Table 4.13 shows the average number of engagement of news when different emoji/ reactions as the first emotion. Results shows in Table 4.12 suggest that news has the largest average number of engagement when news receives the largest amount of “Love” among all types of reactions. And the average engagement (853.75) of news with “Love” ranked No.1 is 1.6 times larger than the engagement of news with “Angry” as the main emotion, and 6 times larger than news with “Wow” as the main reaction. Results indicate that news with “Love” as the main emotional reaction will have more engagement than news with other emoji as the main emotion. Moreover, the two reactions of “Love” and “Haha” are considered as emotion of happiness. Thus, the result analysed from emoji follows results from comments, what is that the higher the news engagement, the more inclined the audience is to give a happy emotional feedback.

Table 4.13 The statistical numbers of engagement of each news when different emoji ranked No.1.

Emoji	Engagement		
	Mean	Min	Max
Angry	532.44	82	1365
Haha	417.67	23	1984
Love	853.75	14	4471
Sad	162.69	22	372
Wow	122.82	19	274

The reaction of “Angry” is also an important emotion according to the results showed in Table 4.13. News in the sample with “Angry” as the first emotion in reactions have the second largest average engagement, which suggest that, to a large extent, news receives more “Angry” reactions will obtain more engagement on VG’s Facebook page. News with the most appearance of “Sad” and “Wow” will be the least engaged.

Emotions of News Titles and Engagement

Table 4.14 presents the relations between emotions of news titles (not emotions in comments or emoji) and engagement. The first column of Table 4.14 shows the four types emotions in all 84 pieces of news titles which have no disgust detected by Senpy in all of them. The second column presents the mean of engagement of news with different types of emotions in titles. Data shows that news with the emotion of anger has the largest average number of engagement which is 836, along with the largest number of comments, reactions and sharing times. News with happiness has the second largest number of engagement, then followed by news with an emotion of sadness. News with an emotion of fear have the smallest number of engagement. Table 4.14 shows that the order of the average number of comments, emoji and sharing times is exactly the same as the engagement. These analyses suggest that news with the emotion of anger posted on VG’s Facebook page have the largest number of audiences joining the discussion, giving a feedback or sharing the news, and could be spread wider than news with other types of emotions. On the contrary, news with the emotion of fear on VG’s

Facebook page has the smallest number of engagement, comments, reactions and sharing times, which may indicate that fearful news attract fewest Facebook users and have the lowest intensity of diffusion.

Table 4.14 The average number of engagement, comments, emoji and sharing times of news with different emotions in titles.

Emotions of news titles	Engagement	Comments	Emoji	Sharing
Happiness	585.14	133.51	440.6	11.02
Fear	238.76	76.43	156.10	6.2
Sadness	390.05	90.05	290.39	9.6
Anger	836	321	454.5	60.5

4.3.3 Emotion, Speed of Feedback and Spreading Time Span

This section will analyse the relationship between emotion of the news (emotions detected from news titles, not comments or reactions) and the speed of feedbacks given by audiences on VG's Facebook page and spreading time span of the news. There are 4 types of emotions which are happiness, sadness, fear and anger except disgust in all the 84 pieces of news titles in sample. Results show that news posted on Facebook with different emotions, the time lag for getting a comment or feedback and the length of time for news dissemination (time for obtaining the last comment) are different.

Table 4.15 The mean of time lag between the publishing time of news with different types of emotions and the time for getting the first comment and the last comment.

Emotions	Mean of minimum time lag (mins)	Mean of maximum time lag (mins)
Happiness	25.58	3420.71 (2.4 days)
Sadness	23.13	3759.69 (2.6 days)
Fear	16.81	3614.59 (2.5 days)
Anger	3.06	8990.65 (6.2 days)

(Note: the first column shows the emotions of news titles. Minimum time lag means the time between the news release and the first comment giving; maximum time lag is the time between the news posted and the last comment given by audiences, which is also considered as the spreading time span of the news.)

Before figuring out findings, the time lag between the time of each news release and the first comment and the last comment of the news given by Facebook users on VG's Facebook page will be calculated. In order to avoid the impact of extreme data on the results and obtain relatively accurate data, I delete 6 news items in sample which only have one piece of comment in each of them, and the time lag that public making these six comments and the publishing of these news items is quite long, which are 436 (7.2h), 3629 (60.5h), 1690 (28.2 h), 1050 (17.5h), 1236 (20.6h) and 1775 (29.6h) minutes.

Findings presented in Table 4.15 show that news with an emotion of anger get the first comment in a shortest time, which have an average time lag of 3.06 minutes, and the time between the last comment and the news release (spreading period) is the longest which is 8990.65 minutes (6.2 days). News with fear get their first comments with a longer time lag (16.81 minutes) than angry news, but with a shorter time lag than news with sadness and happiness emotions. However, spreading period of news with fear is only longer than happy news and shorter than news with emotions of anger and sadness. Even though results suggest that there is more happy emotion on VG's Facebook page, news with happiness emotion takes the longest time to get a comment (25.58 minutes) and have the shortest spreading time (2.4 days). Analyses suggest that news with an emotion of anger could motivate audiences on VG's Facebook to make a comment or emotional feedback faster than news with other types of emotions, and information with anger could spread longer than news with happiness, sadness and fear. Conversely, news with the emotion of happiness takes the longest time to inspire audiences to give a comment to the news posted on VG's Facebook page, and such news has the shortest spread time compared to news with emotions of anger, fear and sadness. Succinctly, news with anger could get feedback 8 times faster than happy news, and spread almost 3 times longer than news with an emotion of happiness.

4.3.4 Summary of Research Question 2

In sum, this section has addressed RQ 2*: How do emotions affect public's engagement of the news and news diffusion on VG's Facebook page?* I will summarize the findings based on the three sub-questions as following.

a) What is the relationship between emotions and emotional strength which is measured according to the number of emotional votes each news receives (reaction/emoji) and the frequency of emotions in comments?

Happiness has the strongest correlation with emotional strength both in comments and emoji, which indicates that the stronger the news's emotional strength, the more happiness it may be in its comments; the more happiness in the news' comments, it is more likely to bring about a stronger emotional feedback strength. Results also show that the two negative emotions anger and fear are more likely to appear together.

b) What is the relationship between the emotions and engagement of the news which is the sum of the number of comments, sharing and emoji/reactions?

Happiness in comments and “Love” in emoji have the strongest positive correlation with intensity of diffusion which is measured by the amount of engagement. For the emotions in feedback part (comment and emoji), if the engagement of the news is larger, people are more likely to express happiness as an emotional feedback to the news; news with sadness as the first emotion in comments has the smallest number of engagement. For emotions in news titles, angry news posted on VG’s Facebook page could get more engagement, comments, reactions and sharing times than news with emotions of happiness, sadness and fear. Conversely, news with the emotion of fear has the smallest number of engagement, which may indicate that fearful news report reaches the smallest number of audiences and has the lowest intensity of diffusion.

c) What is the relationship between emotion of the news and the speed of comments given by audiences and the news spreading time span on VG’s Facebook site?

Angry news gets a comment much faster than news with emotions of happiness, sadness and fear, and spreads longer than information with the other three emotions. Happy news takes the longest time to obtain a comment from public and spread shorter than news with sadness, anger and fear. Succinctly, news with anger could get feedback 8 times faster than happy news, and spread almost 3 times longer than news with an emotion of happiness.

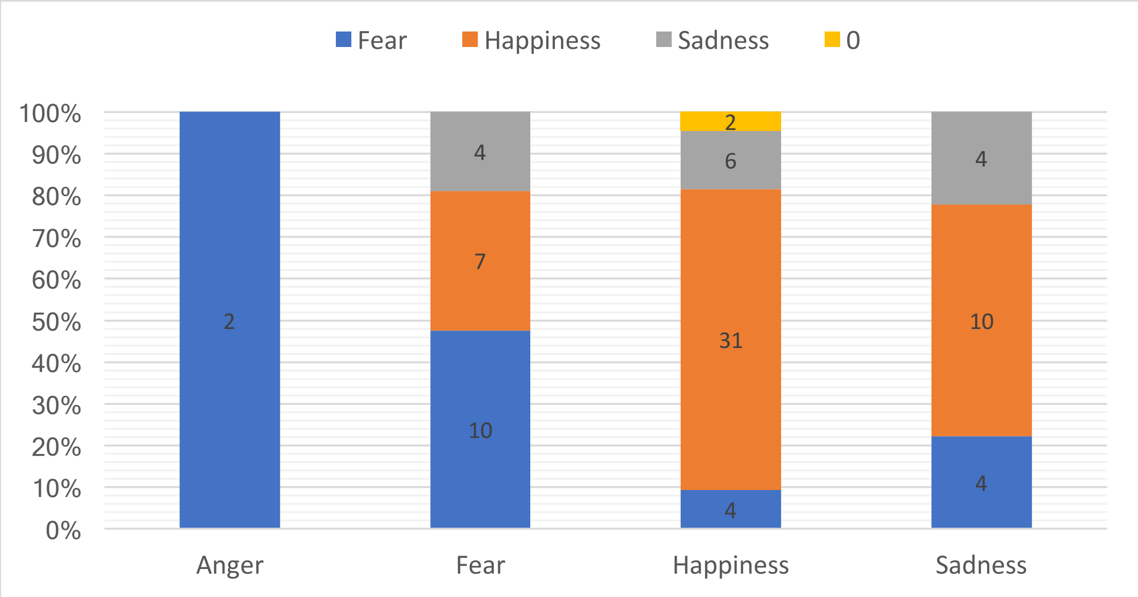
4.4 Research Question 3 & 4: Emotions and Agenda Effect

This section will answer research question 3 & 4: *How does emotions of the news posted on VG’s Facebook page affect public’s emotion which conveyed by news commentators? Which emotion has a stronger agenda effect on the public?* In order to answer these two questions, I will examine to what extent the emotions of the news correspond with emotions in comments of the news and emotions expressed by reactions. As presented in section 4.2.4, comments of each news have a significant main emotion which has the largest total number among all emotions in comments of the news. Thus, the analysis of this part will focus on the emotions of news titles and the first emotion of comments and the first emoji/reaction in each news, and the results present in Figure 4.5 and Figure 4.6.

Figure 4.5 shows that there are 45 news items (54 percent) have the same emotions in titles and comments in all 84 news: 10 news items with fear have the emotion of fear as the first emotion in comments; 31 pieces of news with happiness in titles have the number of happiness ranked No.1 in their comments; 4 sad news have sadness as the main emotion in comments. As section 4.3.1 discussed that the negative emotions fear, anger and sadness are highly correlated, which indicates that they are highly appeared together, which are also proved in Figure 4.5. All two news items with anger in titles take fear as the first emotion in comments, and 4 fearful news have sadness ranked No.1 in comments, while 4 sad news items have the most occurrences of fear in comments. However, Figure 4.5 also shows that there is still a large proportion of news with negative emotions that are dominated by happiness (7 fearful news and 10 sad news have happiness as the main emotion).

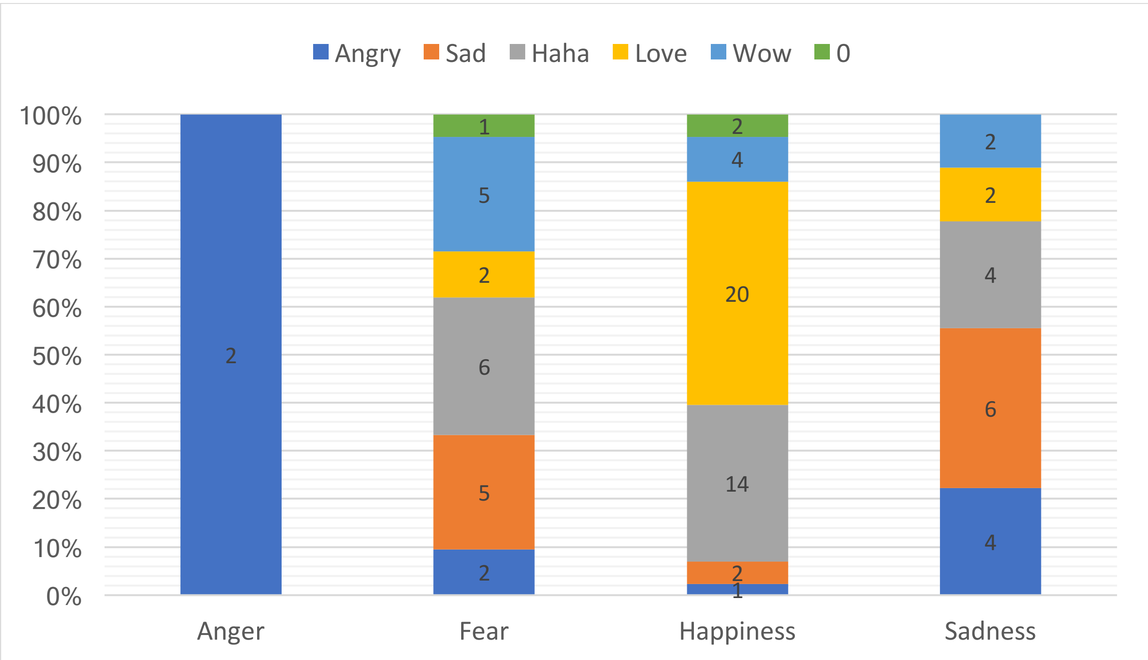
Figure 4.6 presents the relationships between the emotions of news titles and the main emoji of each news. As mentioned before, types of emotions from the detector, Senpy, are different from the types of emoji/ reactions. For instance, there are no happiness, fear and disgust in reactions, while “Haha”, “Love” and “Wow” cannot be found in emotions of news titles. However, there are still two common negative emotions anger (Angry) and sadness (Sad), and “Love” and “Haha” are also considered as the emotion of happiness. Thus, the analysis of relationships between the emotions of news titles and the main reaction of news could be conducted. Data in Figure 4.6 shows that there are 42 news items (50 percent) with emotions of titles corresponding with the first reactions: 2 news items with anger have the largest number of “Angry” among all the reactions; 34 pieces of news with the emotion of happiness take “Haha” and “Love” as the main reactions, and 6 sad news have “Sad” ranked No.1. Results presented in Figure 6 almost corresponded with the results showed in Figure 4.5, not only the proportion of the matching emotions in news titles and reactions, but also the proportion of news titles with negative emotion have “Love” and “Haha” as the main reaction.

Figure 4.5 Emotion of news and the first emotion of comments in each news.



(Note: Horizontal elements present emotions of news titles which have four types of emotions in all 84 news titles. Vertical shows distributions of the first emotions of comments under the news with different types of emotions. “0” means there is no comment/emotion in the news.)

Figure 4.6 Emotion of news and emoji which has the largest number among all types of reactions in each news.



(Note: horizontal elements present emotions of news titles which have four types of emotions in all 84 news titles. Vertical shows distributions of the emoji under the news with different types of emotions. “0” means there is no emoji in the news.)

These analyses have given answers to RQ3, that more than half part of the news express the same emotions in their contents and comments, which means that more than half part of the news' emotional agenda conforms with the public's emotions which expressed in comments and reaction on VG's Facebook page. Moreover, although news is published on Facebook in a negative emotion (fear and sadness), the public response an emotion of happiness. Furthermore, the emotional feedbacks received by fearful and sad news is diverse, and the proportion of each emotion in feedbacks is not much different, which is more obvious in emoji/reaction part. The majority of news (31 out of 43 in comments, 34 out of 43 in emoji) with an emotion of happiness, to a large extent, corresponds with the emotion in comments and emoji, and angry news is fully consistent with the fear emotion in comments and "Angry" reaction in emoji, which indicates that both happiness and anger has stronger agenda effect than fear and sadness, which has answered RQ 4.

4.5 Summary of Findings

Key findings of this thesis will be summarized as follows. The main emotion in VG's Facebook page is happiness, which have been supported in four directions. Firstly, happiness has the largest proportion (over 50 percent) among all types of emotions on VG's Facebook page. Secondly, among the average proportion of each emotion in comments and emoji of each news, happiness takes up a much larger scale than other emotions and plays a prominent role in various emotions. Thirdly, number of happiness has the most frequency to rank No.1 among all types of emotions, and the average ranking position of happiness in all 84 news is much higher than other emotions. Finally, emotions in comments of emoji of each news have a certain concentration, and each news has a main emotion in both comments and reactions, and it is decided by the type of the first emotion which has the largest number among all emotions in comments and reactions.

To the relations between emotions and audiences' behaviour and news diffusion, audiences to a larger degree will give news posted on VG's Facebook page more emotional feedbacks as the increasing of numbers of happiness found in comments of news, and publics prefer to give a happy feedback to the news while the engagement of the news is large. News with the emotion of anger has the largest number of engagement, comments, reactions and sharing times. On the contrary, news with the emotion of fear on VG's Facebook has the fewest engagement and have the lowest intensity of diffusion. News with emotion of anger gets a comment faster and spreads longer than news with emotion of happiness, sadness and fear, whereas happy new takes the longest time to get a comment from public and has the shortest spreading time span. All negative emotions (anger, sadness, fear) in this study get feedback faster than news with positive emotions (happiness), and information with negative emotions (anger, sadness, fear) spread longer than news with happiness. News with anger could get feedback 8 times faster than happy news, and spread almost 3 times longer than news with an emotion of happiness. Negative emotions, fear and anger, are highly correlated and more likely to be used together.

For the emotional agenda effect, more than half part of the news' emotional agenda conforms with the public's emotions which expressed by commentators on VG's Facebook page. Public also express a large scale of happiness after they read news with negative emotions, fear and sadness. Happiness and anger has a stronger agenda effect than fear and sadness.

Chapter 5 Discussion

This chapter will discuss the key findings of this study, and examine how do these findings support or against previous research. The beginning of this chapter will discuss the first research question and I argue that happiness is the emotion with the largest amount in VG's Facebook page, then explain why there are more positive emotions in Facebook. After that, the second research question relating to emotion and diffusion effect will be analysed, and I will discuss the debates between positivity bias and negativity bias on social media according to the findings of this study. Then, the emotional agenda effect related to the third and fourth research questions will be discussed. I argue that there is a significant agenda effect of the emotions of news posted on VG's Facebook page on the public's emotions. Following this, the limitation and generalizability of this research is provided. The final section of this chapter discusses the possibility of future research triggered by this study.

5.1 The Main Emotion on VG's Facebook Page

The first research question of this thesis is: *What is the main emotion on VG's Facebook page?* It was constructed based on the following backgrounds. Even though many researchers have worked in the field of emotions analysis in social media, such as Facebook and Twitter, results from these research projects always vary, and the debate continues up to now. Some of them argue that there is more negative information than positive ones in social media (Robertson et al., 2013; Xu, 2017), and other scholars argue that there are more positive emotions than negative on social media (Sas, Dix, Hart & Su, 2009; Sas et al., 2009, p.120; Reinecke & Trepte, 2014). Scholars also found out that people from different countries have different emotion preference in social media (Xu, 2017; Yu and John-Baptiste, 2016), and there is not munch similar research done in Norway. In addition, lots of research always focus on the polarity of emotion (negative, positive or neutral), rather than on the emotion level to analyse the specific emotions of news posted in social media.

This research tries to find the distribution of emotions on VG's Facebook page. Study conducted at an emotional level, and try to find out emotions of news posted on VG's Facebook site analysed as well as the emotions of comments and emoji/reaction given by audiences rather than the polarity of emotion. All the emotions of textual content were detected by Senpy which is emotion detection tool and has happiness, sadness, fear, anger and disgust five types of emotions. Due to the difference of types of emotions in emoji and Senpy, emotions in the comments and emoji are analysed parallelly.

After analysis of the sample data, I would like to argue that happiness is the main emotion on VG's Facebook page which has been supported in four dimensions. (1) 51.2 percent of comments (N = 7876) have the emotion of happiness, 23.4% of comments are fear, 22.9% are sadness, 2.1% are anger and 0.4% are disgust. There are also 51.2 percent news titles (N = 84) have the emotion of happiness, 25 percent of news are fear, 21.4% of them are sadness and only 2.4 percent are anger. There are 57.69 percent of "Love" and "Haha" which are considered as "happiness" in emoji (N = 8560, without "Like"),18.90 percent of them are "Angry", 14.31 percent are "Sad" and 9.09 percent are "Wow". (2) Happiness has the largest average proportion (44.72 percent) among all types of emotions in comments of each news, which is almost twice larger than the mean of proportion of sadness and fear. "Love" and "Haha" account for an average of 25.32 percent and 24.22 percent respectively which are also higher than other reactions. (3) 57.14 percent news items in all 84 have happiness as the most frequency emotions in comments, and there are only three types emotions which are happiness, sadness and fear to be the most frequent emotions in comments of 84 news. Among all the emotions ranked No.1 in comments of each news, happiness contributes a proportion of 70 percent. The average ranking position of happiness in comments is 1.49, sadness is 2.26, fear is 2.33, anger is 4.16, disgust is 4.86. In emoji, "Love" and "Haha" also have the largest ranking values than other reactions. (4) The amount of emotions ranked No.1 among all emotion in comments of each news account for 57.25 percent, and the number of the first emoji accounts for 75.81 percent in the total number of reactions, which indicate that emotions in each news have a certain concentration, and every piece of news has a main emotion tendency which is decided by the type of the first emotion.

5.1.1 Why More Happiness in Facebook

Findings show that over 50 percent of information collected on VG's Facebook page have the emotion of happiness, which have supported the argument that there are more positive emotions than negative ones on Facebook (Panger, 2017; Lin & Utz, 2015; Yu & John-Baptiste, 2016; Ferrara & Yang, 2015a; Ferrara & Yang, 2015b). Sas et al. (2009), and Bazarova et al. (2015) give out the reasons. They argue that people are inclined to express positive emotions in network-visible Facebook channels, for instance, on timeline (Bazarova et al., 2015) which could be seen by all friends on Facebook. By sharing information on this kind of channel, people could "derive additional emotional benefits, and the talking about positive experiences helps people relive, prolong and remember them, and consequently feeling even better about themselves" (Sas et al., 2009, p.127), and replying to the posts makes people "feeling more satisfied overall when they receive more likes and gratifying comments" (Bazarova et al., 2015, p.160). In the case of this research, VG's Facebook site is a public page which could be accessed by all Facebook users, and people's comments and emoji expressed to the news also could be read by public. Results of this study found out that audiences, to a larger degree, tend to give more emotional feedbacks (give a comment, emoji) to news posted on VG's Facebook page as the increasing of numbers of happiness found in comments of news. If there are more happiness in the news' comments, the news is more likely to bring about a stronger emotional feedback strength which is measured by the number of emotional votes each news receives (emoji) and the frequency of emotions in comments. To this level, results could prove the interpretation from Bazarova et al. and Sas et al. about why there are more positive emotions on Facebook.

Moreover, by comparing the distribution of emotions in different countries from the cultural level, Xu (2017) argue that 75.6 percent of events posted on Weibo (social media platform in China) are negative, which is different with the pattern of emotion distribution on VG's Facebook page where contains more happiness than negative emotions. Based on the different culture background, Lu and Gilmour (2004) argued that happiness is a kind of high arousal emotion in western cultures, whereas it is a low arousal emotion in China (cited in Lim, 2016, p. 107). Hence, I may argue that high arousal emotions are existing in a large scale both on VG's Facebook page and Chinese social media. Furthermore, Lim (2016) listed that anger and fear are high arousal emotions, while sadness is a kinds of low arousal emotion, which classified based on previous research in the context of western culture.

5.2 Emotion and News Diffusion

This section will discuss the second research question: *How do emotions affect public's engagement of the news and news diffusion on VG's Facebook page?*

5.2.1 Engagement and Emotions in Comments, Emoji

Outcomes of this research show that news with happiness as the main emotion in comments has an average number of 581.67 engagement which are more than twice of the engagement of news with sadness as the most frequent emotion in comments, and the number of engagement of the news with sadness as the first emotion in comments is the least. In emoji, news that received the largest amount of "Love" among all types of reactions has a number of 853.75 engagement which is 1.6 times larger than news with "Angry" ranked No.1. News with "Sad" and "Wow" as the main reaction have the least engagement. These findings indicate that news with the emotion of happiness in comments and "Love" reaction as the dominate emotion could have more engagement which measured by the number of comments, reactions and sharing. As the increasing of numbers of engagement, people are more likely to give happy feedback to the news, and people are inclined to express sad emotion while the engagement of the news is low. These findings partly support the argument made by Joyce and Kraut (2006) who pointed out that positive emotions could encourage participation to continue to the conversation and post longer comments.

5.2.2 Emotions of News Titles and Engagement

Many previous studies have conducted to analyse the relationship between emotion and engagement what is a sum of the number of comments, reactions expressed by audiences and sharing times. In this research, engagement is an indicator of the effect of news diffusion, the larger number of engagement, the more audience the news could reach. But the majority studies focus on personal posts or specific topics such as political election, and very few of them focus on the emotions of media's public page on Facebook, and find out how do emotions of news report affect public's engagement.

Results of this study suggest that news with an emotion of anger could get the largest number of engagement, comments, reactions, sharing times, which may indicate that angry news could attract the largest number of reader. Moreover, happy news reaches the second largest number of reader which is 30 percent less than angry news. News with fear has the fewest number of engagement, which supports the argument that fear of negative evaluation can make people more reluctant to transmit news (Rosen & Tesser, 1972). However, these findings not only against Berger and Milkman's (2010) argument that online news with positive emotion is more likely to be shared (Berger, 2014; Cappella et al., 2015) and sad news is less likely to be shared, but also disagree Ferrara and Yang's statement (2015b) that positive information on social media could reach lager number of people than negative information, what is so called as "positivity bias" (Ferrara & Yang, 2015b, p.1). Results in this research is hardly to define whether positive or negative news could attract larger people on Facebook, because both of the two emotions which reach the largest people and fewest people are negative. The effect of diffusion of the positive emotion, happiness, is intermediate.

5.2.3 Emotion of News, Speed of Feedback and Time Span of Diffusion

Majority of prior scholars try to find out what kind of emotion in posts on social media could be shared easier (Pfitzner, Garas &Schweitzer, 2012; Nelson-Field, Riebe & Newstead, 2011), or spread faster and broader (Ferrara & Yang, 2015b; Liu, 2012; Stieglitz, S., & Dang-Xuan, 2013). But this study fills the gap of the relationship between emotions of news report posted on newspapers' (VG) public page on Facebook and the speed of feedback given by audiences and the time span of news diffusion.

Results in Table 4.15 suggest that there is only 3.06 minutes (on average) for publics releasing the first comment to news with an emotion of anger posted on VG's Facebook page. Happy news has the longest time lag to get the first comments, which is 25.58 minuets. The time lags of the first comment for sad and fear news are longer than angry news and shorter than happy news. Moreover, news with anger has the longest time span of diffusion, around 6.2 days on average. The average spreading period of happy news is 2.4 days which is the shortest one.

Berger and Milkman's (2010) argue that anger is an emotion that could promote actions, which is proved in this study. Findings suggest that news with the emotion of anger could evoke users on VG's Facebook giving a comment faster than news with other types of emotions, and the spreading time span of angry is longer than news with other emotions.

Conversely, news with the emotion of happiness take the longest time to inspire audiences to give a comment compared with angry, fearful and sad news on VG's Facebook page, and such happy news has the shortest spreading time span compared to news with emotions of anger, fear and sadness. To the emotion polarity level, analyses also could suggest that news with negative emotions (anger, fear and sadness) on VG's Facebook page get comments faster and spread longer than news with positive emotions (happiness) in the case of this study. However, this finding against the argument from Wu et al. (2011). They analysed information posted on Twitter and found out that, information with positive emotion persisted longer than negative ones.

5.2.4 Positivity Bias or Negativity Bias

The debates of whether positivity bias or negativity bias existing in VG's Facebook page haven't been addressed in this study. As analysed in the literature review section 2.4.1, Reinecke and Trepte (2014) proposed a term "positivity bias in SNS communication" (p.98).

Ferrara and Yang (2015b) developed the so-called positivity bias or pollyanna hypothesis (Garcia, Garas & Schweitzer, 2012; Boucher & Osgood,1969; cited in Ferrara & Yang, 2015b, p.1) based on their finding that public are more likely to share positive information because positive information can reach more audiences. Even though more than half part of content (news, comments and emoji) in this study are happiness, angry news which is negative could reach largest number of audiences (largest number of engagement, comments, reactions and sharing times) on VG's Facebook page than news with fear, sadness and happiness, which against the positivity bias.

If there is no positivity bias in VG's Facebook page, can I argue that there is a negativity bias? The answer seems to be no. Stieglitz and Dang-Xuan (2012) explain the term negativity bias is formulated based on the argument that posts on social media with negative emotions can get more comments and retweets than positive information, which also against results in this study what has been discussed in section 5.2.2: angry news could get the largest number of engagement, comments, reactions and sharing times, but news with the other negative emotion, fear, has the fewest engagement. Findings in this study also show that happy news gets the second largest amount of engagement, comments, reactions and sharing times. These findings also indicate the need of emotional level sentiment analysis. Both anger and fear are negative emotions, but the former has the strongest diffusion effect whereas the latter one has the weakest diffusion effect.

Moreover, Park (2015) has extend the negativity bias by "examining how negative emotions triggered by negative news" in Twitter. He argues that negative news could make reader feel angrier and more disgusted (Park, 2015, p.353). However, outcomes of this research present that even though news posted on VG's Facebook page in a negative emotion, especially news with fear and sadness, public also response happiness as the first emotion to the news.

This study here can't define whether there is a positivity or negativity bias. There are more positive emotions (happiness, "Love", "Haha" and "Wow") than negative emotions (fear, sadness, anger, "Angry", "Sad"), but news with the negative emotion of anger evokes people giving out an emotional feedback faster and spread longer than news with other emotions (happiness, fear, sadness in this study). The present research also found out that negative emoji are more likely to be used together than positive emoji. The difference could be interpreted that there is more subtler difference when Facebook users experience positive emotions, comparing users experience negative emotions in this research.

Moreover, previous research has examined positivity or negativity bias on different topics, which may lead to a big difference on results. People argue that there is a positivity bias on social media, to a large extent, keep eyes on the personal posts (Bazarova, 2015; Utz, 2011; Forest and Wood, 2012; Qiu, Lin, Leung, and Tov, 2012; Sas et al., 2009; Ferrara & Yang, 2015b), while scholars focus on negativity bias always conducting studies relating to political events (Stieglitz & Dang-Xuan, 2012; Park, 2015). This study focuses on the topic neither personal postings or specific events, but new reports posted on newspaper's Facebook page. In addition, although related studies took content on social media as the object, they were conducted in different countries and regions in where people have different culture background. As mentioned on section 2.4.1, research conducted by Ferrara and Yang (2015b) argue that there is more positive emotion on social media, and it happened in America. Study did by Stieglitz and Dang-Xuan, 2012) who support negativity processed in Germany, and research that conducted by Xu (2017) points out that there is "anger" bias on social media happened in China. Hence, this study which was conducted in the context of Norway has the different results from previous research.

5.3 Emotional Agenda Effect

The third and fourth research questions of this thesis are*: How do emotions of the news posted on VG's Facebook site affect public's emotions which conveyed by news commentators? Which emotion has a stronger agenda effect on the public?* This study show that emotions of news posted on VG's Facebook page have a significant agenda effect on public's emotion. Outcome shows that almost 50 percent of news convey the same emotion with comments and emoji which made and expressed by public, which indicates that more than half part of the news' emotional agenda conforms with the audiences' emotions which expressed by commentators on VG's Facebook page. This argument supports the result made by Coleman and Wu (2010), they examined the relationships between emotion of TV programs and emotions of audiences, and found media's emotion corresponded with public's emotion.

Findings in this study also show that news with the emotion of anger is highly reflected as the emotion of fear in comments and "Angry" reactions in emoji. More than 70 percent happy news get the emotion of happiness both in comments and emoji, which indicated that emotion of anger and happiness have a stronger agenda effect comparing with fear and sadness. However, this outcome against Coleman and Wu's (2010) argument that only negative emotions has significant agenda-setting effect and positive emotions shows no agenda-setting effect.

In this study. I also find that the emotional feedbacks of fearful and sad news are diverse, and the distribution of feedback emotions is relatively uniform. Pfitzner, Garas and Schweitzer (2012) pointed out that emotional diverse tweets are five times easier to be shared, which is not consistent with the outcome of this study: sad and fearful news have weaker capability to be shared comparing with angry and happy news.

5.4 Limitations and Generalizability

Limitations of this study present as follows. Firstly, as mentioned in section 3.4, the emotion detection tool, Senpy, is not a perfect machine which couldn't guarantees 100 percent accuracy of emotions in textual content (news and comments in this study). Even though all the emotions detected by Senpy have been examined and modified manually, errors still exist. For instance, result shows that all the sample news have received 1618 "Angry" reaction in emoji, but there are only 167 anger emotion in comments which are detected by Senpy. Moreover, when I examine the correlation between the emotions and emotional strength in section 4.3.1, the emotion of sadness in comments are highly correlated with emotional strength, but "Sad" in emoji has the weakest correlation with emotional strength. However, the accuracy of the result could be verified by emoji what is voted directly by audiences. Furthermore, types of emotion in Senpy is a little bite few, which can't represent all emotional state. Secondly, from a statistical point of view, sample in this study is not big enough which may skew the results. For instance, in the process of analysing relationships between emotions of news titles and engagement, speed of feedback and time span of diffusion, there are only 2 news items with the emotion of anger in news titles, which may exaggerate the results.

Thirdly, the results of this study could hardly generalize to research about emotions in other newspaper's Facebook page, either in Norway or out of Norway. Each media has its own unique style and positioning, and their different directions of reporting on the news may lead to different emotions. Even different media institutions in the same city, editors will have different choices for news posted on social media, which may also generate different distributions of emotions, not to mention that applying outside Norway. As analysed in section 5.4, political events or tendency may affect emotions conveyed in social media.

Although every media claims to be independent, it has certain political tendencies. This study didn't figure out VG's political tendency, and results here can not apply to media with other political tendencies.

5.5 Future Research

This study only analyses emotions on VG's Facebook page, and VG's emotions in other social media platforms such as Twitter haven't been examined. Actually, almost all the media institutions have multiple pages on different social media platforms, and media's emotion on different social media platforms could be compared and analysed. Furthermore, emotions of similar media in different countries in social media also could be studied, and find out, to what extent, the differences in cultural background can affect news' emotion expression on social media, or figure out/compare the different emotion patterns in social media in different countries. Finally, there is a potential possibility to analyse the relationships between emotional bias and spiral of silence theory, and examine whether medias or news reports form public's opinion on the emotional level in social media, or whether people are afraid to express different emotions from the majorities to avoid isolation on social media platforms, specially, on political events.

Chapter 6 Conclusion

This study has solved some questions regarding emotions on VG's Facebook page: what is the main emotion on VG's Facebook page; how do emotions affect public's engagement of the news and news diffusion on VG's Facebook page; How do emotions of news posted on VG's Facebook site affect public's emotions which conveyed by news commentators; and which emotion has a stronger agenda effect on the public.

The first two questions were formulated based on the existing literature referring the debates on positivity bias or negativity bias on social media, and whether news reports posted on social media with negative emotions have a stronger diffusion effect compared with positive ones. The former debate derives from the disagreement about whether there are more positive emotions or negative emotions on social media, and whether positive emotion could reach larger audiences or not. Moreover, people from different countries have different emotion preference on social media (Xu, 2017; Yu and John-Baptiste, 2016; Hyvärinen & Beck, 2018). The latter one focuses on the news reports (not personal updates) on Facebook. Some scholars argue that news with negative emotions could attract more attention and is more likely to be shared on social media (Berger & Milkman, 2010; Hansen et. al. 2011; Valenzuela, Piña & Ramírez, 2017), which may promote news editor to choose news with negative emotions posted on media's public page on social media in order to attract more attention and traffic to their official website. However, other researchers argue that Facebook (the object platform in this research) is a front stage for people to show good side to maintain their better images, which means that people are more hesitating to share or show negative emotions on Facebook (Valenzuela, Piña & Ramírez, 2017). The last two research questions were mainly constructed from the argument made by Coleman and Wu (2010). They find out that public's emotion corresponds with media's emotional agenda by analysing TV programs. However, there are very few research focus on the emotion agenda effect of news reports posted on Facebook.

This study collected 84 news items and 7876 comments posted on VG's Facebook page in the last three days in August 2018. Emotions in textual content (news titles and comments) were detected by Senpy which extract emotions in a detailed level (output specific types of emotion) rather than polarity level (positive, negative and neutral). After analysing the reactions expressed by public and emotions of comments and news titles, I find that: the main emotion on VG's Facebook page is happiness which has the largest proportion (over 50 percent) among all types of emotions, takes up a much larger scale than other emotions on average in comments and reactions of each news, has the highest ranking position, contributes over 70 percent in emotions ranked No.1 in comments of all 84 news items. Emotions in comments and emoji of each news have a certain concentration, which means that every piece of news has a main emotion in comments and reactions. For the second research question, I find that publics prefer to give a feedback with emotion of happiness to the news while the engagement of the news is large. News with the emotion of anger could reach the highest number of users, whereas news with the emotion of fear reach the smallest number of audiences and have the lowest intensity of diffusion. News with the emotion of anger get a comment faster and spread longer than news with other emotions, while happy news takes the longest time to get a feedback from public and has the shortest spreading time span. All negative emotions (anger, sadness, fear) in this study get a comment faster than news with positive emotions (happiness), and information with negative emotions (anger, sadness, fear) spread longer than news with happiness. To the third and fourth research question, findings show that more than half part of the news' emotional agenda corresponds with the public's emotions which expressed by commentators on VG's Facebook page. Public also express a large scale of happiness after they read news with negative emotions, and both the two emotions, happiness and anger, have stronger agenda effect than fear and sadness.

Emotion plays a very important role in the information transmission (Ibrahim, Ye & Hoffner, 2008; Hyvärinen & Beck, 2018) and construction of discourse (Edwards, 1999) in social media. This project has analysed previous research to learn about theories and applications of emotion and emotion analysis and the role of emotion in news diffusion in social media, and find out that there was not much research like this has been done in Norway. Methods and tools for trying to analyse emotions in textual content in social media also introduced. Then I examine emotions distributions in VG's Facebook page and figure out the dissemination effect of the emotion of news published on social media by traditional media, and how emotions affect public's emotion. I hope this thesis will provide a small step on the topic of emotion's media effect in the context of social media in Norway.

References

Ames, M., & Naaman, M. (2007, April). Why we tag: motivations for annotation in mobile and online media. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 971-980). ACM.

Almashraee, M., Díaz, D. M., & Paschke, A. (2016). Emotion Level Sentiment Analysis: The Affective Opinion Evaluation. In *EMSA-RMed@ ESWC*.

Arpan, L. M., & Nabi, R. L. (2011). Exploring anger in the hostile media process: Effects on news preferences and source evaluation. *Journalism & Mass Communication Quarterly*, *88*(1), 5-22.

Balmas, M., & Sheafer, T. (2010). Candidate image in election campaigns: Attribute agenda setting, affective priming, and voting intentions. *International journal of public opinion research*, *22*(2), 204-229.

Barrett, L. F., & Russell, J. A. (Eds.). (2014). *The psychological construction of emotion*. Guilford Publications.

Batson, C. D., Shaw, L. L., & Oleson, K. C. (1992). Differentiating affect, mood, and emotion: toward functionally based conceptual distinctions.

Baumeister, R. F., DeWall, C. N., Vohs, K. D., & Alquist, J. L. (2010). Does emotion cause behavior (apart from making people do stupid, destructive things). *Then a miracle occurs: Focusing on behavior in social psychological theory and research*, 12-27.

Bayer, M., Sommer, W., & Schacht, A. (2012). Font size matters—emotion and attention in cortical responses to written words. *PloS one*, *7*(5), e36042.

Bazarova, N. N., Choi, Y. H., Schwanda Sosik, V., Cosley, D., & Whitlock, J. (2015, February). Social sharing of emotions on Facebook: Channel differences, satisfaction, and replies. In *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing* (pp. 154-164). ACM.

Ben-Ze'ev, A. (2001). *The subtlety of emotions*. MIT press.

Berger, J., & Milkman, K. (2010). Social transmission, emotion, and the virality of online content. *Wharton research paper*, *106*, 1-52.

Bollen, J., Mao, H., & Pepe, A. (2011, July). Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. In *Fifth International AAAI Conference on Weblogs and Social Media*.

Boucher, J., & Osgood, C. E. (1969). The pollyanna hypothesis. *Journal of Memory and Language*, *8*(1), 1.

boyd, D. (2006). Friends, friendsters, and myspace top 8: Writing community into being on social network sites.

boyd, D. (2014). *It's complicated: The social lives of networked teens*. Yale University Press.

boyd, D. M. (2010). "Social Network Sites as Networked Publics: Affordances, Dynamics, and Implications." In *Networked Self: Identity, Community, and Culture on Social Network Sites* (ed. Zizi Papacharissi), pp. 39-58

boyd, D. M., & Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship. *Journal of computer-mediated Communication*, *13*(1), 210-230.

Bradley, M. M., & Lang, P. J. (1999). *Affective norms for English words (ANEW): Instruction manual and affective ratings* (Vol. 30, No. 1, pp. 25-36). Technical report C-1, the center for research in psychophysiology, University of Florida.

Bucher, T., & Helmond, A. (2017). The affordances of social media platforms. *The SAGE . handbook of social media*, 233À253.

Burke, M., & Develin, M. (2016, February). Once more with feeling: Supportive responses to social sharing on Facebook. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (pp. 1462-1474). ACM.

Bruns, A. (2019). After the 'APIcalypse': social media platforms and their fight against critical scholarly research. *Information, Communication & Society*, *22*(11), 1544-1566.

Cabanac, M. (2002). What is emotion?. *Behavioural processes*, *60*(2), 69-83.

Cataldi, M., Ballatore, A., Tiddi, I., & Aufaure, M. A. (2013). Good location, terrible food: detecting feature sentiment in user-generated reviews. *Social Network Analysis and Mining*, *3*(4), 1149-1163.

Cattell, R. B. (1940). Sentiment or attitude? The core of a terminology problem in personality research. *Character & Personality; A Quarterly for Psychodiagnostic & Allied Studies*.

Celli, F., Ghosh, A., Alam, F., & Riccardi, G. (2016). In the mood for sharing contents: Emotions, personality and interaction styles in the diffusion of news. *Information Processing & Management*, *52*(1), 93-98.

Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. Mobile networks and applications, 19(2), 171-209.

Chopra, F. K., & Bhatia, R. (2016). A Critical Review of Sentiment Analysis. *International Journal of Computer Applications*, *149*(10).

Coleman, R., & Wu, H. D. (2010). Proposing emotion as a dimension of affective agenda setting: Separating affect into two components and comparing their second-level effects. *Journalism & Mass Communication Quarterly*, *87*(2), 315-327.

Chung, D. S. (2008). Interactive features of online newspapers: Identifying patterns and predicting use of engaged readers. *Journal of Computer-Mediated Communication*, *13*(3), 658-679.

Coe, K., & Scacco, J. M. (2017). Content Analysis, Quantitative. *The International Encyclopedia of Communication Research Methods*, 1-11.

Dang-Xuan, L., Stieglitz, S., Wladarsch, J., & Neuberger, C. (2013). An investigation of influentials and the role of sentiment in political communication on Twitter during election periods. *Information, Communication & Society*, *16*(5), 795-825.

Denis, A., Cruz-Lara, S., & Bellalem, N. (2013). General Purpose Textual Sentiment Analysis and Emotion Detection Tools. *arXiv preprint arXiv:1309.2853*.

Devitt, A., & Ahmad, K. (2007). Sentiment polarity identification in financial news: A cohesion-based approach. In *Proceedings of the 45th annual meeting of the association of computational linguistics* (pp. 984-991).

Doveling, K., von Scheve, C., & Konijn, E. A. (Eds.). (2010). *The Routledge handbook of emotions and mass media*. Routledge.

Duggan M. *Online harassment 2017*.

Edwards, D. (1999). Emotion discourse. *Culture & psychology*, *5*(3), 271-291.

Ekman, P. (1982). What emotion categories or dimensions can observers judge from facial behavior?. *Emotions in the human face*, 39-55.

Ekkekakis, P. (2012). Affect, mood, and emotion. *Measurement in sport and exercise psychology*, *321*.

Fan, J., Han, F., & Liu, H. (2014). Challenges of big data analysis. *National science review*, *1*(2), 293-314.

Farnadi, G., Sitaraman, G., Rohani, M., Kosinski, M., Stillwell, D., Moens, M. F., ... & De Cock, M. (2014). How are you doing?: Emotions and personality in Facebook. In *2nd Workshop on Emotions and Personality in Personalized Services (EMPIRE 2014); workshop at the 22nd Conference on User Modelling, Adaptation and Personalization (UMAP 2014)* (pp. 45-56).

Ferrara, E., & Yang, Z. (2015a). Measuring emotional contagion in social media. *PloS one*, *10*(11), e0142390.
Ferrara, E., & Yang, Z. (2015b). Quantifying the effect of sentiment on information diffusion in social media. *PeerJ Computer Science*, *1*, e26.
Forest, A. L., & Wood, J. V. (2012). When social networking is not working: Individuals with low self-esteem recognize but do not reap the benefits of self-disclosure on Facebook. *Psychological science*, *23*(3), 295-302.
Forgas, J. P., & Wyland, C. L. (2006). Affective intelligence: Understanding the role of affect in everyday social behavior. *Emotional intelligence in everyday life*, 77-99.
Fowler, J. H., & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *Bmj*, *337*, a2338.
Frijda, N.H. (2009). Mood. *The Oxford companion to emotion and the affective sciences*, 258-259.
Fuchs, C. (2014). Social media and the public sphere. *tripleC: Communication, Capitalism & Critique. Open Access Journal for a Global Sustainable Information Society*, *12*(1), 57-101.
Garcia, D., Garas, A., & Schweitzer, F. (2012). Positive words carry less information than negative words. *EPJ Data Science*, *1*(1), 3.
Gibson, J. (1979), The theory of affordance. *The ecological approach to visual perception*.
Golder, S. A., & Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science*, *333*(6051), 1878-1881
Goodall, C. E., Slater, M. D., & Myers, T. A. (2013). Fear and anger responses to local news coverage of alcohol-related crimes, accidents, and injuries: Explaining news effects on policy support using a representative sample of messages and people. *Journal of Communication*, *63*(2), 373-392.
Goode, L. (2009). Social news, citizen journalism and democracy. *New media & society*, *11*(8), 1287-1305.
Gross, K., & Brewer, P. R. (2007). Sore losers: News frames, policy debates, and emotions. *Harvard International Journal of Press/Politics*, *12*(1), 122-133.
Grzywinska, I., & Borden, J. (2012). The impact of social media on traditional media agenda setting theory. the case study of occupy wall street movement in USA. *Agenda setting: old and new problems in old and new media, Wroclaw*.
Hagenau, M., Liebmann, M., & Neumann, D. (2013). Automated news reading: Stock price prediction based on financial news using context-capturing features. *Decision Support Systems*, *55*(3), 685-697.
Hansen, L. K., Arvidsson, A., Nielsen, F. Å., Colleoni, E., & Etter, M. (2011). Good friends, bad news-affect and virality in twitter. In *Future information technology* (pp. 34-43). Springer, Berlin, Heidelberg.
Hasell, A., & Weeks, B. E. (2016). Partisan provocation: The role of partisan news use and emotional responses in political information sharing in social media. *Human Communication Research*, *42*(4), 641-661.
Hatzivassiloglou, V., & McKeown, K. R. (1997, July). Predicting the semantic orientation of adjectives. In *Proceedings of the 35th annual meeting of the association for computational linguistics and eighth conference of the European chapter of the association for computational linguistics* (pp. 174-181). Association for Computational Linguistics.
Hill, A. L., Rand, D. G., Nowak, M. A., & Christakis, N. A. (2010). Emotions as infectious diseases in a large social network: the SISa model. *Proceedings of the Royal Society of London B: Biological Sciences*, *277*(1701), 3827-3835.

Hogan, B. (2010). The presentation of self in the age of social media: Distinguishing performances and exhibitions online. *Bulletin of Science, Technology & Society*, *30*(6), 377-386.
Hyvärinen, H., & Beck, R. (2018, January). Emotions Trump Facts: The Role of Emotions in on Social Media: A Literature Review. In *Proceedings of the 51st Hawaii International Conference on System Sciences*.
Ibrahim, A., Ye, J., & Hoffner, C. (2008). Diffusion of news of the shuttle Columbia disaster: The role of emotional responses and motives for interpersonal communication. *Communication Research Reports*, *25*(2), 91-101.
Izard, C. E. (2010). The many meanings/aspects of emotion: Definitions, functions, activation, and regulation. *Emotion Review*, *2*(4), 363-370.
Jalonen, H. (2014, April). Social Media–An Arena for Venting Negative Emotions. In *International Conference on Communication, Media, Technology and Design* (Vol. 24, p. 26).
Jalonen, H. (2014, November). Negative emotions in social media as a managerial challenge. In *European Conference on Management, Leadership & Governance* (pp. 128-135). Academic Conferences International Limited.
Jindal, N., & Liu, B. (2006, August). Identifying comparative sentences in text documents. In *Proceedings of the 29th annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 244-251). ACM.
Jockers, M. (2017). Introduction to the Syuzhet package. *The Comprehensive R Archive Network*.
Johannessen, M. R. (2015, August). Please like and share! A frame analysis of opinion articles in online news. In *International Conference on Electronic Participation* (pp. 15-26). Springer, Cham.
Johnson, A. J., Lee, S. K., Cionea, I. A., & Massey, Z. B. (2018). The Benefits and Challenges of New Media for Intercultural Conflict. In *Reconceptualizing New Media and Intercultural Communication in a Networked Society* (pp. 171-197). IGI Global.
Joyce, E., & Kraut, R. E. (2006). Predicting continued participation in newsgroups. *Journal of Computer-Mediated Communication*, *11*(3), 723-747.
Ju, A., Jeong, S. H., & Chyi, H. I. (2014). Will social media save newspapers? Examining the effectiveness of Facebook and Twitter as news platforms. *Journalism Practice*, *8*(1), 1-17.
Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, *53*, 59-68.
Kim, S. M., & Hovy, E. (2007). Crystal: Analyzing predictive opinions on the web. In *Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL)*.
Kitchin, R. (2013). Big data and human geography: Opportunities, challenges and risks. *Dialogues in human geography*, *3*(3), 262-267.
Kramer, A. D. (2012, May). The spread of emotion via Facebook. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 767-770). ACM.
Kramer, A. D., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences*, *111*(24), 8788-8790.
Krippendorff, K. (1980). *Content analysis; an introduction to its methodology* (No. 04; P93, K7.).
Krämer, N. C., & Haferkamp, N. (2011). Online self-presentation: Balancing privacy

concerns and impression construction on social networking sites. In *Privacy Online* (pp. 127-141). Springer, Berlin, Heidelberg.
Ku, L. W., Liang, Y. T., & Chen, H. H. (2006). Opinion Extraction, Summarization and Tracking in News and Blog Corpora.
Kümpel, A. S., Karnowski, V., & Keyling, T. (2015). News sharing in social media: A review of current research on news sharing users, content, and networks. *Social media+ society*, *1*(2), 2056305115610141.
Lai, Shengqiang & Tang, Xuemei (2016). On the impact of emotional information on online rumor spread. *Journal of Intelligence*,35(1),116-121, (My translation).
Lee, C. S., & Ma, L. (2012). News sharing in social media: The effect of gratifications and prior experience. *Computers in human behavior*, *28*(2), 331-339.
Leung, L. (2013). Generational differences in content generation in social media: The roles of the gratifications sought and of narcissism. *Computers in Human Behavior*, *29*(3), 997-1006.
Lim, N. (2016). Cultural differences in emotion: differences in emotional arousal level between the East and the West. *Integrative medicine research*, *5*(2), 105-109.
Lin, R., & Utz, S. (2015). The emotional responses of browsing Facebook: Happiness, envy, and the role of tie strength. *Computers in human behavior*, *52*, 29-38.
Lin, W. H., Wilson, T., Wiebe, J., & Hauptmann, A. (2006, June). Which side are you on?: identifying perspectives at the document and sentence levels. In *Proceedings of the tenth conference on computational natural language learning* (pp. 109-116). Association for Computational Linguistics.
Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis lectures on human language technologies*, *5*(1), 1-167.
Liu, B. (2015). *Sentiment analysis: Mining opinions, sentiments, and emotions*. Cambridge University Press.
Liu, B., & Zhang, L. (2012). A survey of opinion mining and sentiment analysis. In *Mining text data* (pp. 415-463). Springer, Boston, MA.
Lu, L., & Gilmour, R. (2004). Culture and conceptions of happiness: Individual oriented and social oriented SWB. *Journal of happiness studies*, *5*(3), 269-291.
Macskassy, S. A., & Michelson, M. (2011, July). Why do people retweet? anti-homophily wins the day!. In *Fifth International AAAI Conference on Weblogs and Social Media*.
Maks, I., & Vossen, P. (2012). A lexicon model for deep sentiment analysis and opinion mining applications. *Decision Support Systems*, *53*(4), 680-688.
Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt.
McCombs, M. E., & Shaw, D. L. (1972). The agenda-setting function of mass media. *Public opinion quarterly*, *36*(2), 176-187.
McDougall, W. (1926). An introduction to social psychology (Rev. ed.). *Boston: John W. Luce*.
Mihara, S., Tsugawa, S., & Ohsaki, H. (2015, August). Influence maximization problem for unknown social networks. In *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015* (pp. 1539-1546). ACM.
Mittelstadt, B. D., & Floridi, L. (2016). The ethics of big data: current and foreseeable issues in biomedical contexts. *Science and engineering ethics*, *22*(2), 303-341.
Mohammad, S. M., Kiritchenko, S., & Zhu, X. (2013). NRC-Canada: Building the state-of-the-art in sentiment analysis of tweets. arXiv preprint arXiv:1308.6242.
Mowrer, O. (1960). Learning theory and behavior.
Mosseri Adam. (2016, June 29). Building a better news feed for you. Retrieved March 20,

2018 from https://newsroom.fb.com/news/2016/06/building-a-better-news-feed-for-you/
Munezero, M. D., Montero, C. S., Sutinen, E., & Pajunen, J. (2014). Are they different? Affect, feeling, emotion, sentiment, and opinion detection in text. *IEEE transactions on affective computing*, *5*(2), 101-111.
Myrick, J. G., & Wojdynski, B. W. (2016). Moody news: The impact of collective emotion ratings on online news consumers' attitudes, memory, and behavioral intentions. *new media & society*, *18*(11), 2576-2594.
Nabi, R. L. (1999). A cognitive-functional model for the effects of discrete negative emotions on information processing, attitude change, and recall. *Communication theory*, *9*(3), 292-320.
NCH (2005). *Putting U in the picture – mobile phonebullying survey 2005*.
Nelson-Field, K., Riebe, E., & Newstead, K. (2011). To shock or inspire: Understanding which emotions drive video sharing on Facebook. In *ANZMAC. Presented at the Annual Australia and New Zealand Marketing Academy Conference Perth, WA,. Retrieved from http://anzmac. org*.
Neuendorf, K. A. (2016). *The content analysis guidebook*. Sage.
Nguyen, T. H., Shirai, K., & Velcin, J. (2015). Sentiment analysis on social media for stock movement prediction. *Expert Systems with Applications*, *42*(24), 9603-9611.
Norwegian National Ethics Committee. Guidelines for research ethics in the social sciences, humanities, law and theology 2016.
Ortony, A., & Turner, T. J. (1990). What's basic about basic emotions?. *Psychological review*, *97*(3), 315.
Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends® in Information Retrieval*, *2*(1–2), 1-135.
Pang, B., Lee, L., & Vaithyanathan, S. (2002, July). Thumbs up?: sentiment classification using machine learning techniques. In *Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10*(pp. 79-86). Association for Computational Linguistics.
Pang, B., & Lee, L. (2005, June). Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. In *Proceedings of the 43rd annual meeting on association for computational linguistics* (pp. 115-124). Association for Computational Linguistics.
Panger, G. T. (2017). *Emotion in social media* (Doctoral dissertation, UC Berkeley).
Panksepp, J. (1994). Basic emotions ramify widely in the brain, yielding many concepts that cannot be distinguished unambiguously... yet. *The nature of emotion*, 86-88.
Park, C. S. (2015). Applying "negativity bias" to Twitter: Negative news on Twitter, emotions, and political learning. *Journal of Information Technology & Politics*, *12*(4), 342-359.
Pfitzner, R., Garas, A., & Schweitzer, F. (2012, May). Emotional divergence influences information spreading in twitter. In *Sixth international AAAI conference on weblogs and social media*.
Pozzi, F. A., Fersini, E., Messina, E., & Liu, B. (2016). *Sentiment analysis in social networks*. Morgan Kaufmann.
Purcell, K., Rainie, L., Mitchell, A., Rosenstiel, T., & Olmstead, K. (2010). Understanding the participatory news consumer. *Pew Internet and American Life Project*, *1*, 19-21.
Qiu, L., Lin, H., Leung, A. K., & Tov, W. (2012). Putting their best foot forward: Emotional disclosure on Facebook. *Cyberpsychology, Behavior, and Social Networking*, *15*(10), 569-572.
Rainie, L., Kiesler, S., Kang, R., Madden, M., Duggan, M., Brown, S., & Dabbish, L. (2013).

Anonymity, privacy, and security online. *Pew Research Center*, *5*.
Reinecke, L., & Trepte, S. (2014). Authenticity and well-being on social network sites: A two-wave longitudinal study on the effects of online authenticity and the positivity bias in SNS communication. *Computers in Human Behavior*, *30*, 95-102.
Robertson, S. P., Douglas, S., Maruyama, M., & Semaan, B. (2013). Political discourse on social networking sites: Sentiment, in-group/out-group orientation and rationality. *Information Polity*, *18*(2), 107-126.
Rieder, B. (2013, May). Studying Facebook via data extraction: the Netvizz application. In *Proceedings of the 5th annual ACM web science conference* (pp. 346-355). ACM.
Riff, D., Lacy, S., & Fico, F. (2014). *Analyzing Media Messages: Using Quantitative Content Analysis in Research*. Routledge.
Rimé, B. (2009). Emotion elicits the social sharing of emotion: Theory and empirical review. *Emotion review*, *1*(1), 60-85.
Russell, J. A., & Feldman Barrett, L. (2009). Core affect. *The Oxford companion to emotion and the affective sciences*, *104*.
Satapathy, R., Cambria, E., & Hussain, A. (2018). *Sentiment analysis in the bio-medical domain: techniques, tools, and applications* (Vol. 7). Springer.
Sas, C., Dix, A., Hart, J., & Su, R. (2009, September). Dramaturgical capitalization of positive emotions: The answer for Facebook success?. In *Proceedings of the 23rd British HCI group annual conference on people and computers: Celebrating people and technology* (pp. 120-129). British Computer Society.
Schröder, M., Baggia, P., Burkhardt, F., Pelachaud, C., Peter, C., & Zovato, E. (2011, October). EmotionML–an upcoming standard for representing emotions and related states. In *International Conference on Affective Computing and Intelligent Interaction* (pp. 316-325). Springer, Berlin, Heidelberg.
Schachter, S., & Singer, J. (1962). Cognitive, social, and physiological determinants of emotional state. *Psychological review*, *69*(5), 379.
Seyeditabari, A., Tabari, N., & Zadrozny, W. (2018). Emotion Detection in Text: a Review. *arXiv preprint arXiv:1806.00674*.
Singh, V. K., Piryani, R., Uddin, A., & Waila, P. (2013, March). Sentiment analysis of movie reviews: A new feature-based heuristic for aspect-level sentiment classification. In *2013 International Mutli-Conference on Automation, Computing, Communication, Control and Compressed Sensing (iMac4s)* (pp. 712-717). IEEE.
Shearer. E. and Matsa. K. E. (2018). News Use Across Social Media Platforms 2018.
Shouse, E. (2005). Feeling, emotion, affect. *M/c journal*, *8*(6), 26.
Skuza, M., & Romanowski, A. (2015, September). Sentiment analysis of Twitter data within big data distributed environment for stock prediction. In *2015 Federated Conference on Computer Science and Information Systems (FedCSIS)* (pp. 1349-1354). IEEE.
Snyder, B., & Barzilay, R. (2007). Multiple aspect ranking using the good grief algorithm. In *Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Proceedings of the Main Conference* (pp. 300-307).
Staiano, J., & Guerini, M. (2014). Depechemood: a lexicon for emotion analysis from crowd-annotated news. arXiv preprint arXiv:1405.1605.
Statista.com, 2019. Number of monthly active Facebook users worldwide as of 2nd quarter 2019. Retrieved from https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/
Stets, J. E. (2006). Emotions and sentiments. In *Handbook of social psychology* (pp. 309-335). Springer, Boston, MA.
Stieglitz, S., & Dang-Xuan, L. (2012, January). Political communication and influence

through microblogging--An empirical analysis of sentiment in Twitter messages and retweet behavior. In *2012 45th Hawaii International Conference on System Sciences* (pp. 3500-3509). IEEE.
Stieglitz, S., & Dang-Xuan, L. (2013). Emotions and information diffusion in social media—sentiment of microblogs and sharing behavior. *Journal of management information systems*, *29*(4), 217-248.
Strapparava, C., & Valitutti, A. (2004, May). Wordnet affect: an affective extension of wordnet. In *Lrec* (Vol. 4, No. 1083-1086, p. 40).
Sui, Yan & Li, Yan (2012). On social transmission of personal emotion in the age of mass communication. *Modern Communication Journal of Communication University of China*,34(12),10-15.
Sun, E., Rosenn, I., Marlow, C. A., & Lento, T. M. (2009, March). Gesundheit! modeling contagion through facebook news feed. In *Third international AAAI conference on weblogs and social media*.
Sánchez-Rada, J. F., Iglesias, C. A., Corcuera, I., & Araque, O. (2016, October). Senpy: A pragmatic linked sentiment analysis framework. In *2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA)* (pp. 735-742). IEEE.
Thoits, P. A. (1989). The sociology of emotions. *Annual review of sociology*, *15*(1), 317-342.
Trilling, D., Tolochko, P., & Burscher, B. (2017). From newsworthiness to shareworthiness: How to predict news sharing based on article characteristics. *Journalism & Mass Communication Quarterly*, *94*(1), 38-60.
Tufekci, Z. (2014, May). Big questions for social media big data: Representativeness, validity and other methodological pitfalls. In *Eighth International AAAI Conference on Weblogs and Social Media*.
Tufekci, Z. (2017). *Twitter and tear gas: The power and fragility of networked protest*. Yale University Press.
Turner, J. H. (2009). The sociology of emotions: Basic theoretical arguments. *Emotion Review*, *1*(4), 340-354.
Turney, P. D. (2002, July). Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews. In *Proceedings of the 40th annual meeting on association for computational linguistics* (pp. 417-424). Association for Computational Linguistics.
Tran, T., Nguyen, D., Nguyen, A., & Golen, E. (2018, May). Sentiment analysis of marijuana content via facebook emoji-based reactions. In *2018 IEEE International Conference on Communications (ICC)* (pp. 1-6). IEEE.
Trussler, M., & Soroka, S. (2014). Consumer demand for cynical and negative news frames. *The International Journal of Press/Politics*, *19*(3), 360-379.
Utz, S. (2012). Social network site use among Dutch students: Effects of time and platform. In *Networked sociability and individualism: Technology for personal and professional relationships* (pp. 103-125). IGI Global.
Utz, S. (2015). The function of self-disclosure on social network sites: Not only intimate, but also positive and entertaining self-disclosures increase the feeling of connection. *Computers in Human Behavior*, *45*, 1-10.
Valenzuela, S., Piña, M., & Ramírez, J. (2017). Behavioral effects of framing on social media users: How conflict, economic, human interest, and morality frames drive news sharing. *Journal of Communication*, *67*(5), 803-826.
Viswanath, B., Mislove, A., Cha, M., & Gummadi, K. P. (2009, August). On the evolution of user interaction in facebook. In *Proceedings of the 2nd ACM workshop on Online social networks* (pp. 37-42). ACM.
Wanta, W., Golan, G., & Lee, C. (2004). Agenda setting and international news: Media

influence on public perceptions of foreign nations. *Journalism & Mass Communication Quarterly*, *81*(2), 364-377.
Warren, S. D., & Brandeis, L. D. (1890). The right to privacy. *Harvard law review*, 193-220.
Weber, P. (2014). Discussions in the comments section: Factors influencing participation and interactivity in online newspapers' reader comments. *New media & society*, *16*(6), 941-957.
Weeks, B. E., & Holbert, R. L. (2013). Predicting dissemination of news content in social media: A focus on reception, friending, and partisanship. *Journalism & Mass Communication Quarterly*, *90*(2), 212-232.
Whittaker, E., & Kowalski, R. M. (2015). Cyberbullying via social media. *Journal of School Violence*, *14*(1), 11-29.
Wood, I., & Ruder, S. (2016, May). Emoji as emotion tags for tweets. In *Proceedings of the Emotion and Sentiment Analysis Workshop LREC2016, Portorož, Slovenia* (pp. 76-79).
Wu, S., Tan, C., Kleinberg, J., & Macy, M. W. (2011, July). Does bad news go away faster?. In *Fifth International AAAI Conference on Weblogs and Social Media*.
Xu, Xiang (2017). Research on the Effect and Features of Emotional Bias in the Communication of Sina Social News: An Web Mining and Empirical Analysis Based on Sina Social News. *Chinese Journal of Journalism and Communication.*4,76-94
Xu, T., Peng, Q., & Cheng, Y. (2012). Identifying the semantic orientation of terms using S-HAL for sentiment analysis. *Knowledge-Based Systems*, *35*, 279-289.
Yao, T. F., Nie, Q. Y., Li, J. C., Li, L. L., Lou, D. C., Chen, K., & Fu, Y. (2006). An opinion mining system for Chinese automobile reviews. *Frontiers of Chinese Information Processing*, 260-281.
Yassine, M., & Hajj, H. (2010, December). A framework for emotion mining from text in online social networks. In *2010 IEEE International Conference on Data Mining Workshops* (pp. 1136-1142). IEEE.
Yi, J., Nasukawa, T., Bunescu, R., & Niblack, W. (2003, November). Sentiment analyzer: Extracting sentiments about a given topic using natural language processing techniques. In *Third IEEE international conference on data mining* (pp. 427-434). IEEE.
Yu, H., & John-Baptiste, S. (2016). Emotion expression on social networking sites: A study of young persons' use of Facebook and Twitter in the UK. Global science and technology forum.
Yu, L. C., Wu, J. L., Chang, P. C., & Chu, H. S. (2013). Using a contextual entropy model to expand emotion words and their intensity for the sentiment classification of stock market news. *Knowledge-Based Systems*, *41*, 89-97.
Zhang, X., Fuehres, H., & Gloor, P. A. (2011). Predicting stock market indicators through twitter "I hope it is not as bad as I fear". *Procedia-Social and Behavioral Sciences*, *26*, 55-62.
Zhao, J., Dong, L., Wu, J., & Xu, K. (2012, August). Moodlens: an emoticon-based sentiment analysis system for chinese tweets. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 1528-1531). ACM.
Zillmann, D., Chen, L., Knobloch, S., & Callison, C. (2004). Effects of lead framing on selective exposure to Internet news reports. *Communication research*, *31*(1), 58-81.
Özgüven, N., & Mucan, B. (2013). The relationship between personality traits and social media use. *Social Behavior and Personality: an international journal*, *41*(3), 517-528.