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DETECTING CONSUMER EMOTIONS ON SOCIAL NETWORKING WEBSITES

Faculty of Business and Management
Master of Science Thesis
May 2019

ABSTRACT

PRASHANTH MADHALA: Detecting consumer emotions on social networking websites.
Tampere University of Technology
Master of Science Thesis, 87 pages, 1 Appendix pages
March 2019
Master's Degree Programme in Industrial Engineering and Management
Major: International Sales and Sourcing
Examiner: Professor Nina Helander

Keywords: Social networking, consumer, emotions, sentiment, customer behavior, business intelligence, marketing intelligence, activity recognition, image captioning, face emotion detection, sentiment analysis.

The social networking environment goes beyond connecting friends. It also connects customers with companies and vice versa. Customers share their experience with friends, followers, and companies and these experiences carry sentiments and emotions thereby creating big data. There is an ocean of data that is available for companies to extract and make meaning out of it by applying to different business contexts such as consumer feedback analysis and marketing & communications. For companies to benefit from consumer emotion data, they must make use of computational methods that can save time and work consumed by traditional consumer research methods such as questionnaires and interviews.

The objective of this research is to explore existing literatures on detecting consumer emotions from social networking data. The author carried out a systematic literature review on research articles from three bibliographic databases with the intent to find out social networking data extraction process, dataset sizes, computational methods used, consumer sentiments, emotions studied, limitations and its application in a managerial context. To further understand consumer emotion detection, a case study in the form of a Twitter marketing campaign was conducted to emulate the process of consumer emotion detection on a company that is selling stress management products and services.

The results indicate that most companies use Twitter networking platform to carry out consumer emotion analysis. The dataset sizes range from small to very large. The studies have used variety of computational methods, some with accuracies to measure the performance. These methods have been applied in various industries such as travel, restaurant, healthcare, and finance to name a few. Managerial applications include marketing, supply chain, feedback analysis, product development, and customer satisfaction. There are few limitations that were identified from using these methods. The case study results and discussion with the case company CIO communicated the potential for the use of some of the methods for consumer behavior research. The valuable feedback from the CIO revealed that by customizing existing methods, their company can create new tools and methods to understand their customers by providing better recommendations and customize their offerings to individual customers.

PREFACE

This research study is aimed at understanding consumer emotions on social networking websites and was carried out in the department of Industrial Engineering and Management, Tampere University of Technology (TUT) Tampere, Finland. I would like to thank the university for providing me the opportunity and resources to pursue my master's degree in Industrial Engineering and Management.

First, I would like to thank Dr. Jari Jussila for his concrete belief and recognition in my ability for which I am deeply grateful, this research study wouldn't have been possible without his freedom, support, and invaluable guidance. I also thank him for helping me publish my first research publication and providing me the opportunity to work with him at HAMK. I would like to thank Professor Nina Helander for her expert guidance and for her support to the students and staff in the department of Industrial Engineering and Management. I am grateful to Karan Menon for his guidance and counsel.

I would like to thank my friends who have been supportive of me during my difficult times. Special thanks to my late grandfather, Thirupathi, my grandmother, Lakshmi, to my late maternal grandparents. I want to thank Aadarsh, Divya and Lohith. I wish to thank my father Srinivasa Rao for his constant support and encouragement. Finally, to my late mother Uma Maheswari for her unconditional love and affection.

Tampere, 18.3.2019

Prashanth Madhala

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LIST OF SYMBOLS AND ABBREVIATIONS

API	Application Programming Interface
CIO	Chief Information Officer
DMO	Destination Marketing Organization
DoT	Degree of Trust
FP	False Positive
HTML	Hypertext Markup Language
NB	Naïve Bayes
NLP	Natural Language Processing
PyPI	The Python Package Index
SNS	Social Networking Sites
SNW	Social Networking Websites
SVM	Support Vector Machine
UGC	User Generated Content

1. INTRODUCTION

1.1 Social Media

According to Kaplan and Haenlein (2010), social media can be defined as a collection of internet-based applications that support the basis of Web 2.0 (both ideological and technological), thereby enabling the production and exchange of User Generated Content (UGC). Social media is a communication medium that facilitates intercommunication and interaction between billions of individuals on a global scale; and has affected the way consumers perceive marketing messages directed at them. Social Media platforms and their providers create many opportunities for influence that did not exist previously (Williams *et al*., 2012).

YouTube (video sharing), Flickr (image sharing), Twitter (micro blogging), LinkedIn (business networking), Facebook (social networking) are some of the examples of Social Media (Whiting and Williams, 2013). Social media is used for variety of reasons. For example, Whiting and Williams (2013) researched and concluded ten uses and gratification themes when investigating the motive behind people using social media; the ten themes concluded by the authors are shown in the following table.

Table 1. *Uses and gratification themes concluded by Whiting and Williams (2013).*

No	Theme	Explanation
1	Social Interaction	In their study, 88 percent of the study respondents used social media for social interaction. For example, they connect with their family and friends using social media. This is further extended to make new friends.
2	Information seeking	80% of the study respondents seek out information with the help of social media. For example: Information regarding sales, products, events, birthdays, and businesses.
3	Pass time	As many as 76% of the respondents used social media to pass time when they are at work or at school, or if they are bored.
4	Entertainment	64% of the respondents considered social media as a source of entertainment. For example, watching various videos, listening to music, and playing games.

5	Relaxation	60% percent of the respondents used social media to relax. For example, as a buffer to get away from real world.
6	Expression of opinions	56% of the respondents saw social media as a medium for expressing their thoughts and opinions, and to condemn others.
7	Communicatory utility	50% of the respondents mentioned that social media gives them something to talk about. For example, their friend, or something that happened on Facebook.
8	Convenience utility	52% of the respondents said that social media is convenient. For instance, it is very easy to use anytime because of its easy availability.
9	Information sharing	40% of the respondents stated that they used social media to share information. For example. To advertise their business, share pictures or updates.
10	Surveillance	32% of the study respondents mentioned surveillance. For example, to look at what's happening in other people's lives.

Table 1 talks about the uses and gratification themes of social media concluded by Whiting and Williams (2013) in their study "*why people use social media: a uses and gratifications approach"*. The table shows various themes where social media has been used by people. The emergence of social media has significantly altered the way in which people, communities and organizations communicate, which has attracted attention from industry and academia (Ngai, Tao and Moon, 2015).

Inclusiveness (ability to be a part of a community without any difficulty), easy participation (allows an individual to share opinions with ease), and availability of knowledge are some of the benefits of social media (Uren *et al.,*2016). The benefits not only involve social interaction/exchange but also for establishing reputation, opportunities in career, and generating revenue (Tang, Gu and Whinston, 2012). Social media serves as a utility for communications and activities within the organizations (Mangold and Faulds, 2009), for creation of online knowledge sharing communities (Fernando, 2010), and brand management (Jin, 2012). For companies, the methods of interacting with customers has significantly changed with the advent of social media where customers educate other customers about products, brands, problems, and services; the explosion of internet communication through social media has a major role in influencing consumers in various aspects such as creating awareness, information acquisition, opinions, behaviors with regards to purchase and post-purchase, and evaluation; when companies like Proctor and Gamble, General Electric entered the social media sphere, they carefully aligned their communications to repeatedly convey their organizational values to the online market (Mangold and Faulds, 2009).

1.2 Emotions

Emotions are a central feature in a human being's life. Emotions contain many aspects such as behavior and physiology, experience and feelings, they also include perception and conceptualization; emotions emerge as a result to a situation perceived by the experiencer; a wide variety of emotions occur in an individual when something good or bad occurs (Ortony, Clore and Collins, 1988). According to Ekman (1992), each emotion is unique that it has signals, preceding event, and physiology. They also have similar characteristics with other emotions such as rapid onset or quick beginning, short interval, spontaneous occurrence, automatic evaluation, coherence among replies; these extraordinary traits are a result of our evolution and are distinguishable from other affective events. Ekman (1992) also defined six basic emotion namely anger, fear, sadness, disgust, enjoyment, and surprise. He coined these basic emotions based on similar facial expressions of each emotions prevalent across human cultures.

Emotions are bioregulatory reactions that focus on advocating physiological states either directly or indirectly to ensure survival and survival that promotes well-being; emotions are accompanied by behaviors that is carried out by certain type of mental function or operation (Manstead, Frijda and Fischer, 2004). Positive emotions (for example: Happiness) are expressed by individuals when they experience something that is fair or just and negative emotions (for example: Anger) when they experience an unjust event (Lewis, Haviland-Jones and Barrett, 2008). Emotions can be witnessed as a result of other psychological phenomenon such as perception, alertness or concentration, and memory; an untrained person or a scientist is convinced or know what anger, fear, or sadness when they notice it (Barrett, 2006).

According to Nussbaum (2001), emotions make the core of our mental and social lives; they are very complex aspects that form an integral part of a thinking creature's psychological mechanism; emotions involve judgements where external objects (and events) are evaluated because of its importance to an individual's well-being. Emotions are expressed when positive or negative events happen to an individual or to a person that the individual relates to; sometimes emotions are triggered without an individual's involvement. For instance, by looking at a photograph of a child in distress can trigger emotions such as anger and sympathy; different events trigger different emotions in an individual (Haidt, 2003). People vary with respect to their awareness and knowledge regarding events, people, and various circumstances that generate emotions; presence of significant emotional intelligence could possibly assist in efficient leadership in human beings (George, 2000). According to Scherer (2005), there are five components of emotion namely cognitive (assessment or appraisal) – evaluating situations and objects; neurophysiological (physical symptoms); motivational (action tendencies) – formulation and direction of action; motor expression (oral and facial) – response communication ,and intention with regards to behavior; subjective feeling (experience of emotion) – interaction with environment and keeping a watch on inner state. Emotions which developed during the process of human evolutions are responsible for new action propensities, new types of motivation, wide variety of behaviors required to handle or manage the environment and life's needs (Izard, 1991).

1.3 Consumer Business

Laitamäki and Kordupleski (1997) say that the purpose of an organization is to create products and services which the customer deems valuable and further adds that an organization's success is guaranteed only if they provide competitive customer added value; the value is determined by the satisfaction of the products purchased to the price paid. According to the service centered dominant logic by Vargo and Lusch (2014), a customer's role is that of a coproducer of service; as a result, marketing process is a direct result of customer interaction and customer acts as fundamental resource during this process; the value of a product or a service is determined by the consumer based on his/her perception of value, and a company only has the control of creating value propositions; co-production and relational exchanges are a result of active consumer participation. The benefits achieved through cost models, service quality and market share do not ensure success as the fundamental aspect of a successful business is determined by its value creation process (Reichheld, Robert Jr and Hopton, 2000).

According to Lemke, Clark and Wilson (2011), a consumer's personal encounter with a firm either directly or in-directly can be conceptualized as consumer experience and the perception of superiority of the consumer experience as customer experience quality. The authors introduce a model of customer experience quality where the consumer's idea of value is of four types namely utilitarian (functional), hedonic (pleasure), relational, and cost/sacrifice (economical) that produces several outcomes where customers involve in purchase, customers are committed and can be retained, customers engage in word of mouth; however, other dimensions that make up the model include communication encounter (communication), and service encounter (quality of product, quality of service – value for time, attitudes towards customer, customization, etc.).

Application of customer equity to marketing and organization strategy puts customer and customer value as the fundamental aspect of organizational activities. A firm's current customers become responsible for the inflow of revenue and profits in the future, therefore this should be the spotlight for marketing activities; there are three key factors that support customer equity and they are value equity (price, convenience, and quality), brand equity (subjective and abstract evaluation of the company), and relationship equity (loyalty programs and affinity programs); in value equity, companies must look to provide high quality service, reduce customer's time, effort and cost in relation with the product or service; in brand equity, companies must make emotional connection with the customers. for example: either through campaigns or direct marketing, by showcasing high standard of corporate ethical behavior; in relationship equity, companies must reward customers according to their behaviors with material benefits (loyalty programs), or affinity programs and knowledge building programs where companies can track and under consumer preferences while saving costs (Lemon, Rust and Zeithaml, 2001).

1.4 Research background

Social Media and Consumers

The use of social networking websites allows users to express their views with others and in this way, social media acts as a valuable source of data for getting insights about consumers. The expression of views through online medium has also paved various avenues for research in social media data, primarily in marketing sector to enhance customer satisfaction (Abirami and Askarunisa, 2017). Social media content includes emotional experiences, opinions regarding everyday situations including products consumed and life experiences (Li and Li, 2013). Consumers seek opinion of their friends or family members in the online platform when buying new products or seeking new services (Kumar, 2014). Results from Petz *et al.* (2015) convey that microblogs contain mostly subjective information and as such consumers write about product perceptions (e.g. feelings and reactions) which are outlined with facts. Therefore, product reviews are being posted online by consumers who bought and experienced the product, these reviews are found to be helpful for others (M. *et al.*, 2017a). Apart from sharing experiences with other consumers, some offer their views directly to the firms about products and services; few consumers post negative reviews to help communicate the short-comings of a product to the company while others who are angry and dissatisfied post in a negative manner to harm company's reputation in an attempt to seek revenge for mistreatment (Bougie, Pieters and Zeelenberg, 2003; Grégoire, Laufer and Tripp, 2010; Kähr *et al.*, 2016; Obeidat *et al.*, 2017).

A meaningful amount of time is spent on social media by users who form a big percentage of consumers that involve in the act of consumption of online services (Trusov, Bucklin and Pauwels, 2008; Hollenbeck and Kaikati, 2012; Ashley and Tuten, 2015). Consumers use social media applications such as Facebook, Twitter and Instagram to share among friends and colleagues about their lifestyle related to products they consume, their political orientation, places they travel and to keep themselves informed regarding up-to-date information of their preferred brands (Dimitriu and Gueslaga, 2017). Social media allows companies to engage with customers online to form relationships and create customer experiences (Mollen and Wilson, 2010). Consumers show their brand orientation by liking or following (Kabadayi and Price, 2014). For instance, F.C. Barcelona's Facebook page generates content which is liked, commented and shared by consumers where it could mean that consumers have personal affiliation towards a particular player of the football team, political orientation towards pro-independent parties of Catalonia and even brand association with respect to the football club's corporate sponsors or promotors (Vatrapu, Mukkamala, Hussain and Flesch, 2016). Some research also points that engagement between social media brands have an effect on purchases (Goh, Heng and Lin, 2013).

Social Media and Big Data

Large population of customers and their generated data are analyzed using big data and social media is a platform for generating big data because it facilitates information diffusion and opinion sharing; however, analyzing such high volumes data requires sophisticated analytical technology (Li, Li and Zhu, 2016). Big data is created through many sources such as traffic from the internet, mobile transactions, user generated content (UGC), finance, healthcare, purchases and social media. This also includes intentionally generated data from sensors and business transactions (George, Haas and Pentland, 2014). The adoption of social media by organizations and society has led to generation of massive volumes of data which are unstructured and is termed as Big Social Data (Vatrapu, Mukkamala, Hussain and Flesch, 2016). The study of social media data allows firms to achieve successful communication with its customers and also helps to understand consumer's opinion about company's products and services (Lusch, Liu and Chen, 2010; Doan, Ramakrishnan and Halevy, 2011).

Social Media, Emotions, and Consumers

Jussila *et al.* (2017) introduced a novel marketing analytics tool for measuring affective phenomenon which could replace conventional consumer satisfaction measurement systems like surveys, they measured consumer experience in pleasure, arousal and dominance (PAD) dimensions. As consumers communicate in social media platforms, they express emotions which are recorded in the social media history in the form of emotional chronicle (Bernabé-Moreno *et al.*, 2015). Denecke and Nejdl (2009) approached their study in a way that allowed them to differentiate between posts that fall into two categories such as informative and affective which can further be characterized into positive and negative. According to Li and Xu (2014), emotion rich data can be found in the microblogging sites where opinions are shared and discussed; microblogs also facilitate big amount of data that contain emotions and events that evoke these emotions. It can be argued that social media contains wealth of human generated input comprising opinions, views, criticism and reaction towards products, issues and services with sentiments which are further categorized into positive, negative and neutral (Z. Wang *et al.*, 2016a). Following customer's conversations on social media can help companies react to positive and negative feedback (Lee, 2018). A number of managers are keen on decoding consumer's sentiment statements from social media comments and reviews for the sake of investigating product and assessing their services (He *et al.*, 2015)

The accelerated growth of social media has stimulated a moving and prominent area of research called sentiment analysis to extract valuable information from opinions of people on social and business problems (Ghiassi, Skinner and Zimbra, 2013a). Lee (2018) states an example where companies may monitor customer's frequency of postings about a competitor and the related sentiments on different social media platforms to create benchmarks for comparisons; conducting trend analysis of customer's sentiment and deriving product perceptions of competitor's products for improved product designs from these sentiments. Wang *et al.* (2016b) proposed a conference paper titled *'Fine-Grained Sentiment Analysis of Social Media with Emotion Sensing'* where sentiments have further been classified into emotion categories; positive sentiment classified into satisfaction, happiness and excitement whereas negative sentiment classified into anger, sadness and anxiety. Davalos *et al.* (2015) implied that advertisements can be targeted at consumers who post nostalgic Facebook posts; in his study, he found that major percentage of nostalgic posts contained affective content (positive and negative).

1.5 Research questions

From the research background, it is evident that everyday life experiences and moments are shared on various social media platforms. Consumers use products and services daily and they feel the need to share their experience with friends and family members. Social media is a progressive platform that facilitates this activity of opinion sharing where consumers reveal sentiments and emotions when expressing their views related to politics, products, services and other topics. Additionally, these sentiments have positive and negative polarity. When carefully examined, positive and negative sentiments can be further classified into various emotions. Companies and academics see this unstructured raw data as an important and useful resource that can be mined for aggregate level information which can provide key business metrics for understanding consumer behavior. Analyzing these emotions can help companies study consumer behavior and its impact on different areas. Emotion analysis could help companies tailor their marketing campaign towards customers which can complement marketing intelligence. At the same time, this process of sharing creates massive amount of social media data called as Big Social Data. Analyzing big data requires other computational information and technology. It is important for organizations to base their business operations on big data. According to Fosso Wamba *et al.* (2015), big data has the ability and potential to alter current business processes and the management profession caused by the diffusion of 'Internet of things' concepts and social media platforms such as Twitter and Facebook.

Earlier works in similar area of analysis is mentioned. Sheng *et al.* (2017) reviewed various literatures on big data in management research and found various topic and application areas of big data where consumer behavior and consumer sentiment are studied in marketing sector. Poria *et al.* (2017), wrote a comprehensive literature review about state-of-the-art methods used for audio, video and text modalities, for detecting emotions and sentiments; the author also discussed different computational models used in multi-modal analysis; however, the datasets mentioned in the study are existing datasets and were not extracted in real time. Kumar and Ravi (2016) reviewed research studies on applications of text mining in financial domain such as stock market prediction and FOREX rate forecasting. Ravi and Ravi (2015) produced a literature review on distribution of articles based on sentiment, tasks and applications, accuracies, and computational methods. Piryani *et al.* (2017) reviewed various studies in opinion mining and sentiment analysis in various application areas and different dataset types. Bravo-Marquez *et al.* (2014) offers intuition into different resource components for identifying human emotion and opinion using existing datasets as empirical data. Medhat *et al.* (2014) reviewed different algorithms and approaches in sentiment analysis. H. Wang *et al.* (2016) reviewed recent literature on social big data, it's methods and area of focus. Facebook with 2 billion users, Instagram and Twitter with 700 million and 328 million users respectively in 2017 (Chaykowski, 2017; Constine, 2017) convince the volume of consumer data available in the social networking websites and in this study, the focus is only on social networking platforms due to its population size. Therefore, our scope is towards answering the following question:

> *What are the different managerial applications resulting from detection of consumer emotions in social networking data?*

The above question arises from the discussion in the previous paragraph about the work that had already been done and through this study we aim to answer the following questions regarding social networking, consumer and their emotions in social networking context.

Q1: How are the current consumer emotion social networking data extracted in the current literature and from which social networking platform?

Q2: What are the different consumer sentiments and consumer emotions that are investigated in the current literature?

Q3: What are the dataset sizes that are extracted for consumer emotion analysis in existing studies?

Q4: What are the different computational methods used in studying consumer emotions and how are they evaluated in the current literature?

Q5: What are the limitations while detecting consumer emotions in social networking sites in the current literature?

Q6: Where can consumer emotions be applied in a managerial context?

1.6 Structure of thesis

The overall structure of the thesis has the following sections: Introduction, research methodology, results and findings, discussion and conclusions. The Introduction provides an overall description of background of social media, emotions and consumer business. Major discussion involves how consumers express emotions openly in social networks and how social networking websites facilitate generation of large amounts of UGC. Narratives leading to the scope of this research and selection of research questions are also mentioned in this chapter.

In the second chapter, research methodology is explained. The type of research methodology that is used is explained in chapter 2.1 and the application of the type of research methodology is thoroughly explained in chapter 2.2. Chapter 2.3 focuses on the research methodology that was used to carry out empirical research and evaluation. It is also in this section that research question 6 is further subdivided into 5 parts or sub questions and ends with the evaluation criteria. Results of the thesis is elaborated in chapter 3. Results overview is explained in Chapter 3.1 in tabular format. Empirical evaluation to the thesis is presented in chapter 3.2. Chapter 4 discusses the summary of the results, scientific contributions as a result of this study, managerial contributions, evaluation of the study and future research in the application of consumer emotion detection.

2. RESEARCH METHODOLOGY

2.1 Literature Review

The literature review in this thesis study is based on Fink (2014)'s 'Conducting Research Literature Reviews'. According to her, research literature review is a systematic, explicit, accurate and reproducible method used for the purpose of identifying, assessing and combining existing body of completed and documented works by researchers, scholars and practitioners.

A research literature review can be performed based on an individual's work in diverse fields of specializations such as health, education, psychology, finance, law, social services and business. The conclusion of a systematic research literature review is based on the authentic works of scholars and researchers. The idea is to focus on great quality authentic research instead of interpreting the findings; this is one way to assure that the results are under reviewer's supervision and correctly carried out. There are several steps on how to perform Fink's research literature review. It can be divided into seven tasks and is shown in Figure 1.

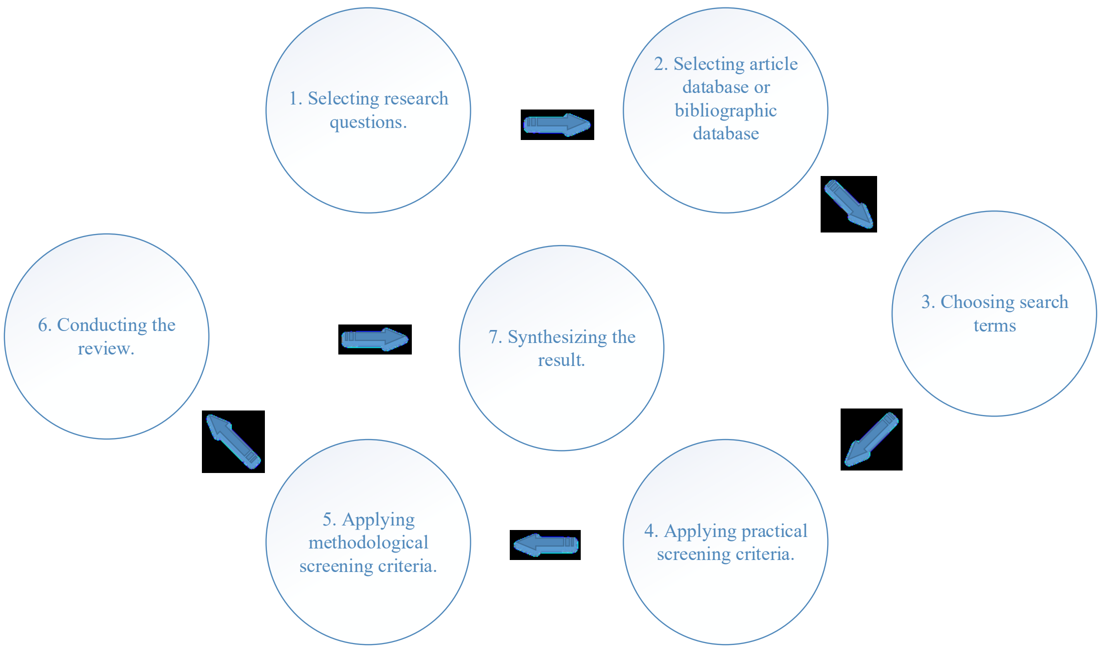

Figure 1. *Seven steps in conducting Fink (2014) model of research literature review.*

In the Figure 1 is a depiction of research literature review adapted from Fink (2014). There are seven tasks that are carried out to achieve Fink's model of conducting a review and can be explained as follows in Table 2.

***Table 2**. Tasks and explanation of steps involved in conducting a literature review.*

Tasks	**Explanation**
Selecting research questions	The review is lead or carried out after stating a precise research question.
Selecting bibliographic or article databases, Web sites, and other sources	A bibliographic database, which is accessed online is an accumulation of research articles, books and reports that can contribute data to answer research questions. Complete reports of original studies can be found in bibliographic databases. Literature reviews can also be referred from other sources such as experts from the field of interest, the web, list of references contained in the articles.
Choosing search terms	Search terms which are words and phrases are used to get the relevant articles, books and reports. The search terms are based on research concepts that are linked to the research questions. Appropriate grammar and logic are required to conduct the search.
Applying practical screening criteria	Once search terms are entered, the results return many articles. Among these, not all are relevant. The relevant articles are retrieved by screening the literatures; this is done by setting a criterion for inclusion and exclusion. Practical screening criteria consists of elements such as language, type of article, publication data and source of funding.
Applying methodological screening criteria	Methodological screening criteria is about including criteria for the purpose of evaluating scientific quality.
Doing the review	Reliable and authentic reviews hold adopting a standardized form for extracting data from articles and training reviewers to summarize and supervise the quality of the review, additionally pilot testing the procedure.
Synthesizing the results	Results of the literature review could be combined descriptively. Descriptive syntheses are clarification or analysis of the literature review's findings based on the experience of the reviewer, quality and substance of the available literature. The review can include also meta-analysis which involves employing statistical techniques to merge more studies.

Various tasks and explanation of Fink's methodology of performing a research literature review is explained in Table 2. A research literature review is conducted for many reasons. For example, to understand what is presently known in a specific topic of interest. Sometimes, it is asked to include a research literature review in a master's thesis or honor's thesis, dissertation and to obtain funds for planning a program, developing and evaluating it.

2.2 Application of literature review

The research literature review methods outlined in the previous section are explained in the context of the thesis study in this section. Task 1 is selecting research questions: The research statement question and the research questions are mentioned in Chapter 1.5. There are 6 research questions that is aimed to be answered through this study. For task 2, article databases or bibliographic database chosen were IEEE Xplore: which provides access to high standards of technical literature in engineering and technology, second, ScienceDirect: ScienceDirect contains engineering and physical science publications and third, Web of Science: provides access to multiple databases that reference cross disciplinary research. The research databases that were selected for this study can provide the relevant information which is needed for conducting the thesis study.

In task 3, search terms are chosen. The search terms are used to find the appropriate articles in all the bibliographic databases and similar search terms were used, which are "social media" emotion* consumer (see Appendix A). Task 4 is about applying practical screening criteria. Here, research studies for the review are selected based on inclusion and exclusion criteria. From all the databases only journal articles, research reviews and research articles were selected. The inclusion and exclusion criteria are mentioned as follows:

Inclusion criteria:

1) Include studies that are published in English language
2) Include only journal and research articles
3) Include studies that talk about consumer emotions in social media context
4) Include articles that mention data extraction methods

Exclusion criteria:

1) Exclusion of duplicates
2) Exclude articles without automated data extraction methods
3) Exclude articles that are not specifically talking about social networking platforms
4) Exclude articles that perform analysis on existing datasets. The following image displays the inclusion and exclusion criteria.

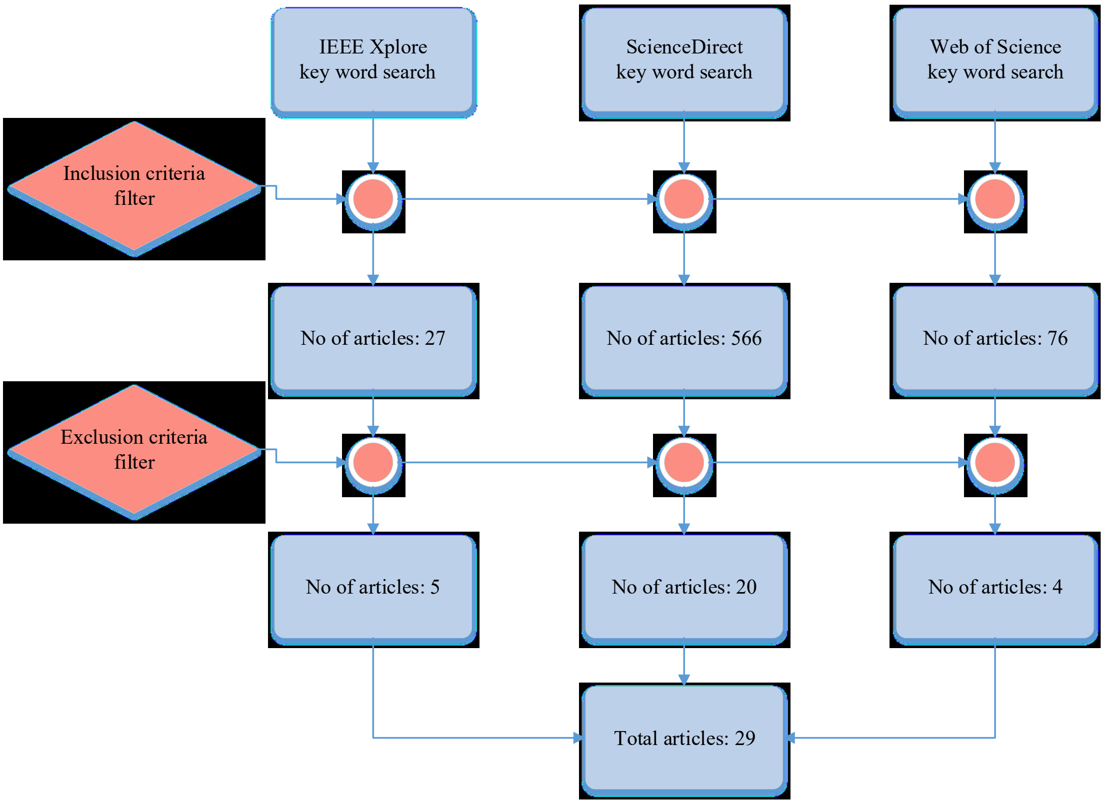

Figure 2*. Flow diagram of articles' inclusion and exclusion criteria.*

Figure 2 shows the flow diagram of article's inclusion and exclusion criteria. In the beginning, inclusion criteria were based on research article abstracts that talk about consumer emotions in social media context; this did not yield practical results and therefore we included articles based on paper content. The papers that resulted in the final inclusion and exclusion were 5 from IEEE Xplore (out of 86 articles), 4 from Web of Science (out of 145 articles), 20 from ScienceDirect (out of 1457 articles). In total, the papers add up to 29.

2.3 Mixed Methods Methodology

According to Creswell (2012), if the research contains data that is both qualitative and quantitative in nature, then both quantitative and qualitative data can be used to study the research problem that is placed. The mixed methods research design approach or technique is used for gathering, analyzing, and combining both qualitative methodology and quantitative methodology to perceive a research problem (Creswell and Plano Clark, 2011). Mixed methods research design is used when either of the research design, for instance: qualitative or quantitative is not enough for gathering insight into a problem (Creswell, 2012). A complicated understanding or a 'picture' can be developed by evaluating both outcome (Green and Caracelli, 1997). This allows the researcher to produce an alternate perspective in a study (Creswell, 2012).

Jick (1979) provides an example that a leader's effectiveness can be judged by interviewing, witness his/her behavior, and execution of one's task; The focus is on the effectiveness and irrespective of the modes of evaluation. Similarly, in this study to understand the research questions formulated in chapter 1.5, first a systematic literature review is conducted to gather articles relevant to the study. After careful analysis, to get a different perspective of the research problem. A case study methodology is conducted to gather multiple perspectives.

2.3.1 Case Study Methodology

A case study methodology was conducted to understand several perspectives of the research questions. According to Zainal (2007), a case study allows a researcher to inspect or investigate a data under a certain circumstance. For instance, it can be limited to a small geographical location or small number of subjects. According to Bonoma (1985), a case study involves not only qualitative, but also quantitative data sources. Various sources of data support 'perceptual triangulation' that aids in understanding the business unit which is under observation.

In relation to the previous chapter, a case study was conducted. The primary data source for the case study was Twitter, a social networking platform. This is also because of its rise in popularity and adoption by various companies to communicate with their stakeholders (Rybalko and Seltzer, 2010). The case study was conducted in the form of a marketing campaign for a stress management company who sell products and services. The time duration of the campaign was 22 days between the months of August 2018 and September 2018. The campaign tweet was posted in Finnish language where the company asked its followers to join the campaign in exchange for a lucky draw prize. The participants were required to tweet a message with an image to convey how they manage or cope with stress.

The campaign tweet posted for the campaign was *"Syyskuu tuo mukanaan arjen monet haasteet. On kiirettä, mutta myös intoa! Mikä on sinun paras stressinhallintakeinosi? Osallistu Moodmetricin Twitter-kampanjaan - voit voittaa @Moodmetric-älysormuksen. Kampanjan ohjeet: http://www.moodmetric.com/fi/uutiset/ #moodmetricstressinhallintakeino"*.

The above tweet translates to *"September brings many challenges to everyday life. There is haste, but also enthusiasm! What is your best stress management tool? Take part in Moodmetric's Twitter campaign - you can win the @ Moodmetric ring. Campaign Guidelines: http://www.moodmetric.com/en/news/ #moodmetricstressmanagement"*. A screenshot of the tweet is shown in the following image.

Figure 3. *Marketing campaign tweet which translates to "What is your best stress coping habit?".*

Figure 3. shows the initial tweet of the campaign. It was also tweeted with the hashtag "#moodmetricstressinhallintakeino" which translates to "moodmetric stress management tool". The hashtag was used to encourage more participation in the twitter campaign.

Data Collection

Quantitative Data

The tweets were gathered with many tools such as Twitter API credentials, a library called twitter library 1.18.0[1] from Python Package Index (PyPI) and Python programming language. The PyPI[2] is a software depository for Python Programming Language. With these tools, up to 100 tweets can be extracted with one request and within 1-week time window from a single request.

An integrated development environment for python called Spyder[3] is utilized for coding purposes. The total number of unique tweets and images were 47, retweets and any

1 https://pypi.org/project/twitter/
2 https://pypi.org/
3 https://www.spyder-ide.org/

other duplicates were excluded from the data analysis. Every tweet has many components such as text, tweet ID, and media to name a few. The images were extracted from the media component using the tweet URL that is present inside the media component of the tweet. The following image shows the information regarding APIs, libraries and algorithms used for the case study.

1. Data	2. Image caption detection and face detection	3. Translation	4. Sentiment detection	5. Emotion analysis
Twitter (API), Twitter Library from PyPI (1.18.0), Python programming language	Microsoft's Image Processing with the Computer Vision API and Microsoft Face API Facial Recognition Software	Googletrans library from PyPI	VADER sentiment analysis and SentiStrength	IBM Watson tone analyzer
Tweets were gathered in the months of August 2018 and September 2018	Image captions and face emotions were extracted from tweet images using the above API	Finnish language tweets are translated into English language using the MIT licensed library from PyPI	Sentiment for the tweets are calculated using two sentiment detection algorithms. The sentiments are classified into *'positive'*, *'negative'*, and *'neutral'*	Tweets are also analysed for its emotional content. The content was analysed for emotions such as *'anger'*, *'disgust'*, *'fear'*, *'joy'*, and *'sadness'*.

***Figure 4**. Algorithms, libraries and APIs used in the analysis of the tweet content.*

As seen from Figure 4, different APIs, libraries and algorithms are necessary in order to analyze the tweet for its sentiment, emotion and image captions. Without the Twitter API credentials it is not possible to gather tweets on our own. The availability of Twitter libraries for different applications eases the process of data collection. To detect captions from the tweet images, Microsoft's Image Processing with the Computer Vision API[4] was used. The API has the capacity of handling or processing 20 images per minute. The API returns several attributes for the image. The tags and description (caption) are among such attributes and is also the focus of this study. For instance, the description can be *'man in a red shirt taking a photo at the beach'* and tags for the description can be (*'man', 'beach', 'holding', 'camera', 'shirt', 'red', 'sun glasses', 'camera', 'water', 'sand'*). Microsoft Face API[5] – Facial Recognition Software was used to detect consumer faces and their emotions from the images. Like the Image Processing API, the Face API process up to 20 images per minute and returns various attributes with regards to the face. For the purpose of this study, only the emotion attribute is considered. The emotion attribute returns emotions such as *'anger', 'contempt', 'disgust', 'fear', 'happiness', 'neutral', 'sadness',* and *'surprise'* with values attributed to it between 0 and 1.

The tweets must be converted into English language before they are analyzed for their sentiment. The translation was achieved with the help of MIT licensed PyPI library called Googletrans[6] version 2.4.0. The text component of the tweet was analyzed with the help of SentiStrength[7], a sentiment detection algorithm and VADER (Valence

[4] https://azure.microsoft.com/en-us/services/cognitive-services/computer-vision/
[5] https://azure.microsoft.com/en-us/services/cognitive-services/face/
[6] https://pypi.org/project/googletrans/
[7] http://sentistrength.wlv.ac.uk/

Aware Dictionary and sEntiment Reasoner)[8] sentiment detection algorithm. The notion behind using two different sentiment detection algorithms is to gather multiple perspectives and to understand if they are similar or different in the process of detecting sentiments. In SentiStrength, a text like *'I love the weather at the beach today'* would yield a positive strength of +3 and a negative strength of -1. The overall scale of the text is +2 (*'positive'*). This basis is used for calculating the sentiment for the tweets. VADER classifies tweet into pos (positive), neg (negative), neu (neutral) and compound. The scores calculated using VADER are normalized between -1 (most extreme negative) and +1 (most extreme positive). Therefore, the text *'I love the weather at the beach today'* would return *'pos'*: 0.412, *'neu'*: 0.588, *'neg'*: 0.0, and *'compound'*: 0.6369. Therefore, the sentiment is *'positive'*.

In addition to the sentiment detection, the text component of the tweet is analyzed for its emotions using IBM Watson's Tone Analyzer API[9]. The Tone Analyzer provides scores for each emotion that is detected in the text. The text '*I love the weather at the beach today'* returns the emotion *'Joy'*. The tweet image contained several tags as mentioned earlier and to extract the sentiment and emotion associated with each tag, a 'for' loop was created using Python programming language to count the sentiments and emotions that occur for each unique tag. For instance, over the course of analysis, an activity like *'Running'*, if present in multiple tweets would have sentiment and emotion attributed to it due to its presence in the tweet.

Qualitative Data

Due to fewer number of tweets, qualitative assessment was performed manually. The tweets containing the text and images were manually evaluated/annotated for two categories namely 'Valence' and 'Arousal'. The two attributes were annotated based on the understanding gathered from Zimmerman *et al*. (2015). The case company has its own categories of activity in its product's mobile application. Hence, the manual annotation considered the same activity categories (case company) in its evaluation. The activities are '*Work', 'Relax', 'Dining', 'Travel', 'Sport', 'Family', 'TV/Web', 'Art', 'Sleep',* and *'Other'* (Jussila *et al.*, 2018). The qualitative assessment for both valence and arousal dimension was performed on a scale between -5 to +5 by looking at the tweet text and image. The above-mentioned activities were mapped for its valence and arousal attributes based on this scale. For example, if the participant tweet is related to sporting activities then the tweet is assigned to the *'Sport'* activity. Similarly, tweets were also screened for other activity categories. For further assessment of all the results, a qualitative semi-structured interview was conducted with the case company's CIO. The focus was on the application of consumer emotions in managerial context and the following questions were asked.

1) How is the company currently making use of consumer emotions?

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[8] https://github.com/cjhutto/vaderSentiment

[9] https://www.ibm.com/watson/services/tone-analyzer/

2) What challenges does the company have in collecting data and analyzing consumer emotions?
3) How could the quantitative results, qualitative content + quantitative results and qualitative results is made use of in the company?
4) What is most valuable method for making use of consumer emotions?
5) How can the company implement the introduced methods in their business?

2.4 Evaluation Criteria

The methodology for evaluating the study was referred from Shenton (2004) which is based on criteria used for finding the authenticity of qualitative research methodology established by Guba (1981). The research methodology follows four different criteria.

a) Credibility: The criteria address the researchers' internal validity, where they attempt to confirm if their study investigates what it is intended for. Several factors make up credibility of the study. For example: the use of research methodology and data gathering techniques for conducting the study; establishing familiarity with the case-study organization; random sampling to eliminate researcher bias in selecting the participants for genuine representation of the whole population; triangulation where multiple methods such as observation and interviews are used and has its own benefits for qualitative research.

b) Transferability: This criterion is about the external validity which deals with how the findings of a study can be implemented in other conditions. For example: to a wider population or a similar context; other factors include the number of participants, restrictions related to the type of people that produced the data, data collection methods, length and duration of the data collection.

c) Dependability: The researcher makes use of techniques to demonstrate the outcome of attaining similar results if they repeated the same work under similar circumstances using the same methods. For example: Using overlapping methods. In other words, the processes that were employed in the study should be reported at length. This is to help the future researcher to carry out the work.

d) Confirmability: In this criterion, a researcher should admit the limitations of their own study and the resulting effect of those limitations. The researcher must use triangulation to reduce the effect of one's own bias. Researcher must admit his/her own beliefs and assumptions.

3. RESULTS AND FINDINGS

3.1 Overview

After screening the articles for inclusion and exclusion criteria, the final count reduced to 29 research articles from the three databases. The overview of the research articles is in displayed Table 3, which shows author, title and publication of the research article.

***Table 3**. Overview of reviewed empirical research studies.*

No	Author	Title	Publication
1	(Nguyen *et al.*, 2017)	Event-Driven Trust Refreshment on Ambient Services	IEEE Access
2	(Zhang *et al.*, 2016)	A semi-supervised topic model incorporating sentiment and dynamic characteristic	China Communications
3	(Vatrapu, Mukkamala, Hussain, Flesch, *et al.*, 2016)	Social Set Analysis: A Set Theoretical Approach to Big Data Analytics	IEEE Access
4	(Mehmood *et al.*, 2017)	UTiLearn: A Personalised Ubiquitous Teaching and Learning System for Smart Societies	IEEE Access
5	(Nan Cao *et al.*, 2012)	Whisper: Tracing the Spatiotemporal Process of Information Diffusion in Real Time	IEEE Transactions on Visualization and Computer Graphics
6	(Jabreel, Moreno and Huertas, 2017)	Semantic comparison of the emotional values communicated by destinations and tourists on social media	Journal of Destination Marketing & Management
7	(D'Avanzo, Pilato and Lytras, 2017)	Using Twitter sentiment and emotions analysis of Google Trends for decisions making	Program-Electronic Library and Information Systems
8	(Abirami and Askarunisa, 2017)	Sentiment analysis model to emphasize the impact of online reviews in healthcare industry	Online Information Review
9	(Park, Jang and Ok, 2016)	Analyzing Twitter to explore perceptions of Asian restaurants	Journal of Hospitality and Tourism Technology

10	(Sun *et al.*, 2018)	Detecting users' anomalous emotion using social media for business intelligence	Journal of Computational Science
11	(Singh, Shukla and Mishra, 2017)	Social media data analytics to improve supply chain management in food industries	Transportation Research Part E: Logistics and Transportation Review
12	(Benthaus, Risius and Beck, 2016)	Social media management strategies for organizational impression management and their effect on public perception	The Journal of Strategic Information Systems
13	(He *et al.*, 2015)	A novel social media competitive analytics framework with sentiment benchmarks	Information & Management
14	(Xu, Yang and Wang, 2015)	Hierarchical emotion classification and emotion component analysis on Chinese micro-blog posts	Expert Systems with Applications
15	(Gao, Xu and Wang, 2015)	A rule-based approach to emotion cause detection for Chinese micro-blogs	Expert Systems with Applications
16	(M. *et al.*, 2017b)	Consumer insight mining: Aspect based Twitter opinion mining of mobile phone reviews	Applied Soft Computing
17	(Aswani *et al.*, 2018)	Search engine marketing is not all gold: Insights from Twitter and SEOClerks	International Journal of Information Management
18	(Vidal, Ares and Jaeger, 2016)	Use of emoticon and emoji in tweets for food-related emotional expression	Food Quality and Preference
19	(Davalos *et al.*, 2015)	'The good old days': An examination of nostalgia in Facebook posts	International Journal of Human-Computer Studies
20	(Ibrahim, Wang and Bourne, 2017)	Exploring the effect of user engagement in online brand communities: Evidence from Twitter	Computers in Human Behavior
21	(Mostafa, 2013)	More than words: Social networks' text mining for consumer brand sentiments	Expert Systems with Applications
22	(Tombleson and Wolf, 2017)	Rethinking the circuit of culture: How participatory culture has transformed cross-cultural communication	Public Relations Review

23	(Chae, 2015)	Insights from hashtag #supply-chain and Twitter Analytics: Considering Twitter and Twitter data for supply chain practice and research	International Journal of Production Economics
24	(Leek, Houghton and Canning, 2017)	Twitter and behavioral engagement in the healthcare sector: An examination of product and service companies	Industrial Marketing Management
25	(Li and Li, 2013)	Deriving market intelligence from microblogs	Decision Support Systems
26	(Philander and Zhong, 2016)	Twitter sentiment analysis: Capturing sentiment from integrated resort tweets	International Journal of Hospitality Management
27	(Nisar and Yeung, 2018)	Twitter as a Tool for Forecasting Stock Market Movements: A Short-window Event Study	The Journal of Finance and Data Science
28	(Ghiassi, Skinner and Zimbra, 2013b)	Twitter brand sentiment analysis: A hybrid system using n-gram analysis and dynamic artificial neural network	Expert Systems with Applications
29	(Daniel, Neves and Horta, 2017)	Company event popularity for financial markets using Twitter and sentiment analysis	Expert Systems with Applications

In Table 3, information regarding the selected author, articles and name of the publication is mentioned. As mentioned earlier in chapter 2.2, all the research articles chosen to study were published in journals, where earliest article is from the year 2012 and latest from the year 2018. This study aims to seek understanding into the data collection methods, dataset features, different social networking platforms and the type of emotions examined in different articles. Table 4 describes the important variables for each study. The following table shows results based on sentiment categories less than three.

Table 4*. Social networking platforms, methods of data extraction, and dataset sizes based on sentiment categories (less than 3).*

Article No.	**Social Networking Platform**	**Data Extraction Method**	**Dataset Size**
7	Twitter	API	1700 tweets
8	Twitter	API	1941 tweets
9	Twitter	API	86015 tweets
10	Sina Weibo	Internet Crawler	10275 microblogs

11	Twitter	API	1338638 tweets
13	Twitter, Facebook	API, HTML Parsing, RSS	Not described
14	Sina Weibo	Crawling	9960 microblogs
19	Facebook	Open graph API	375 857 posts
21	Twitter	QDA Miner	3516 tweets
23	Twitter	API	22 399 tweets
25	Twitter	API	2358477 tweets
26	Twitter	API	34315 tweets

In Table 4, studies than contain fewer sentiment categories of two or less in displayed along with the SNS platform, data extraction method, and dataset sizes. In the following table studies with three sentiment categories are displayed.

Table 5. *Social networking platforms, methods of data extraction, and dataset sizes based on 3 sentiment categories.*

Article No.	**Social Networking Platform**	**Data Extraction Method**	**Dataset Size**
2	Sina Weibo	API	25838961 posts
3	Facebook	SODATO	11384 posts and comments
4	Twitter	API	4221 tweets
5	Twitter	API	10275 microblogs
16	Twitter	twitteR package	2685 tweets
17	Twitter	API	61 456 tweets
18	Twitter	twitteR package	20 490 tweets
20	Twitter	API	76 166 tweets
27	Twitter	API	60944 tweets

In Table 5, studies than contain three sentiment categories are displayed along with the SNS platform, data extraction method, and dataset sizes. In the following table studies with more than three sentiment categories are displayed.

Table 6. *Social networking platforms, methods of data extraction, and dataset sizes based on more than 3 sentiment categories.*

Article No.	**Social Networking Platform**	**Data Extraction Method**	**Dataset Size**
12	Twitter	API	17 million user generated tweets, 200000 company generated tweets
22	Facebook, Twitter	Radian 6	16 005 posts

28	Twitter	API	10345184 tweets
29	Twitter	API	192935 tweets

Table 6 shows studies more than three sentiment categories with the respective social networking platforms, data extraction methods, and dataset size. The following table shows articles by emotion categories.

***Table** 7. Social networking platforms, methods of data extraction, dataset size sorted under emotion categories (up to 10).*

Article No.	Social Networking Platform	Data Extraction Method	Dataset Size	Emotion Categories
1	Not explicitly mentioned	SocioScope	Not mentioned	1 category
7	Twitter	API	1700 tweets	6 categories
10	Sina Weibo	Internet Crawler	10275 microblogs	5 categories
17	Twitter	API	61 456 tweets	6 categories
18	Twitter	twitteR package	20 490 tweets	3 categories
19	Facebook	Open graph API	375 857 posts	9 categories

Information regarding various social networking platforms, data extraction methods, dataset size and emotion categories (less than 10) for different articles is shown in Table 7. The following table shows article information classified under more than 10 emotion categories.

***Table 8**. Social networking platforms, methods of data extraction, dataset size sorted under emotion categories (Above 10).*

Article No.	Social Networking Platform	Data Extraction Method	Dataset Size	Emotion Categories
6	Twitter	Crawler	60000 tweets	289 categories
14	Sina Weibo	Crawling	9960 microblogs	19 categories
15	Sina Weibo	API	18000 posts	22 categories
24	Twitter	API	838 tweets	37 word categories

Information regarding various social networking platforms, data extraction methods, dataset size and emotion categories (more than 10) for different articles is displayed in the above table. Information regarding limitations and evaluation of computational methods for articles grouped under a common computational method is displayed in the following table.

***Table 9**. Articles grouped under a common computational method (Sentiment analysis).*

Article No	Computational Methods	Evaluation of Computational Methods	Primary Limitations
2	Dynamic sentiment-topic model (DST), Gibbs sampling method, Topic detection and tracking (TDT), Sentiment approaches	DST model achieves best perplexity outperforming DTM and LDA models. DST model outperforms other models with regards to classifying sentiments (positive or negative or neutral)	Not described
3	Fuzzy-set based sentiment analysis with α- cuts	With α- cuts > 0.9 (0-1), 7.18 % of the Facebook user group expressed negative sentiment and 19.9% expressed positive sentiment.	Not described
4	Sentiment analysis: Naïve bayes algorithm	Results from the analyzed data show that 78% of the consumers show positive sentiment for distance and eLearning.	Not described
7	Sentiment detection module and Emotion detection module	Case Study 1: ‘Motorola’ and ‘moto x’ has highest % of oriented tweets - 42.9% and 39.4% resp. ‘moto g’, ‘moto x’, ‘motorola’, ‘oneplus’ search queries provide with tweets with emotion - 10.1%, 10%, 9.1%, 8.1%. Tweets contain avg of 48.3% ‘joy’, 24.3% ‘surprise’ emotions. All queries had strong positive orientation (average 86.3%) Case Study 2: Tweets contain 74.5% negative sentiment, 94.1% no emotions (both globally), 50% contain ‘fear’ emotion in NY. Case Study 3 – ‘Trump’ query: prevalent emotion – ‘joy’, ‘Ted	Not described

		Cruz' query - prevalent emotion 'joy', 300 'Ben Carson' - prevalent emotion 'joy', 'Scott walker'- mixture of prevalent emotions on each analyzed day.	
8	Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Multi-criteria decision making (MCDM), Sentiment Analysis and Natural Language Processing (NLP).	Ranking based evaluation - Sentiment scores indicate which hospital ranked number one in different areas for 'infrastructure', 'cost', 'time' – Hospital 10. 'Medicare' and 'nursing' – Hospital 6. Ranking by TOPSIS – Hospital 3, Simple additive weighting – Hospital 10, Website – Hospital 3. Based on hypothesis, TOPSIS is the most preferred method.	Review bias. It means not all the people give genuine reviews.
9	Text mining, Sentiment analysis, Statistical computation with ANOVA	High percentage of positive sentiment found in Thai restaurant, 34.96%. High percentage of Negative sentiment – Chinese, 15.76%, High percentage of neutral sentiment – Japanese, 57.83%	Short data collection period. Data collected includes tweets from commercial organizations which may cause skewed results for example, advertisement tweets can impact quality of the analysis.
12	SentiStrength 2, Naïve Bayes, Data analysis	User generated positive tweets increased by 4.3% and negative tweets decreases by 3.5%, successful deployment of social media management tools.	Analysis was based on companies that have success with social media management tools and unconscious interviewer bias.
19	Sentiment analysis	82.1% of the posts contained both positive and negative words. 76.3% of the posts expressed positive emotions. 45.2% of the posts	Study was performed only on one social networking platform. The

		describing negative emotions. 36.7% contained only positive emotions and 5.6% contained negative emotions. The summary of the findings was that Facebook posts primarily comprise of positive sentiment. Nostalgia is a significant factor on Facebook.	study does not have access to user's network (friends and family).
20	Sentiment analysis and data analysis	15350 tweets contain sentiment of which 12% are positive, 8% are negative. 'AmazonHelp' tweets are 2.1% negative sentiment and 6.2% positive sentiment. AmazonHelp to customers tweets comprised 6.2% positive sentiment, 2.1% negative sentiment. Customers to AmazonHelp tweets contained 4.2% positive sentiment, 7.2% negative sentiment. 4.8% decrease in negative sentiment between beginning and final stage. Through high levels of consumer engagement negative customer sentiments were converted into neutral sentiments. Significant decrease of negative sentiments (-10%) for lengthy tweets and those with short tweets (-3%).	One limitation of this study is it only focused on five retail brands that are based in the United Kingdom.
29	Sentiment analysis	During the days where there are special events the tweets have primarily positive or very positive sentiment. The most remarkable event in Microsoft case study is event number 2, Where the event attracted much agitation by users because it is related to the presentation of the new Microsoft CEO, Satya Nadella. Also for event number 4 was characterized by the announcement that the company made regarding	Not described

		the largest amount of displacements. The company displaced more than 18,000 employees. Event number 7 also showcases the same displeasure as that the event 4, more than 7800 job cuts producing negative comments from the users. In Walmart case study there are only three main events. The most defining event was marked by the announcement made by the Walmart on the action to increase the wages of its employees This announcement generated great satisfaction.	

Table 9 discusses about the evaluation of computational methods with regards to the studies that used sentiment analysis methods to understand consumers emotions in social networking context. The limitations are also displayed. The following table shows second common method used in the studies.

***Table 10**. Articles grouped under a common computational method (Machine learning methods).*

Article No	Computational Methods	Evaluation of Computational Methods	Primary Limitations
11	Content analysis, Word and hashtag analysis, Sentiment analysis based on SVM, Hierarchical clustering with p-values using multiscale bootstrap resampling	8560 positive and 2104 negative messages overall, Binary representation scheme – unigram feature - 12, 257 (features) > SVM classifier with 90.80% accuracy on test data, Bigram feature – 44, 485 (features) with 74.46% accuracy. Term frequency – unigram feature - 12, 257 (features) > SVM Classifier with 86.27% accuracy on test data, Bigram feature – 44, 485 (features) with 71.68% accuracy.	Limited data collection period/time, Approach does not consider user's profile or basic information to increase the credibility of the analysis
14	Emotion component analysis, ECA (based on	Group 4 (G4, which are fine grained emotions) is optimized	The Chinese word segmentation is not very good due to

	hierarchy), Feature extraction, Feature selection and classification (Support vector regression, SVR)	with psychological emotion dictionary (in combination with hierarchical classification and feature selection) scores a highest precision of 76.1%, highest recall of 69.5%, highest F-Measure 72.7%.	the presence of oral expressions in the Chinese blog. ECA algorithm is designed with limited factors with certain rationality. The complicate nature of feature classification requires perfecting the algorithm while implementing.
16	SVM classifier, Rating based sentiment detection (RBSD), Emoji detection	‘One Plus5’ query accuracy = 74.31%, ‘Samsung S8’ query accuracy = 86.01%. Model accuracy for battery = 80.68%, camera = 85.18%, display attribute = 74.23%.	Not described
25	Sentiment analysis - SVM classifier, Naïve Bayes. Subjectivity analysis	Out of 11 929 posts, 7510 were positive and 3947 were negative. SVM provides better accuracy over Naïve Bayes classifier. Representation scheme - binary = 88.1% vs 71.7%, TF = 87.7% vs 70.3%, TF*IDF = 79.4% vs 67.4%.	First, with regards to the API call limitation of the experimental platform, the number of opinions employed in system evaluation is finite. Current reliability measurement does not consider a user's profile or basic information. Complete profile and other basic information could be a factor in credibility.
28	Supervised machine learning algorithm - DAN2, Support	Accuracy for strong positive emotions using DAN2 – 96%. Accuracy for mildly negative and strongly negative emotions – 89.9% and 95.1%	Analysis was performed only on a single corpus (single brand).

	vector machine (SVM).		

Table 10 shows results from the studies that used machine learning methods for analysis and calculations in addition to the limitations. The following table shows studies that performed content analysis in combination with other methods.

***Table 11**. Articles grouped under a common computational method (Content analysis).*

Article No	Computational Methods	Evaluation of Computational Methods	Primary Limitations
6	Semantic Content Analysis	Destination Management Organizations (DMOs) – use average (170 different emotional adjectives 1344 times in their tweets). There are some values for which there is a huge difference of use, especially 'fresh', 'honest', 'calm' and 'unique'. 'sincerity' is the most heavily communicated emo value (more by tourists). London account employed more emotional adjectives (289) compared to Budapest which is the lowest (143). This also indicates that London is putting more effort into attracting tourism consumers.	The method in place analyzes only tweets that are in English language. The method only considers emotional adjectives. There is no syntactic or sentiment analysis, which leads to no distinction among other words in the tweets.
17	Descriptive analytics, Content analytics, Network analytics, Space-time analytics	48% of original tweets = positive, 20% = neutral, 32% = negative. Emotions – 'sadness', 'fear', 'anger' and 'disgust' in 29% of total tweets, 'joyful' in 24% of the tweets, 47% of tweets have no specific emotion.	Only 1 social networking platform used. Study lacks empirical result validation. Validation of users is another problem.
18	Content analysis, Data analysis	Proportion of tweets that have either emoji or emoticon = 24%. The use of emoji characters are more than emoticons (68.1% vs 30.9%). The use of multiple (either emoji or emoticons) is more for emoji	Details about users are not available and the analysis is representative of general population

		(31.1% vs 4.8%). Maximum number of different emoticons used in a tweet = 4, emoji = 16. Different number of emoticons found in tweets = 50, different number of emoji characters found in the tweets = 254. Emoticons and emojis intended to be used to express positive and negative reaction is 66.7% vs 14.8% respectively. In tweets with content relating to food consumption, positive emotional expression was dominant. On the other hand, tweets not related to food consisted negative emotional reactions. Tweets posted in the context of special occasions, in presence of others, late hours and unhealthy habits often contained emoticon and emoji characters.	
23	Descriptive analytics, Content analytics, Network analytics	67% tweets score 0. 28% tweets have either positive or negative sentiment. Sentiment analysis of clustered tweets show that risk-associated tweets looks to be more negative than other groups of tweets.	Short duration of data collection. Using only a single hashtag #supply-chain limits the volume of data collected

Table 11 discussed about studies that used content analysis in combination with other data analysis methods to perform calculations. The following table shows studies that used lexicon-based approach to understand consumer emotions.

Table 12. *Articles grouped under a common computational method (Lexicon based).*

Article No	**Computational Methods**	**Evaluation of Computational Methods**	**Primary Limitations**
15	Emotion cause analysis, Emotion classifica-	The methods employed helped to find 'happiness' - 504 posts and with causes - 354, 'anger' – 472 and with causes - 452, 'disgust' –	Not described

	tion, Construction of the emotional lexicon and multi-language features extraction.	150 and with causes - 137, ‘fear’ – 140 and with causes - 131, ‘sadness’ – 304 and with causes - 255, ‘neutral’ – 14801. With all features, precision = 82.50%, recall = 69.53%, F-score = 75.46%	
21	Hu and Liu Lexicon	T-Mobile brand has highest negative sentiment of 72%, DHL has highest positive sentiment of 60%. Mean sentiment score is high for Nokia and Mobinil. Overall sentiment score for Nokia is generally better than the sentiment score for Pfizer.	Analysis does not reveal the reason behind consumers’ expression of sentiment, meaning that it fails to identify the sentiment topic.
26	Sentiment analysis - dictionary based approach	Average sentiment score is highest for Aria Las Vegas resort = 0.69, lowest for Bally’s Las Vegas resort = 0.30. High positive/negative ratio score for Tropicana Las Vegas resort = 11.10, lowest for The Quad Las Vegas resort = 2.57. All firms had positive average sentiment score. Results indicate positive sentiment outweighing negative sentiment in general as all the firms had positive average sentiment score and ratios.	Twitter API provides limited search capacity, Study is focused within single market (Las Vegas) and unique category of hospitality firms which is integrated resorts category. With regards to the lexicon used in this research study the measurement is valid across many large sample of tweets, smaller samples or individual comments could be misunderstood.
27	Sentiment analysis - lexicon based approach	21.44% positive tweets, 14.30% negative tweets, 64.27% neutral indicating a balance in opinions. The null hypothesis is accepted based on the results found. Null	One limitation with regards to Umigon30 as the sentiment classifier is its poor precision when looking to

		Hypothesis1: There is no significant relationship/correlation between Twitter sentiment and volume statistics and stock market indicators for a particular day. Null Hypothesis 2: There is no statistically significant predictive relationship between Twitter sentiment statistics and stock market indicators.	find negative sentiment. In a formal accuracy test its ability to precisely find negative tweets was below 50%. The accuracy was better while performing the positive and neutral sentiment classification. The study was limited to localized election event.

Table 12 shows results and analysis from studies that did content analysis along with the limitations of those studies. Many articles performed analysis with other methods. These other methods are grouped together in the following table.

Table 13. *Articles grouped under a common computational method (Other methods).*

Article No	Computational Methods	Evaluation of Computational Methods	Primary Limitations
1	Trust ontology, Theory of concept drift, Event-driven trust refreshment	Methods indicate that Donald Trump gets a higher proportion of votes in time. Which leads to the degree of trust (DoT) of a trustor towards Hilary Clinton to reduce gradually.	Not described
5	Radial layout scheme, Sunflower metaphor.	Case Study 1: Negative sentiments expressed in Australia because of the earthquake, partially in Indonesia, Taiwan, Japan. Case Study 2: Mitt Romney's victory is seen to have positive reactions in Mary Land, New York, Pennsylvania, Indiana, California and Virginia.	Not described

10	Anomaly detection: single and multivariate Gaussian distribution	Accuracy of abnormal user emotion detection = 83.49%	Sparseness of micro-blog data of individual user, abnormal user reaction can only be detected in a week or in a month.
13	Modified Chi-square feature selection, modified N-Gram model	N-Gram correctly recognized 79% of the comments. The values of accuracy showed that the N-Gram correctly marked positive message and negative messages at a success rate of 82.42%.	Not described
22	Case study approach, Inductive reasoning	Discussions using the #SCOTUS #LGBT hashtag comprised in the majority between neutral sentiment to positive sentiment. This finding is arguably not surprising given the reason that there was a rapidly increasing support for the campaign.	The software Radian6 provides some interpretation of 'sentiment'. However, it does not provide a true circumstances or context of tone and meaning.
24	Computational linguistic approach	For information sharing – Industry tweets: Decreased use of overall affect words is correlated with increase in the number of likes. Increased likes are also a significant relationship to positive emotion. Increased use of informal words is also significantly related to increased number of likes. For problem solving – Generic tweets: Increased use of affect and reward words has a significant relationship to the increase in number of likes. Increase in engagement is connected to the use of emotion and reward words irrespective of the type of company. Neutral emotion words tend to increase the number of likes.	Not described

		For Information sharing – Events: Increase in affect words is related to increase in number of likes for service companies. For product companies, increase in use of informal words lead to increase in number of likes.	

Several studies used different computational methods as witness from the above table. However, all the studies found in Table 8, 9, 10, 11,12 used computational methods individually or combinedly. The computational methods include machine learning (supervised, Naïve Bayes, Support Vector Machine), Dynamic sentiment-topic model (DST), Gibbs sampling method, topic detection and tracking (TDT), sentiment analysis, semantic content analysis, sentiment detection and emotion detection module, natural language processing, multicriteria decision making (MCDM), text mining, anomaly detection: single and multivariate gaussian distribution, content analysis, emotion component analysis (ECA), emotion cause analysis and computational linguistic approach. In few studies, the limitations of the computational methods were not described. Managerial applications found in each of the studies is mentioned in the following table.

Table 14*. Managerial applications found in the research articles.*

Article No	**Managerial Applications**
1	Citing the argument that 'trust' is a dynamic concept which is subject to change based on some reasoning, the author communicates the importance of detecting complex and single events that impact the changes of 'trust' over time. The author proposes that the degree of trust (DoT) on the entity that is measured requires to be monitored based on events concerning that entity. In the same way, companies can build strategies to study the 'trust' of their consumers to answer questions related to when and how consumer's 'trust' is refreshed over several events.
2	In real time social media data analytics, large amounts of user generated data are created. In order, to analyze what kind of abstracts topics is being discussed, the author's proposed model helps in detecting the 'topic' and the 'sentiment' polarity associated with the topic.

3	Fuzzy-Set based social sentiment analysis is used in analyzing marketing campaigns where crisp sets of sentiment categories are created for artefacts, actors and different time periods such as before, during and after events. This leads to monitoring consumer behavior during several events for sentiment categories. Crisis management for product specific context is also another area where such an approach could be used.s
4	In the UTiLearn teaching system or Distance eTeaching and eLearning (DTL), their approach allows to monitor the behavior of its users/consumer regarding the effect of the learning system in a particular region, which allows to customize the different courses, study programs and topics according to that region. Applying eLearning at different contexts driven by area-specific and job market specific needs. Basically, this allows for improved scalability and resource planning in the eLearning sector.
5	Collective responses of a community can be analyzed for consumer sentiments based on a given event. The proposed 'Whisper' tool facilitates analytical process of events occurring at various locations. It can be used to compare user opinions between different locations on various subjects either products or political.
6	The author encourages destination management organizations (DMOs) to make use of emotions for creating destination brand value and new ways of marketing for companies in the tourism industries to endorse destinations based on emotional values found in social media. This indicates that destination management organizations can create new marketing strategy by analyzing tourists' reactions in social media and attract visitors to destinations that match their emotional values.
7	The authors propose a framework to experiment social phenomenon using social data by looking at search queries from Google trends. When there is a launch of a product into the consumer market or during an event, there are always reactions to the product features. In other words, In the event of a new product launch, consumers want to know about the product and its features.

	Therefore, it could trigger maximum searches that would make it most searched in the Google trends; Consumer reactions/sentiment of the event can be analyzed based on a customized framework introduced in this study.
8	The author proposed a sentiment analysis model in this study that helps hospital management to understand the user's opinion on different indicators of service quality in the healthcare industry for example Infrastructure, Quality care, attitude, cost and equipment & services which helps to build customer satisfaction metrics. This allows hospital management in business intelligence in assessing the ranking of the hospital among other hospitals further helping decision-making process.
9	The study analyzes customer perceptions and emotional states on restaurants. By employing the right tools, customer satisfaction can be studied along with the what type of themes that are being said about a restaurant. Themes related to hospitality in restaurant context can be examined deeply. For example: Environment, service quality, employee presentation, food taste. This provides insight into perception of consumers with regards to restaurant and understanding what type of value proposition can be communicated to achieve the optimum customer satisfaction. This can also allow restaurant managers to explore the different trends in the food industry and how consumers feel about it.
10	The study proposes a model to detect normal and abnormal emotions. What this means to managers is that negative emotion like 'anger' can have an abnormal effect to the company, this may affect profits during the period and if not checked, the effect can be long term. Companies must analyze consumer feedback in real-time and mitigate the effects of negative word-of-mouth in social networking websites. A revival strategy can be formed based on real-time analysis to fight the negative effects. For example, a specific user who is displaced with regards to emotion can be approached by the company to be served in a better way.

11	In this study, focus is on supply chain management by studying consumer behavior attributed to food industry. Feedback from the consumers helped to find the issues faced by them while purchasing beef and can be highlighted at different operational points in the supply chain. This assists companies to find the root cause for consumer dissatisfaction with regards to a product and take steps to locate where the fault occurs in the supply chain of the product. Coordination of stakeholders in this type of planning can help save time and cost thereby creating a customer-centric supply chain.
12	Companies are involved with social media management tools for communication, marketing, human resources and customer care reasons. Main applications found in the study include customer satisfaction, customer engagement, marketing campaigns and overall business strategy. Creating marketing mix based on target groups to increase attitudinal loyalty among consumers and positive word-of-mouth. Other application is organizational impression management among consumers. Implications include competitor analysis.
13	In this study, managerial applications range from competitor analysis, industry-specific sentiment benchmarking for the purpose of marketing intelligence and business decision-making. Benchmarking of Key performance metrics using sentiment, customer perception of a brand leading to analysis of brand popularity in comparison to competitors. Analysis of media distribution, voice and category of operational clusters.
14	By proposing an algorithm to detect emotions in social networking context, the authors recommend using their algorithm for consumer behavior analysis. By studying the emotion, characteristics of consumers can lead to other areas such as consumer trends and psychological states. Improving marketing techniques and tracking consumer's happiness index based on location.
15	In this study, the authors provide means to discover the causes of emotion that drive consumer behavior by analyzing the results, actions of agents and aspects of objects. Therefore, managers can extract the emotion-

	cause components to understand what the reason for consumer's emotions is. Other applications could be precision marketing for product recommendations, tailoring products to specific consumers and for decision-making.
16	Social networking blogs allow limited character entry, especially in microblogs, which is why use emoji and emoticons to express their feelings in a compact way. This study contributes to improvement in understanding consumers concerning the above-mentioned online linguistic opinion expression.
17	Study provides insight into how to improve search engine marketing and improved guidelines for digital marketing practitioners.
18	The study talks about consumer behavior in food context. Managerial applications include studying consumers in food related context for the purpose of product development, marketing, service feedback analysis and target marketing.
19	This study focused on nostalgic posts generated through Facebook. Managers can focus on marketing which involves nostalgia-based advertisement campaigns. Targeting consumers based on their nostalgic content such as posts and communication.
20	The study explored online retailer's customer engagement in microblogging sphere. Provides insight into key managerial applications such as customer engagement, customer perception management, customer service, marketing, company brand management and customer complaint management.
21	In this study, consumer sentiment towards popular brands was analyzed. Based on the results, manager applications range from improved marketing intelligence, brand perception management, customer relationship management and market research
22	In this study, cross-cultural campaigning was the central focus. Managerial applications include cross-cultural marketing,
23	Managerial applications include analyzing consumer's perception on products and service quality. Improvement in managing supply chain management activities

	such as analyzing market demand, complementing demand forecasting methods and operation planning. Other areas of management are risk management in supply chain.
24	Managerial applications include studying the levels of behavioral engagement of consumers, public relations management, for the purpose of information sharing among consumers about products and events.
25	Different components of marketing intelligence are discussed in this study. Real time consumer monitoring, Consumer emotion analysis over time, consumer engagement and competitor analysis are some of the applications in this study.
26	This research focuses on the practicality of employing sentiment analysis in analyzing consumers in hospitality context. Applications range from marketing intelligence, real-time analysis of a marketing campaign, brand perception analysis.
27	Real time consumer monitoring for the purpose of stock market prediction.
28	Applications range from brand perception analysis, marketing analysis and customer engagement.
29	Main application from this study is event popularity analysis.

In Table 14, detailed description and of various types of managerial applications found in all the research articles is presented. Several managerial themes emerge as a result of studying consumer emotions.

3.2 Empirical Results

The results from the analysis can be divided into three sections namely quantitative, qualitative content + quantitative, and qualitative content. The quantitative results were obtained by means of quantitative methods, the quantitative + qualitative content is a result of qualitative evaluation and combining quantitative methods with qualitative data. Finally, the qualitative as mentioned in the methodology is results presented by semi-structured interview with the company representative.

3.2.1 Quantitative Results

The tweets were analyzed using SentiStrength sentiment detection algorithm and VADER sentiment algorithm. The following image shows the positive, negative and neutral sentiment of the activity extracted from the images and represented in descending order of sentiment score and is indicated by green, red and dark grey respectively.

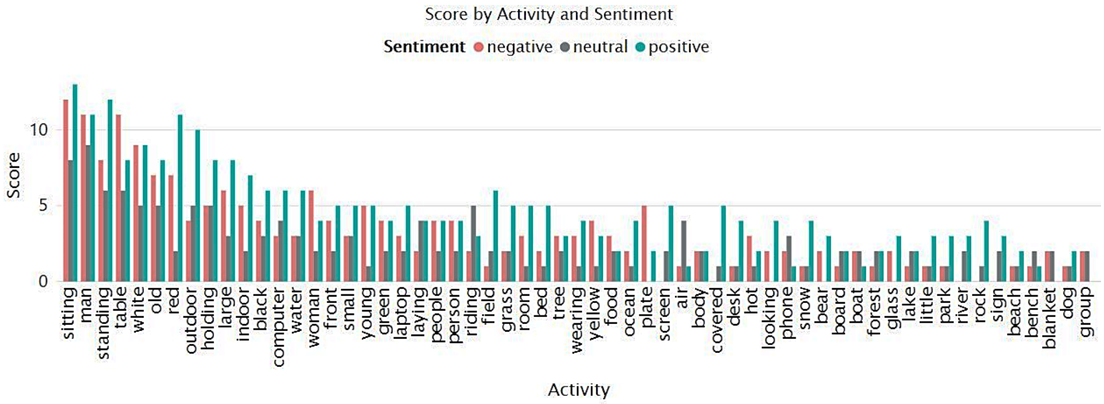
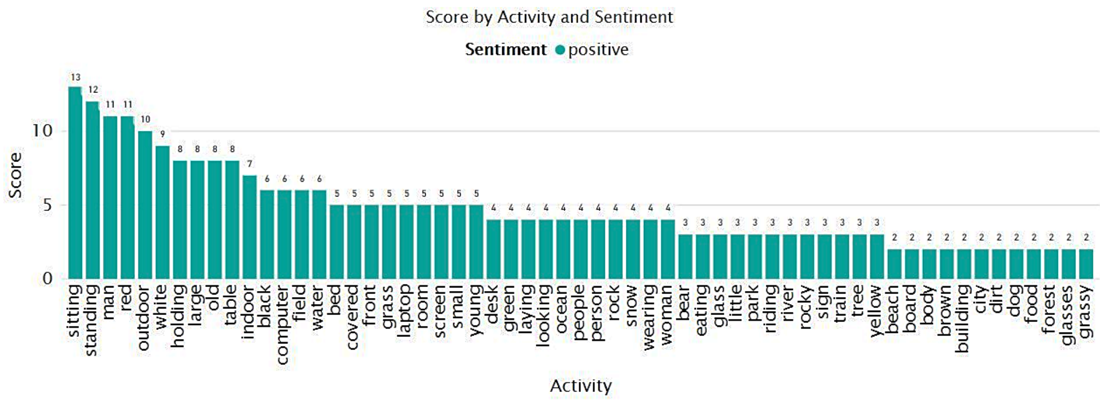


Figure 5*. Sentiment of activity using SentiStrength algorithm.*

Figure 5 illustrates three different sentiments detected using SentiStrength algorithm namely positive, negative and neutral for the activity tags extracted from the images. However, by further breaking down into individual sentiments the results extracted are displayed in the following image.



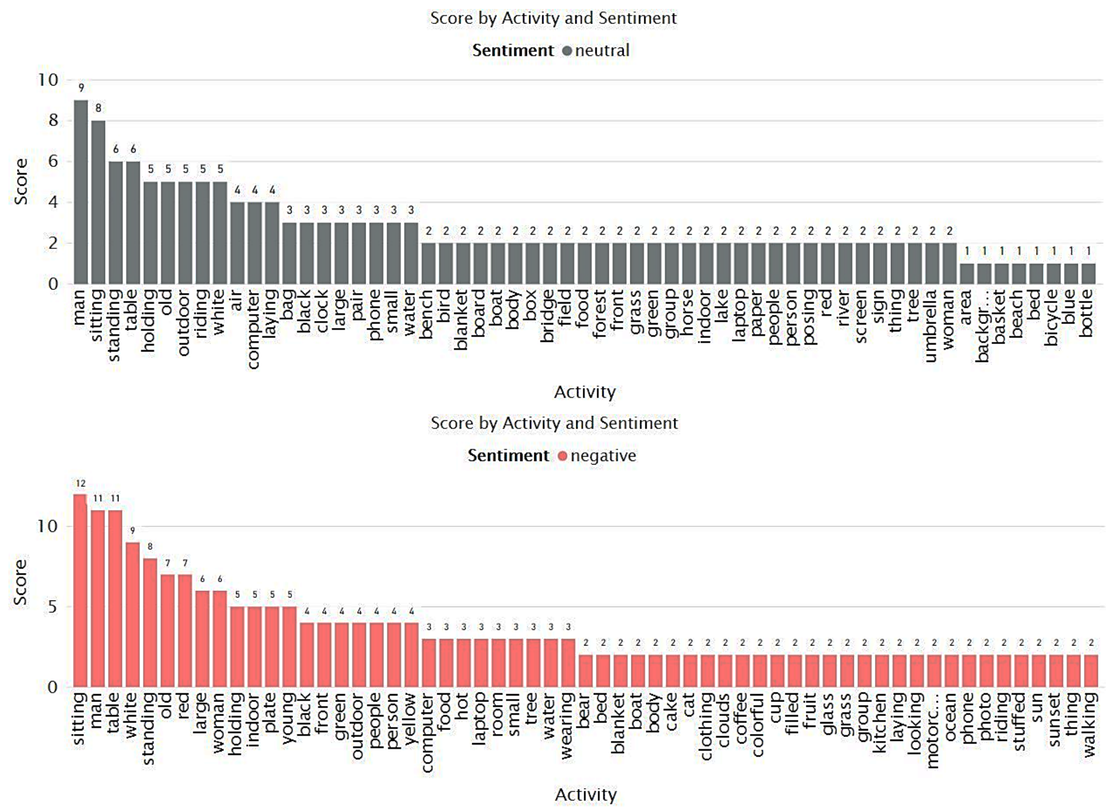


Figure 6*. Positive, negative and neutral sentiment of activity in descending order.*

In Figure 6, sentiment for each activity is plotted in descending order of score. For positive sentiment, *'sitting'*, *'standing'*, *'man'*, *'red'*, *'outdoor'*, *'white'*, *'holding'*, *'large'*, *'old'*, *'table'* are some of the activities with highest score. For negative sentiment chart, *'sitting'*, *'man'*, *'table'*, *'white'*, *'standing'*, *'old'*, *'red'*, *'large'*, *'woman'*, *'holding'*, *'indoor'* are few activities with large score. Whereas in neutral sentiment category, *'man'*, *'sitting'*, *'standing'*, *'table'*, *'holding'*, *'old'*, *'outdoor'*, *'riding'*, *'white'* are some of the activities with high score. The following table displays the activity tags with highest score for each sentiment.

Table 15. *Score for activity tags under each sentiment category (SentiStrength).*

Positive	Negative	Neutral
sitting – 13	sitting – 12	man – 9
standing – 12	man – 11	sitting – 8
man – 11	table – 11	standing – 6
red – 11	white – 9	table – 6
outdoor – 10	standing – 8	holding – 5
white – 9	old – 7	old – 5
holding – 8	red – 7	outdoor – 5
large – 8	large – 7	riding – 5
old – 8	woman – 6	white – 5
table – 8	holding – 5	air – 5
indoor – 7	indoor – 5	computer – 4

black – 6	plate – 5	laying – 4
computer – 6	young – 5	bag – 3
field – 6	black – 4	black – 3
water – 6	front – 4	clock – 3
bed – 5	green – 4	large – 3
covered – 5	outdoor – 4	pair – 3
front – 5	people – 4	phone – 3
grass – 5	person – 4	small – 3
laptop – 5	yellow – 4	water – 3
room – 5	computer – 3	bench – 2
screen – 5	food – 3	bird – 2
small – 5	hot – 3	blanket – 2
young – 5	laptop – 3	board – 2
desk – 4	room – 3	boat – 2
green – 4	small – 3	body – 2
laying – 4	tree – 3	box – 2
looking – 4	water – 3	bridge – 2
ocean – 4	wearing – 3	field – 2
people – 4	bear – 2	food – 2
person – 4	bed – 2	forest – 2
rock – 4	blanket – 2	front – 2
snow – 4	boat – 2	grass – 2
wearing – 4	body – 2	green – 2
woman – 4	cake – 2	group – 2
bear – 3	cat – 2	horse – 2
eating – 3	clothing – 2	indoor – 2
glass – 3	clouds – 2	lake – 2
little – 3	coffee – 2	laptop – 2
park – 3	colorful – 2	paper – 2
riding – 3	cup – 2	people – 2
river – 3	filled – 2	person – 2
rocky – 3	fruit – 2	posing – 2
sign – 3	glass – 2	red – 2
train – 3	grass – 2	river – 2
tree – 3	group – 2	screen – 2
yellow – 3	kitchen – 2	sign – 2
beach – 2	laying – 2	thing – 2
board – 2	looking – 2	tree – 2
body – 2	motorcycle - 2	umbrella – 2

Table 15 lists the Top 50 tags. *'sitting'* is highest in positive and negative. *'man'* has the highest neutral sentiment. Similarly, sentiment for activity tags were calculated with VADER sentiment algorithm and the results are as follows.

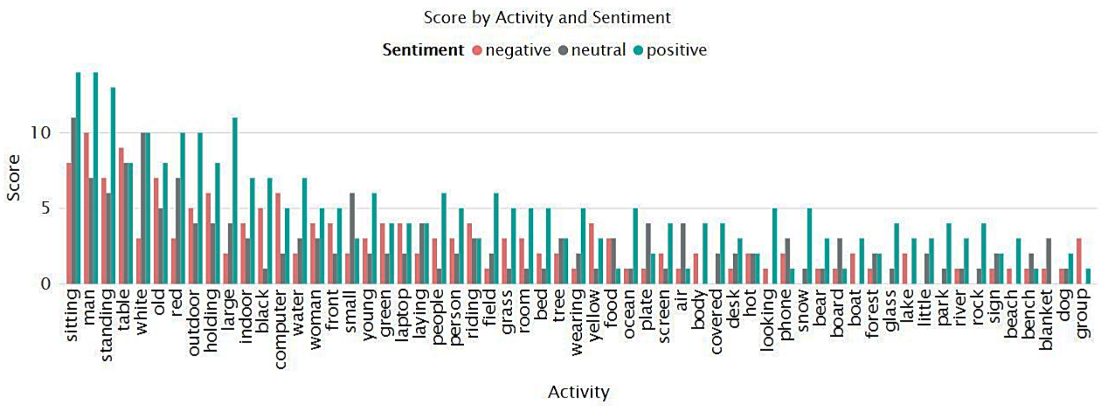
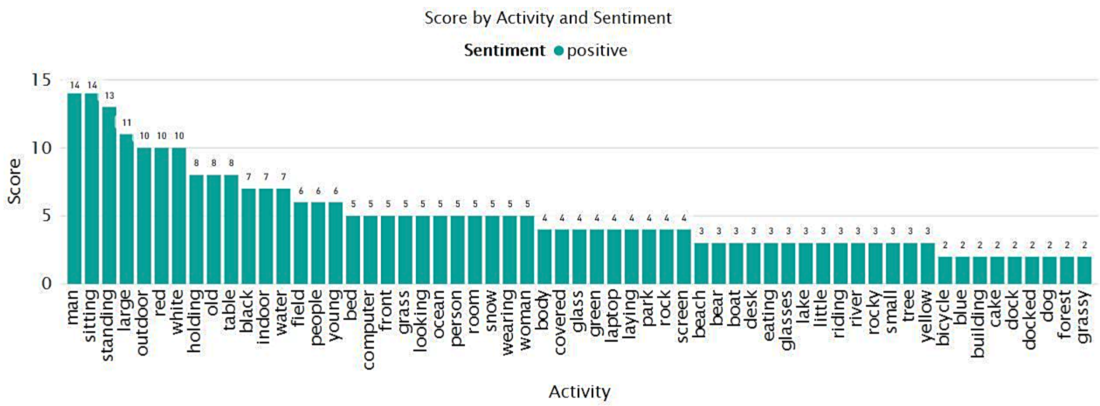
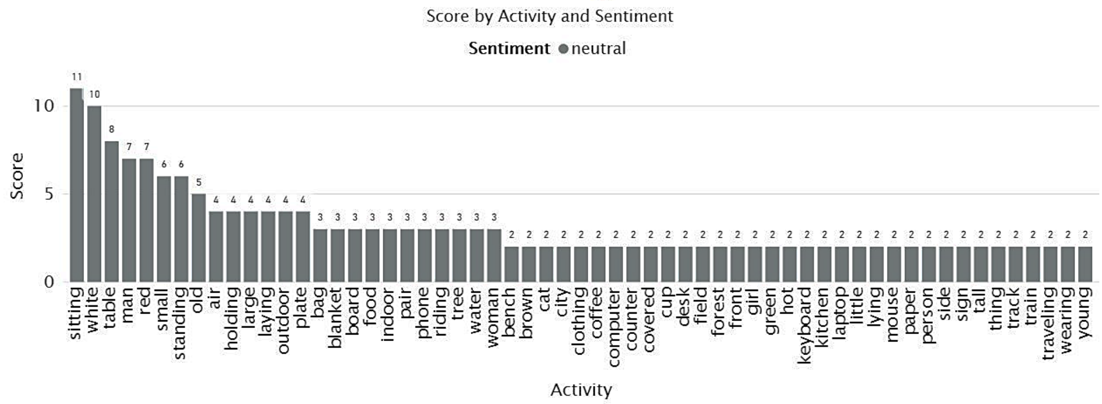


***Figure** 7. Sentiment of activity using VADER Sentiment Analysis.*

Figure 7 illustrates three different sentiments detected using VADER sentiment analysis algorithm. Positive, negative and neutral sentiment for activity tags extracted from the images. The analysis of activity under each sentiment is shown in Figure 8.





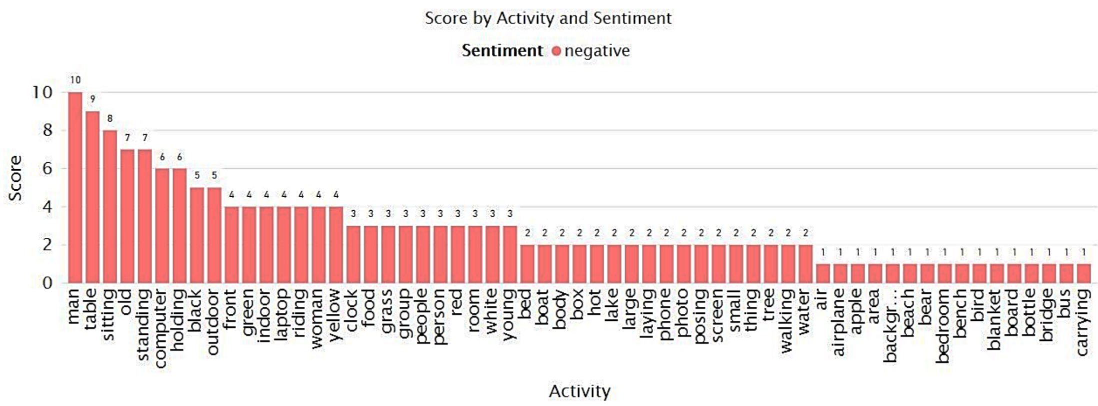


Figure 8*. Positive, negative and neutral sentiment of activity in descending order (VADER).*

In the above figure, sentiment for each activity is plotted in descending order of score. For positive sentiment, *'man', 'sitting', 'standing', 'man', 'large', 'outdoor', 'red', 'white', 'holding', 'old', 'table', 'black'* are some of the activities with highest score. For negative sentiment chart, *'man', 'table', 'sitting', 'old', 'standing', 'computer', 'holding', 'black', 'outdoor', 'front', 'green', 'indoor'* are few activities with large score. Whereas in neutral sentiment category, *'sitting', 'white', 'table', 'man', 'red', 'small', 'standing', 'old', 'air', 'holding', 'large', 'laying', 'outdoor'* are some of the activities with high score. The following table displays the activity tags with highest score for each sentiment.

Table 16*. Score for activity tags under each sentiment category (VADER Sentiment).*

Positive	Negative	Neutral
man – 14	man – 10	sitting – 11
sitting – 14	table – 9	white – 10
standing – 13	sitting – 8	table – 8
large – 11	old – 7	man – 7
outdoor – 10	standing – 7	red – 7
red – 10	computer – 6	small – 6
white – 10	holding – 6	standing – 6
holding – 8	black – 5	old – 5
old – 8	outdoor – 5	air – 4
table – 8	front – 4	holding – 4
black – 7	green – 4	large – 4
indoor – 7	indoor – 4	laying – 4
water – 7	laptop – 4	outdoor – 4
Field – 6	Riding – 4	plate – 4
People – 6	Woman – 4	bag – 3
Young – 6	Yellow – 4	blanket – 3
Bed – 5	Clock – 3	board – 3

Computer – 5	Food – 3	food – 3
Front – 5	Grass – 3	indoor – 3
Grass – 5	Group – 3	pair – 3
Looking – 5	People – 3	phone – 3
Ocean – 5	Person – 3	riding – 3
Person – 5	Red – 3	tree – 3
Room – 5	Room – 3	water – 3
Snow – 5	White – 3	woman – 3
Wearing – 5	Young – 3	bench – 2
Woman – 5	Bed – 2	brown – 2
Body – 4	Boat – 2	cat -2
Covered – 4	Body – 2	city – 2
Glass – 4	Box – 2	clothing – 2
Green – 4	Hot – 2	coffee – 2
Laptop – 4	Lake – 2	computer – 2
Laying – 4	Large – 2	counter – 2
Park – 4	Laying – 2	covered – 2
Rock – 4	Phone – 2	cup – 2
Screen – 4	Posing – 2	desk – 2
Beach – 3	Screen – 2	field – 2
Bear – 3	Small – 2	forest – 2
Boat – 3	Thing – 2	front – 2
Desk – 3	Tree – 2	girl – 2
Eating – 3	Walking – 2	green – 2
Glasses – 3	Water – 2	hot – 2
Lake – 3	Air – 1	keyboard – 2
Little – 3	Airplane – 1	kitchen – 2
Riding – 3	Apple – 1	laptop – 2
River – 3	Area – 1	little – 2
Rocky – 3	Background – 1	lying – 2
Small – 3	Beach – 1	mouse – 2
Tree – 3	Bear – 1	paper – 2
Yellow – 3	Bedroom – 1	person - 2

Table 16 lists the highest activity score under each sentiment with maximum positive score of 14, maximum negative score of 10 and maximum neutral score of 11. *'man'* is highest in positive and negative. *'sitting'* has the highest neutral sentiment. Emotion analysis for activity tags were calculated with IBM Watson emotions and the results are as follows.

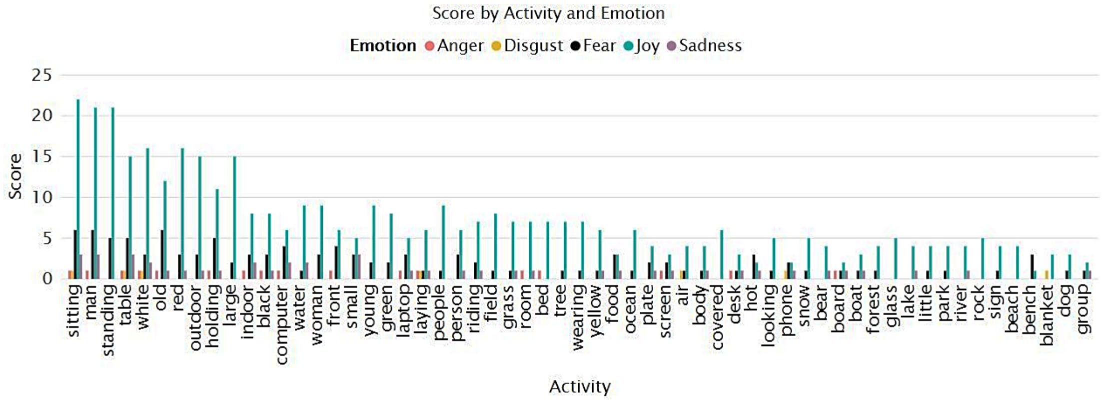
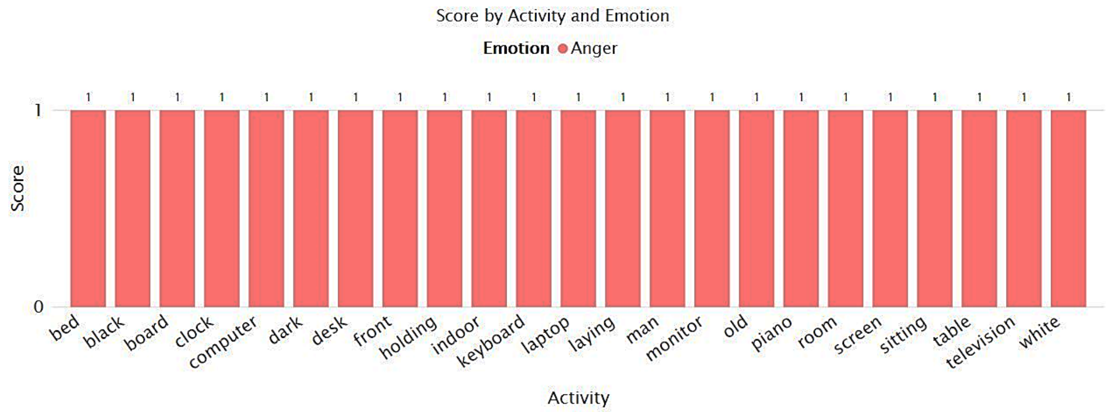
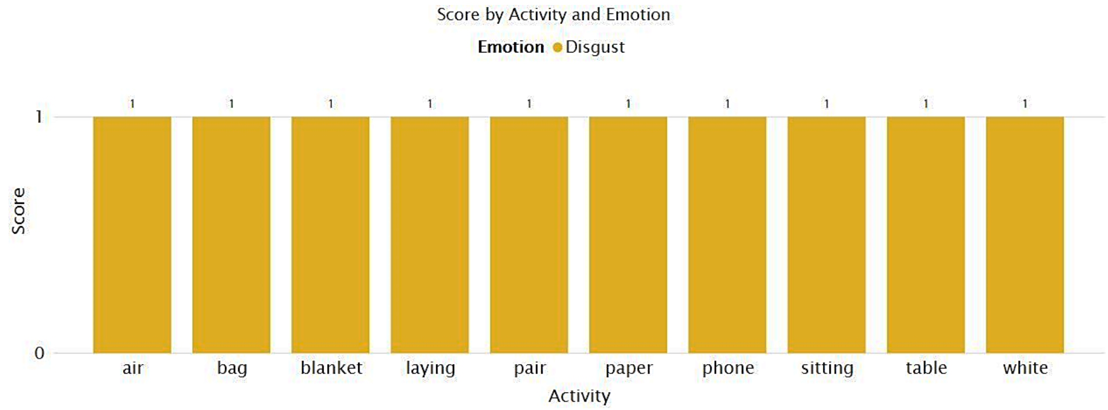


Figure 9*. Overall IBM Watson emotions for activity tags.*

Figure 9 illustrates the overall emotions of the activity tags in descending order of score. Individual emotions such as *'Anger', 'Disgust', 'Fear', 'Joy'* and *'Sadness'* are mapped for activity tags in the following image.





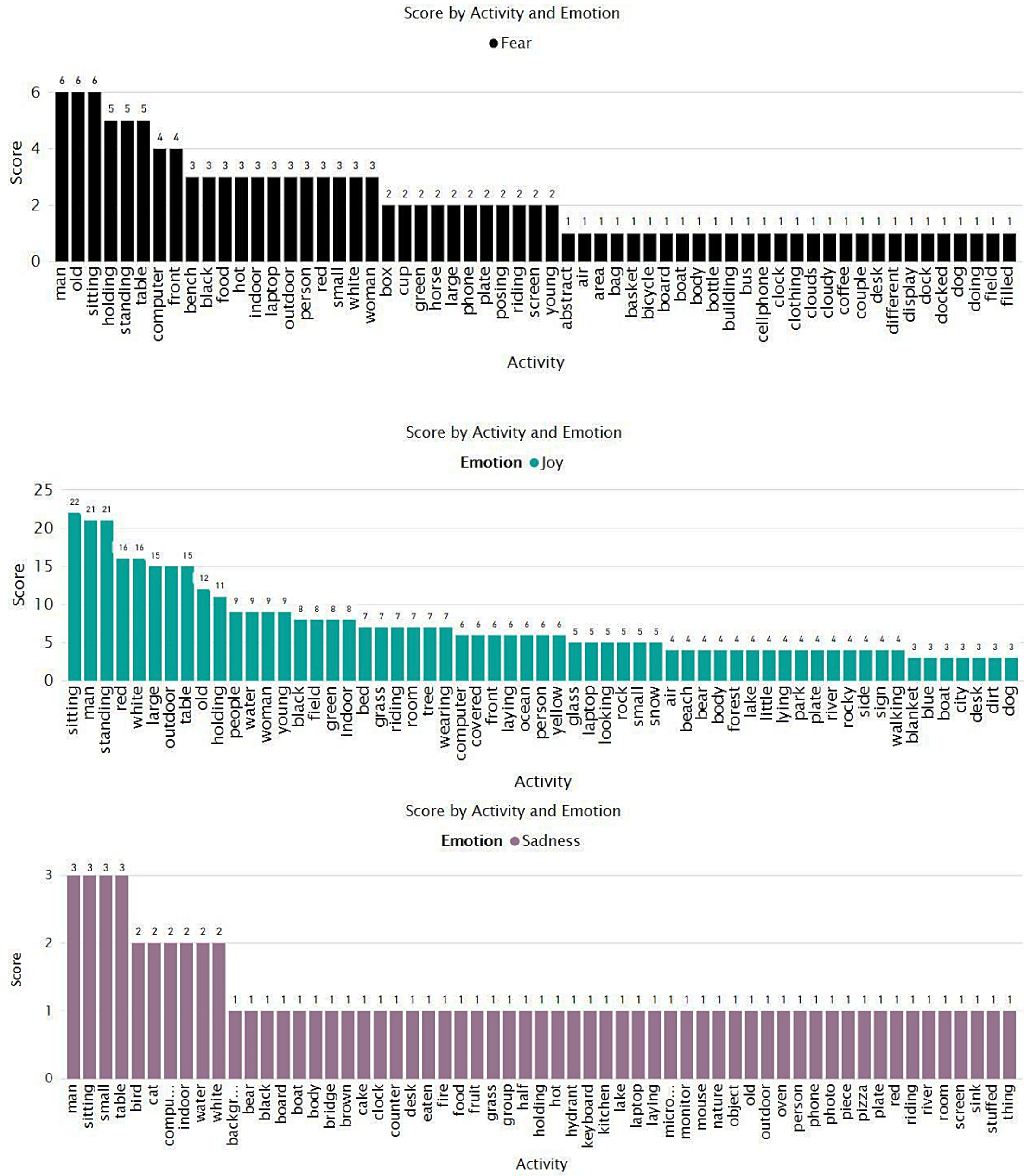


Figure 10. *Individual emotion score for activity tags (IBM Watson).*

In Figure 10, emotions for each activity is plotted in descending order of score. 23 activity tags were fall under *'Anger'* emotion. Only 10 activity tags come under *'Disgust'* emotion category. *'Fear'* with 102 activity tags, *'Joy'* with 191 activity tags and *'Sadness'* with 60 activity tags. *'Joy'* is the most common emotion found during the analysis. The following table displays the activity tags with highest score for each emotion category.

***Table 17**. Highest emotion scores for activity tags under each emotion (IBM Watson).*

Anger	Disgust	Fear	Joy	Sadness
bed – 1	air – 1	man – 6	sitting – 22	man – 3
black – 1	bag – 1	old – 6	man – 21	sitting – 3
board – 1	blanket – 1	sitting – 6	standing – 21	small – 3
clock – 1	laying – 1	holding -5	red – 16	table – 3
computer – 1	pair – 1	standing- 5	white – 16	bird – 2
dark – 1	paper – 1	table – 5	large – 15	cat – 2
desk – 1	phone – 1	computer – 4	outdoor – 15	computer – 2
front – 1	sitting – 1	front – 4	table – 15	indoor – 2
holding – 1	table – 1	bench – 3	old – 12	water – 2
indoor – 1	white - 1	black – 3	holding – 11	white – 2
Keyboard – 1		food – 3	people – 9	background – 1
Laptop – 1		hot – 3	water – 9	bear – 1
Laying – 1		indoor – 3	woman – 9	black – 1
Man – 1		laptop – 3	young – 9	board – 1
Monitor – 1		outdoor – 3	black – 8	boat – 1
Old – 1		person – 3	field – 8	body – 1
Piano – 1		red – 3	green – 8	bridge – 1
Room – 1		small – 3	indoor- 8	brown – 1
Screen – 1		white – 3	bed – 7	cake – 1
Sitting – 1		woman – 3	grass – 7	clock – 1

Table 17 lists different activity tags under each emotion. The score for *'Anger'* and *'Disgust'* tags are all the same with 1. 'man' is highest in *'Fear'* and *'Sadness'* emotions. *'sitting', 'man'* and *'standing'* are the highest emotions with *'Joy'*.

Face emotion results

The face emotions that were detected using Microsoft Face API – Facial Recognition software is given below. The consumer faces were analyzed for emotional attributes such as *'anger', 'contempt', 'disgust', 'fear', 'happiness', 'neutral', 'sadness', and 'surprise'*. The following table shows the results.

Table 18. *Face emotion results from the tweets.*

Tweet	**Gender**	**Primary Emotion**	**All Emotions**
Original tweet: *“Palautumista arjessa uppoutumalla hyvän kirjan vietäväksi. Tämä kirjan lukeminen on lasten syntymien myötä jäänyt taustalle, mut nyt palautuu yhtenä rentoutumiskeinona. @moodmetric #moodmetricstressinhallintakeino https://t.co/4QqzyevWkE”* English translation: *“Returning to everyday life by immersing in a good book. Reading this book has been left behind by the birth of children, but is now being restored as one of the means of relaxation. @moodmetric #moodmetricstress management tool https://t.co/4QqzyevWkE”*	face 1: male	face 1 - *‘neutral’*: 0.987	'face1': {*'anger'*: 0.002, *'contempt'*: 0.001, *'disgust'*: 0.0, *'fear'*: 0.0, *'happiness'*: 0.0, *'neutral'*: 0.987, *'sadness'*: 0.01, *'surprise'*: 0.0}
Original tweet: *“Hitting the gym relieves stress @Moodmetric #moodmetriccampaign @jjussila #moodmetricstressinhallintakeino https://t.co/Ymbht3wYIM”*	face 1: male	face 1 - *‘neutral’*: 0.997	'face1': {*'anger'*: 0.0, *'contempt'*: 0.0, *'disgust'*: 0.0, *'fear'*: 0.0, *'happiness'*: 0.0, *'neutral'*: 0.997, *'sadness'*: 0.002, *'surprise'*: 0.0}
Original tweet: *“Mindful breathing keeps my anxiety and stress out while I'm working...so just inhale and exhale...#moodmetricstressinhallintakeino https://t.co/SDczQ0Gz17”*	face 1: female	face 1 - *'neutral'*: 0.566	'face1': {*'anger'*: 0.005, *'contempt'*: 0.197, *'disgust'*: 0.005, *'fear'*: 0.001, *'happiness'*: 0.17,

			'neutral': 0.566, *'sadness'*: 0.056, *'surprise'*: 0.0}
Original tweet: *"Mindful breathing keeps my anxiety and stress out while I'm working...so just inhale and exhale...#moodmetricstress-inhallintakeino https://t.co/SDczQ0Gz17"*	face 1: male	face 1 - *'neutral'*: 0.926	'face1': {*'anger'*: 0.0, *'contempt'*: 0.054, *'disgust'*: 0.0, *'fear'*: 0.0, *'happiness'*: 0.017, *'neutral'*: 0.926, *'sadness'*: 0.003, *'surprise'*: 0.0}
Original tweet: *"Work and hobby are almost same, but when stress, I build and tweak gadgets and consumer electronics ?, #hardwarehack @Hacksterio @hackadayio and some fun coding. #moodmetricstressinhallintakeino https://t.co/shOI4fOdSp"*	face 1: male	face 1 - *'neutral'*: 0.942	'face1': {*'anger'*: 0.0, *'contempt'*: 0.004, *'disgust'*: 0.0, *'fear'*: 0.0, *'happiness'*: 0.001, *'neutral'*: 0.942, *'sadness'*: 0.052, *'surprise'*: 0.0}
Original tweet: *"Työkiireen keskellä hyvä tapa nollata päätä on järjestää hetkiä työkaverien kanssa ja oppia uutta yhdessä #moodmetricstressinhallintakeino @Moodmetric @GoforeGroup #palvelumuotoilu #muotoilupeli*	face 1: male, face 2: female, face 3: female	face 1 - *'happiness'*: 1.0, face 2 – *'happiness'*: 1.0, face 3 -	'face 1': {*'anger'*: 0.0, *'contempt'*: 0.0, *'disgust'*: 0.0, *'fear'*:

#neukkarinseinä kin hymyilee! kiitos @annakaisa_b https://t.co/ic6EmvtIRu" English translation: *"In the middle of the work circle, a good way to reset the head is to have moments with coworkers and to learn new together #moodmetricstress management mode @Moodmetric @GoforeGroup #serviceforming #showoutgame #children wall even smiles! thanks @annakaisa_b https://t.co/ic6EmvtIRu"*		*'happiness'*: 0.999	0.0, *'happiness'*: 1.0, *'neutral'*: 0.0, *'sadness'*: 0.0, *'surprise'*: 0.0}, 'face 2': {*'anger'*: 0.0, *'contempt'*: 0.0, *'disgust'*: 0.0, *'fear'*: 0.0, *'happiness'*: 1.0, *'neutral'*: 0.0, *'sadness'*: 0.0, *'surprise'*: 0.0}, 'face 3': {*'anger'*: 0.0, *'contempt'*: 0.0, *'disgust'*: 0.0, *'fear'*: 0.0, *'happiness'*: 0.999, *'neutral'*: 0.001, *'sadness'*: 0.0, *'surprise'*: 0.0}
Original tweet: *"Työkiireen keskellä hyvä tapa nollata päätä on järjestää hetkiä työkaverien kanssa ja oppia uutta yhdessä #moodmetricstressinhallintakeino @Moodmetric @GoforeGroup #palvelumuotoilu #muotoilupeli #neukkarinseinä kin hymyilee! kiitos @annakaisa_b https://t.co/ic6EmvtIRu"*	face 1: female	face 1 - *'neutral'*: 0.999	'face 1': {*'anger'*: 0.0, *'contempt'*: 0.0, *'disgust'*: 0.0, *'fear'*: 0.0, *'happiness'*: 0.0, *'neutral'*:

English translation: *"In the middle of the work circle, a good way to reset the head is to have moments with coworkers and to learn new together #moodmetricstress management mode @Moodmetric @GoforeGroup #serviceforming #showoutgame #children wall even smiles! thanks @annakaisa_b https://t.co/ic6EmvtIRu"*			0.999, *'sadness'*: 0.001, *'surprise'*: 0.0
Original tweet: *"When stressed, I play @PUBG #gameofgames #moodmetricstress-inhallintakeino https://t.co/o4SyEHIn5N"*	face 1: male	face 1 - *'neutral'*: 0.953	'face 1': {*'anger'*: 0.0, *'contempt'*: 0.0, *'disgust'*: 0.0, *'fear'*: 0.0, *'happiness'*: 0.047, *'neutral'*: 0.953, *'sadness'*: 0.0, *'surprise'*: 0.0}

The above table shows the tweets, genders found, primary emotion and all emotional values detected from the faces. Out of 47 tweets, only 7 tweets contained images with faces. Only six participants tweeted with a combination of image and a text. Following table shows the combination of sentiment and emotion for tweets with identified face(s).

Table 19. *Sentiment and emotions of tweets with face.*

Tweet	**Sentiment (SentiStrength)**	**Sentiment (VADER)**	**Emotion (Face API)**
Original tweet: *"Palautumista arjessa uppoutumalla hyvän kirjan vietäväksi. Tämä kirjan lukeminen on lasten syntymien myötä jäänyt taustalle, mut nyt palautuu yhtenä rentoutumiskeinona.*	Positive	Positive	face 1 - *'neutral'*: 0.987

@moodmetric #moodmetricstressinhallintakeino https://t.co/4QqzyevWkE" English translation: *"Returning to everyday life by immersing in a good book. Reading this book has been left behind by the birth of children, but is now being restored as one of the means of relaxation. @moodmetric #moodmetricstress management tool https://t.co/4QqzyevWkE"*			
Original tweet: *"Hitting the gym relieves stress @Moodmetric #moodmetriccampaign @jjussila #moodmetricstressinhallintakeino https://t.co/Ymbht3wYIM"*	Neutral	Negative	face 1 - *'neutral'*: 0.997
Original tweet: *"Talvella laskettelu on mulle parasta rentoutumista ?? #moodmetricstressinhallintakeino @Moodmetric #parastatekemistä https://t.co/Kq6W9Jtz7v"* English translation: *"In winter, downhill skiing is the best relaxation for me ?? #moodmetricstressinvestmentmodel @Moodmetric #healthy https://t.co/Kq6W9Jtz7v"*	Positive	Positive	face 1 - *'neutral'*: 0.566
Original tweet: *"Mindful breathing keeps my anxiety and stress out while I'm working...so just inhale and exhale...#moodmetricstressinhallintakeino https://t.co/SDczQ0Gz17"*	negative	negative	face 1 - *'neutral'*: 0.926

Original tweet: *"Work and hobby are almost same, but when stress, I build and tweak gadgets and consumer electronics ?, #hardwarehack @Hacksterio @hackadayio and some fun coding. #moodmetricstressinhallintakeino https://t.co/shOI4fOdSp"*	Negative	Positive	face 1 - '*neutral*': 0.942
Original tweet: *"Työkiireen keskellä hyvä tapa nollata päätä on järjestää hetkiä työkaverien kanssa ja oppia uutta yhdessä #moodmetricstressinhallintakeino @Moodmetric @GoforeGroup #palvelumuotoilu #muotoilupeli #neukkarinseinäkin hymyilee! kiitos @annakaisa_b https://t.co/ic6EmvtIRu"* English translation: *"In the middle of the work circle, a good way to reset the head is to have moments with coworkers and to learn new together #moodmetricstress management mode @Moodmetric @GoforeGroup #serviceforming #showoutgame #children wall even smiles! thanks @annakaisa_b https://t.co/ic6EmvtIRu"*	Positive	Positive	face 1 - '*happiness*': 1.0, face 2 – '*happiness*': 1.0, face 3 - '*happiness*': 0.999
Original tweet: *"Työkiireen keskellä hyvä tapa nollata päätä on järjestää hetkiä työkaverien kanssa ja oppia uutta yhdessä #moodmetricstressinhallintakeino @Moodmetric @GoforeGroup*	Positive	Positive	face 1 - '*neutral*': 0.999

#palvelumuotoilu #muotoilupeli #neukkarinseinäkin hymyilee! kiitos @annakaisa_b https://t.co/ic6EmvtIRu" English translation: *"In the middle of the work circle, a good way to reset the head is to have moments with coworkers and to learn new together #moodmetricstress management mode @Moodmetric @GoforeGroup #serviceforming #showoutgame #children wall even smiles! thanks @annakaisa_b https://t.co/ic6EmvtIRu"*			
Original tweet: *"When stressed, I play @PUBG #gameofgames #moodmetricstressinhallintakeino https://t.co/o4SyEHIn5N"*	Negative	Neutral	face 1 - *'neutral'*: 0.953

The above table shows the original tweet from the participants, it's translated version, sentiment results from SentiStrength and Vader sentiment analysis, and emotion with its associated value.

3.2.2 Qualitative content + Quantitative Results

The tweets containing both the text and images were manually annotated for its valence and arousal dimensions. Simultaneously, activity tags were also manually annotated. The following image depicts the valence and arousal dimension of tweets.

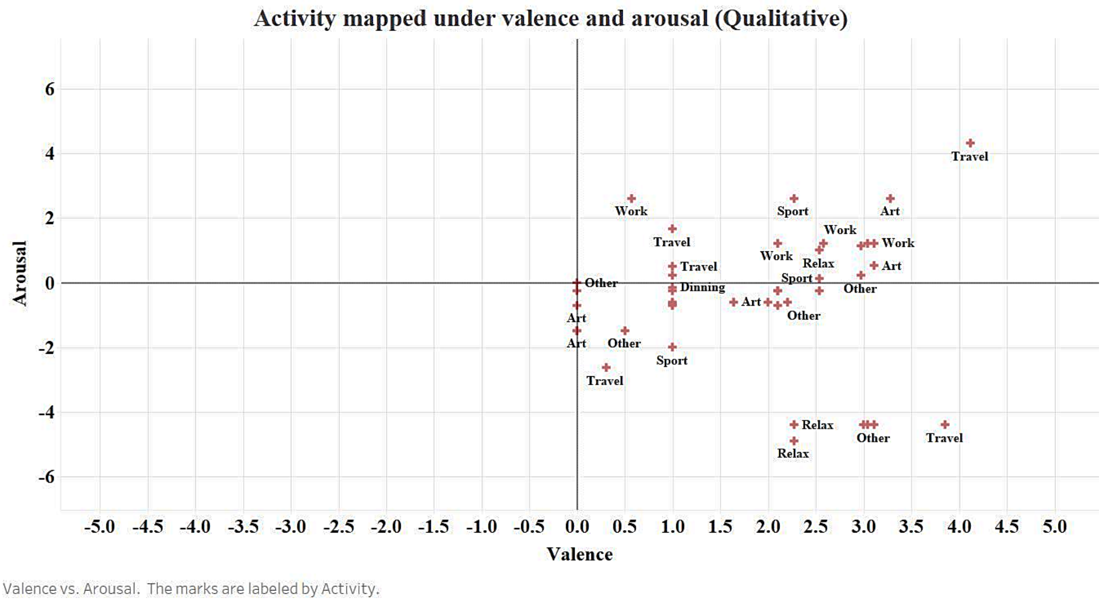


Figure 11. *Activity tags mapped in the valence and arousal dimensions.*

In Figure 11, the activity categories are mapped in the valence and arousal dimension. The activity is market between -5 to +5 on both the valence and arousal dimensions. The following image represents the same points with IBM Watson emotions.

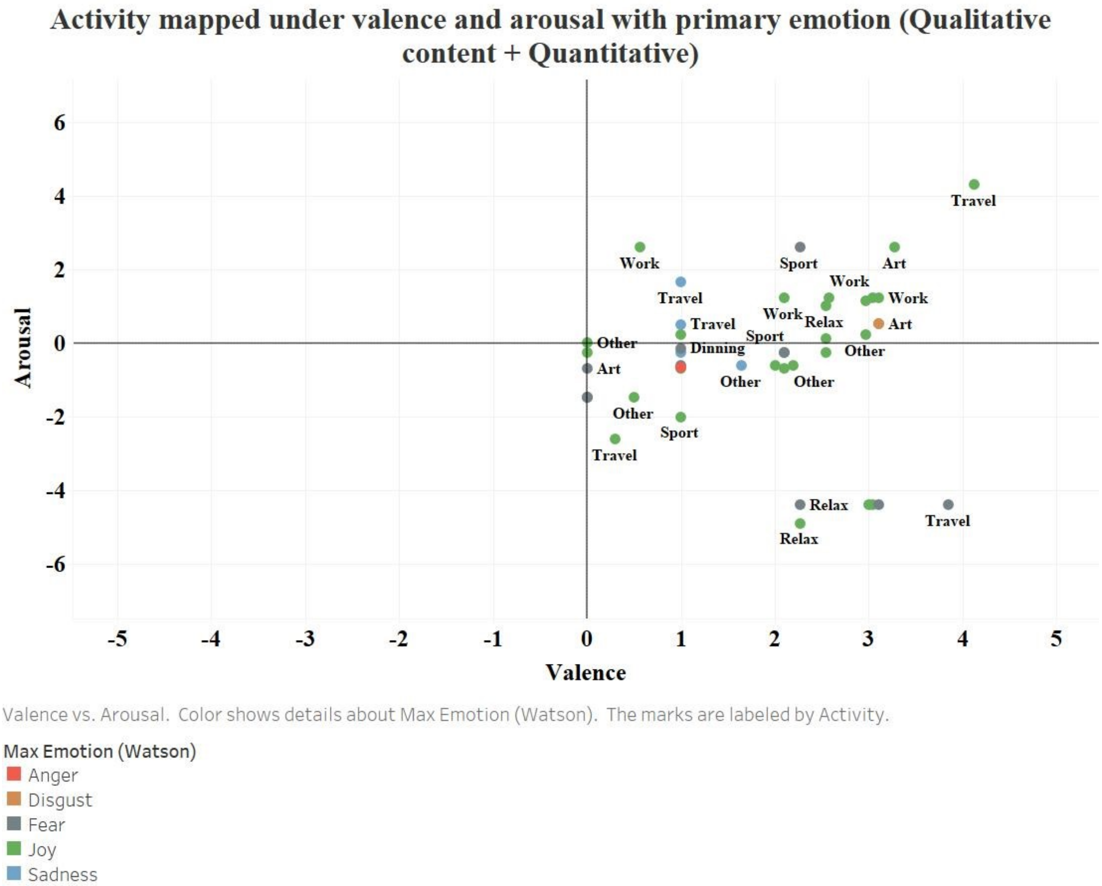


Figure 12. *Activity tags mapped in the valence and arousal dimensions with quantitative emotions.*

In Figure 12, the activity categories are mapped in the valence and arousal dimension with quantitative emotions such as *'Anger', 'Disgust', 'Fear', 'Joy'* and *'Sadness'*. The activity is market between -5 to +5 on both the valence and arousal dimensions.

3.2.3 Qualitative Results

After the analysis of the quantitative results, and qualitative content + quantitative results, the research question 6 and its sub questions need to be answered. To gather answers for these questions, the CIO of the case company was interviewed. The results are as follows.

RQ 6. Where can consumer emotions be applied in a managerial context?
Answer: Vigofere Oy (Moodmetric) provides services that help organizations and individuals to better manage stress. For the company, it is valuable to understand customers emotions towards their and products, services and stress management in general. The services of the company help customers to keep track of their daily activities and gain insight on which activities increase recovery and stress. By providing biofeedback to customers, the customers can learn what works best for them, and adjust their behavior, habits, and activities accordingly.

RQ 6.1 How is the company currently making use of consumer emotions?
Answer: Moodmetric smart ring measures electrodermal activity of the wearer, which is a psychophysiological measure of stress (arousal). In addition, the Moodmetric App contains a diary function that allows customers to record their emotions on valence scale (of Happy, Neutral and Unhappy) about their activities. However, customer inputted data to diary is not transferred to Moodmetric Cloud and hence Moodmetric gets to know about their consumers emotions only when they share them, e.g. in social media. The company has collected user stories for marketing in the form of tweets, blog posts and YouTube videos, which are mostly self-reported emotions or experiences of using the product. The company is interested to know about their customers stress management and recovery activities and experiences also in terms of valence and arousal dimension. Therefore, they were interested in experimenting with Twitter marketing campaign by which emotions could be analysed from user posts.

RQ 6.2 What challenges does the company have in collecting data and analyzing consumer emotions?
Answer: Consumers express their emotions about Moodmetric products and services on several social media platforms, such as Instagram, Facebook, Twitter and YouTube. It's challenging to collect data from multiple social media platforms and, for example, data on Facebook is available only from Moodmetric Page comments and from those closed groups that Moodmetric is moderating. The company does not employ automatic omni-channel social media monitoring tools, so practically all data needs to be collected manually. Furthermore, there is a lack of sentiment and emotion algorithms

that could be used to detect consumer emotions from Finnish language, which was the main market of the product during the time the study was conducted.

RQ 6.3 How could the quantitative, qualitative content + quantitative results and qualitative results be made use of in the company?
Answer: Quantitative results related to activity tags provide information what things have a more positive, neutral or negative association in the images posted by users. This information can be used e.g. in designing marketing messages of the company.

Activity tags associated with positive sentiment can be assumed to describe situations and activities that users find more positive. First of all, an inventory of positively associated activity tags is interesting. Tags like *'outdoor', 'water', 'grass', 'ocean', 'park'* that have often been associated with positive sentiment are something that can be used as image features when the intention is to convey positive messages. However, some recognized activity tags like *'man', 'sitting', 'standing'* that are often featured and associated with positive sentiment are less informative and taken out of context do not make sense.

Activity tags that have been classified as neutral do not as such help in designing marketing messages. Negative activity tags give some indication of features in images that have been perceived as negative by users. To some degree these could be used "Don'ts" when adding illustrations to social media posts. With a larger sample of tweets by users this could be informative.

Tables 15 and 16 provide condensed results of what users perceive as positive, neutral or negative aspects. The tables actually reveal that many often used activity tags can be found both from the positive, neutral and negative sides. SentiStrength and VADER provide similar results. By comparing the results of Computer Vision API and the two sentiment detection algorithms some support is given to the most positively and negatively associated tags. For instance, outdoors have been largely positive by all detection methods and computers negative by all detection methods. Especially, outdoors, nature, forests are often mentioned in research reports, as well as, Moodmetric users as something that help them to recover from stress. The identification of computers as negatively associated is also not a surprise. Long hours sitting with a computer, especially if no breaks are taken, are not beneficial for health and feature also often as problems mentioned by knowledge workers in their daily life. In terms of marketing and communications, people sitting with computers can be used to communicate the need for recovery. A larger sample of tweet analysis might reveal a more comprehensive dictionary that can be used in connection with stress management and recovery as used by customers and enable the company to talk in a more similar language with its customers.

Activity tags with emotions from the images (Figure 10) provides the company additional information. Especially are interesting such tags that have been associated with *'anger', 'disgust'* or *'joy'*. Typically, *'anger'* and *'disgust'* are indicative of stressful situations - and is more valuable to understand than just valence dimension (from negative to positive). Also, *'joy'* is important as it typically indicates situations and activities where the person has a better mood and can help to recover from stressful situations. Emotions thus provide more valuable information for the company.

This visualization (Figure 11) is the most useful for the company, as it provides the mapping of activities in terms of arousal and valence dimensions that is also supported by the Moodmetric application. The categorization by activity provides the most valuable information as it helps to describe and communicate situations that have been found important for recovery. The qualitative analysis also reveals that in contrast to the sentiment detection algorithms applied in the previous analysis - the users did not actually report any activities they considered negative. This was expected, as the idea of the marketing campaign was to source practices and activities that the users have found beneficial for stress management and recovery.

This visualization (Figure 11) could be done also at an individual level, which could help the user to increase self-awareness and better understand how each activity impact him or her in arousal and valence dimension. Such information and visualization could be used to see the impacts of small changes and new ways of working that the user tries in daily life. For instance, if the user would start practicing some stress management method, the impact of this could be visualized in daily, weekly and monthly basis.

Information about emotions added to the visualization (Figure 12) have potential to increase the value of the visualization. However, it is difficult to determine the accuracy of Watson emotion detection based on the visualization. For example, without knowing the actual tweets, it is not possible to say which are those situations that have been detected to include anger or fear. Therefore, this visualization would need additional views, or e.g. function as a user interface to investigate in more detail the tweets that are interesting or surprising based on the visualization. If this visualization would be about tweets of an individual person, it would likely serve as an interesting view to different activities and their emotions as experienced by the user. The combined view of tweets from all users on the other hand can be informative for the company in recognizing emotionally loaded activities

RQ 6.4 What is most valuable method for making use of consumer emotions?
Answer: The most valuable method for the company would include the activities and their positioning in the arousal and valence space. The study clearly points out two distinct use cases how consumer emotions on social media could be utilized by the

company. First, similarly to the Moodmetric App, an activity compass could be developed that visualizes the user's behavior based on his or her social media activity. This could provide interesting insights for the user. Secondly, a similar application could be developed that analyzes all the discussions related to the company's products and services in real-time. This could be used to monitor social media discussions and adjust communications accordingly

RQ 6.5 How can the company implement the introduced methods in their business?
Answer: The introduced methods function as a proof of concept of something that the company could develop and implement in its own business. For organizations such methods could be used to develop a real-time organizational climate and wellbeing measures that could be displayed e.g. on company wall or intranet. In addition, to the compass that visualizes the social media discussion around the company or all its employees in arousal and valence space, trend views could be developed that display daily and weekly trends from social media data. This kind of data could be used to augment data that is received from employee wellbeing and organizational climate surveys. The introduced methods can be also used to increase customer understanding and experiences related to the company's products and services. One next step to explore would be also to see how the methods would perform and the visualizations look like when data is collected from several social media sources, such as Facebook and Instagram, in addition to Twitter. Overall, the study provides several new opportunities for social media analytics that need to be further investigated.

4. DISCUSSION AND CONCLUSIONS

The study was initiated to gather understanding and to answer the subject matter concerning the primary research question "*What are the different managerial applications resulting from detection of consumer emotions in social networking data?*", a systematic literature review methodology was applied in this study. The literature review was conducted using Fink (2014)'s *'Conducting Research Literature Reviews'*. The application of the literature review follows 7 systematic actions. First step is selecting the research questions. A total of six research questions were formulated, the focus of which is to answer how the current social networking data are extracted and from which social networking platform?, what are the different consumer sentiment and consumer emotions that are studied in their analysis?, what are the sizes of the datasets that are extracted for analysis?, what are the different computational methods used in studying consumer emotions (and sentiments) and how are they evaluated?, what are the limitations while detecting consumer emotions in social networking sites?, and finally, where can consumer emotions (and sentiments) be applied in a managerial context?.

Second step of the process is selecting the bibliographic or article databases/websites, and other sources. The selection includes IEEE Xplore, ScienceDirect, and Web of Science. Third step is to choose the search terms for gathering the articles. The search terms used for this study are "social media" emotion* consumer. After this, the practical screening criteria comprising inclusion and exclusion criteria for the article was applied. For the inclusion criteria, only studies that are published in English language was considered, only journals and research articles were included, only studies that discussed consumer emotions in social media context were included, and articles that mentioned data extraction methods were taken in to consideration. For the exclusion criteria, duplicates were excluded, articles were excluded if the data extraction methods are manual and are not automated, articles were excluded if they were not specifically talking about social networking platforms, and articles were excluded if the analysis was performed on existing datasets.

Initially, the total number of articles that were returned for the search terms were 86, 1457 and 145 for IEEE Xplore, ScienceDirect and Web of Science respectively. After the inclusion criteria and exclusion criteria, total number of articles for final analysis were reduced to just 29 in number (IEEE – 5, Web of Science – 4, ScienceDirect – 20).

4.1 Summary of the Results

The results of the systematic literature review are synthesized and presented in Table 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, and 14. The final articles were gathered from publications such as China Communications, IEEE Access, IEEE Transactions on Visualization and Computer Graphics, Journal of Destination Marketing & Management, Program-Electronic Library and Information Systems, Online Information Review, Journal of Hospitality and Tourism Technology, Journal of Computational Science, Transportation Research Part E: Logistics and Transportation Review, The Journal of Strategic Information Systems, Information and Management, Expert Systems with Applications, Applied Soft Computing, International Journal of Information Management, Food Quality and Preference, International Journal of Human-Computer Studies, Computers in Human Behavior, Public Relations Review, International Journal of Production Economics, Industrial Marketing Management, Decision Support Systems, International Journal of Hospitality Management, and The Journal of Finance and Data Science. The earliest article chosen is from the year 2012 and the latest article is from 2018.

Research Question 1 – How are the current consumer emotion social networking data extracted in the current literature and from which social networking platform?

Majority of the articles gathered data using APIs (18 articles). Other data extraction methods include SocioScope (custom-made), SODATO, Crawler (2 articles), Internet Crawler, HTML Parsing, twitteR package (2 articles), Open Graph API, QDA Miner, and Radian 6. With regards to the social networking platforms, majority of the studies were conducted based on Twitter platform, as many as 20 articles. Two articles performed their analysis on both Twitter and Facebook. Other social networking platforms include Sina Weibo (4 articles) and Facebook (2 articles). One study did not mention any social networking platform. Therefore, it is evident that most of the studies that tried to understand consumer emotions were conducted on data which was gathered from Twitter platform.

Research Question 2 – What are the different consumer sentiments and consumer emotions that are investigated in the current literature?

Many research articles classified emotions into 2-5 different types of sentiment classes. Twelve studies classified sentiment into positive and negative classes as seen in Table 4. Nine studies classified sentiments into positive, negative and neutral classes as seen in Table 5. Four studies classified sentiments into more than three categories as seen in Table 6, out of which three studies classified sentiments into five categories; Benthaus *et al*. (2016) classified sentiments into average, positive, negative, ambivalent and neutral categories; Ghiassi *et al.* (2013b) differentiated sentiments into strongly positive, mildly positive, neutral, mildly negative and strongly negative. David *et al.* (2017) classified sentiments into positive, negative, neutral, extremely positive and extremely negative. In Tombleson and Wolf (2017), six different sentiment categories were used namely neutral, mixed, somewhat positive, somewhat negative, negative and positive.

With regards to articles that studied emotions. Nguyen *et al.* (2017) investigated only one emotion, 'trust' (Table 7). The study is based on 'trust' refreshment during several events. D'Avanzo, Pilato and Lytras (2017) studied emotions such as *'anger'*, *'disgust', 'fear', 'joy', 'sadness'* and *'surprise'*. Sun *et al.* (2018) studied *'neutral', 'happy', 'surprised', 'sad',* and *'angry'* emotions. Aswani *et al.* (2018) studies emotions such as *'joy', 'sadness', 'surprise', 'anger', 'fear'* and *'disgust'*. Vidal, Ares and Jaeger (2016) investigated emoticons and categorized several emoticons into three different emotional categories namely *'positive emotional expression'*, *'negative emotional expression'*, and *'neither positive nor negative emotional expression'*. Davalos *et al.*(2015) studied nostalgic posts for positive and negative emotions on Facebook and found nine word categories that were frequently used. The nine-word categories are *'happy', 'cried', 'love', 'hurt', 'annoyed', 'kill', 'hate', 'grief',* and *'sad'*.

More than four studies (Table 8) contained more than 19 categories of emotional adjectives. Jabreel *et al.* (2017) analyzed emotional adjectives used by destination marketing organizations (DMOs). All the emotions were classified based on 5 emotional values and 16 categories and 60 sub-categories. The emotional values are *'Sincerity', 'Excitement', 'Competence', 'Sophistication',* and *'Ruggedness'*. 16 categories are *'Down-to-earth', 'Honest', 'Wholesome', 'Cheerful', 'Dating', 'Spirited', 'Imaginative', 'Up-to-date', 'Cosmopolitan', 'Reliable', 'Intelligent', 'Successful', 'Luxurious', 'Charming', 'Outdoorsy',* and *'Tough'*. The subcategories are as follows: *'Family-oriented', 'Down-to-earth', 'Sustainable', 'Calm', 'Real', 'Traditional', 'Honest', 'Original', 'Wholesome', 'Quality of life', 'Happiness', 'Sentimental', 'Friendly', 'Trendy', 'Daring', 'Exciting', 'Exotic', 'Fashionable', 'Cool', 'Spirited', 'Dynamic', 'Vital', 'Fresh', 'Young', 'Sensorial', 'Unique', 'Imaginative', 'Creative', 'Up-to-date', 'Independent', 'Contemporary', 'Cosmopolitan', 'Tolerant', 'Hospitable', 'Reliable', 'Hard-working', 'Safe', 'Rigorous', 'Intelligent', 'Technical', 'Corporate', 'Innovative', 'Successful', 'Leader', 'Ambitious', 'Powerful', 'Glamorous', 'Luxurious', 'Seductive', 'Smooth', 'Romantic', 'Magical', 'Outdoorsy', 'Get-away', 'Recreational', 'Tough', 'Rugged',* and *'Non-conformist'*. In their study, London expressed the most emotional adjectives 289. In Gao, Xu and Wang (2015), twenty two fine grained emotions are placed into four branches based on actions causing emotions; in the branch of *'results of events'*: *'hope', 'fear', 'joy' and 'distress'*; In the second branch, which is *'actions of agents': 'pride'. 'shame', 'admiration' and 'reproach'*; In the third branch, which is *'aspects of objects': 'liking'* and *'disliking'*; The fourth branch make up the extended emotions which are *'satisfaction', 'fears-confirmed', 'relief', 'disappointment', 'happy-for', 'resentment', 'gloating',* and *'pity'*. Leek, Houghton and Canning (2017) did statistical analysis on 37-word categories.

Not all studies that mentioned emotions backed the use with any emotional theories. However, some authors based their research on emotion theories. D'Avanzo *et al.* (2017) relied on Ekman (1992)'s theory of basic emotions such as *'anger', 'disgust', 'fear', 'joy', 'sadness',* and *'surprise'*. Xu, Yang and Wang (2015) developed four levels of hierarchy containing in total nineteen fine grained emotions namely *'sad', 'disappointed', 'guilty', 'missed', 'surprised', 'panic', 'frightened', 'shy', 'angry', 'dissatisfied', 'annoyed', 'doubtful', 'hateful', 'favoured', 'trustful', 'praiseful', 'wish-ful', 'calm',* and *'happy'* based on seven basic emotions prosed by Ekman (1971). In Aswani *et al.* (2018), the emotions are classified based on Chaumartin (2007) who conducted analysis on emotions such as *'joy', 'sadness', 'surprise', 'anger', 'fear',* and *'disgust'* using study from Strapparava and Valitutti (2004).

Research Question 3 – What are the dataset sizes that are extracted for consumer emotion analysis in existing studies?

From as few as 838 tweets to massive amounts containing 25 million records were analyzed to detect consumer emotions in social networking sites. The maximum dataset size was found in Sina Weibo platform where the authors introduce a Dynamic Sentiment-Topic model that can detect sentiment, track dynamic topics and analyze the shift of sentiment towards a specific topic.

Several software was used in the process of understanding consumer emotions in social networking sites. In some of the articles, there were no explicit mention of what type of software tools were used. QDA WORDSTAT (Davalos et al), R programming language with several libraries such as twitteR, RCurl, R tm package, the plyr, stringr, ggplot2 were used (Mostafa, 2013; Vidal, Ares and Jaeger, 2016; Mehmood *et al.*, 2017). Custom-built software VOZIQ for social media analytics was used by He *et al.* (2015). For visualizing sentiment, Sentiment Viz is employed by Park *et al.* (2016), LIWC sentiment software by both Davalos *et al.* (2015) and Leek *et al.* (2017). Visualization software include 'Whisper' by Nan Cao *et al.* (2012) and StreamGraph by Mostafa (2013). For data mining and analytics, RapidMiner 5.3 was used by Park *et al.* (2016). Other software include Radian6 by Tombleson and Wolf (2017), twiQuery by Jabreel *et al.* (2017). For graphical representation of data, MATLAB was used by Sun *et al*. (2018).

Research Question 4 – What are the different computational methods used in studying consumer emotions and how are they evaluated in the current literature?

All the articles are categorized according to the computational methods in Table 9, 10, 11, 12, and 13. As seen from Table 9, ten studies used sentiment analysis computation method either individually or by combining other methods. Zhang *et al*. (2016) introduces dynamic sentiment-topic model (DST), that can classify sentiments into positive, negative and neutral; the authors also used Gibbs sampling method, and topic detection and tracking. Vatrapu *et al*. (2016) introduced α cut approach towards sentiment analysis methods that allows marketing professionals or academics to determine probability levels for different sentiment categories on their own. In addition to that, it can help them to identify the intersection of sentiments at a given α cut, further allowing them to classify strong-weak expressions of sentiment. Mehmood *et al*. (2017) used sentiment analysis in their study to conclude that 78% of the customers expressed positive sentiment for distance and eLearning. Abirami and Askarunisa (2017) employed TOPSIS, multi-criteria decision making (MCDM), sentiment analysis and natural language processing (NLP) to rank hospitals for different attributes such as 'infrastructure', 'cost', 'time', 'medicare', and 'nursing'. Park, Jang and Ok (2016) analyzed which restaurants contained high positive, negative and neutral sentiments using text mining, sentiment analysis and statistical computation using ANOVA. Benthaus, Risius and Beck (2016) used SentiStrength2, Naïve Bayes and data analysis to study consumer sentiment and deploy social media management tools using which they discovered a significant rise in positive tweets by 4.3% and decrease in negative tweets by 3.5%. Davalos *et al.* (2015) used sentiment analysis technique on Facebook posts to investigate nostalgic posts and concluded that Facebook platform contains primarily positive content. Ibrahim, Wang and Bourne (2017) explored the effect of user engagement by companies using sentiment analysis; the results showed that when AmzonHelp engaged with consumers with response that were lengthier and with positive sentiment lead to significant decrease in negative sentiments and becoming neutral in polarity. Daniel, Neves and Horta (2017) used sentiment analysis to study the impact of consumers on major announcements from major corporate companies like Microsoft and Walmart.

Four studies (Table 10) have made use of machine learning algorithms and methods in their study. Xu, Yang and Wang (2015) used feature extraction, feature selection and classification with support vector regression to categorize emotions; the authors achieved an accuracy of 76.1%. M *et al.*(2017b) reported accuracies of 74.31%, 86.01%, 80.68%, 74.23% for different features of a mobile phone for different companies using SVM classifier. Li and Li (2013) compared two computational methods - SVM and Naïve Bayes, the accuracies are 88.1% vs 71.7% (binary), 87.7% vs 70.3% (term frequency), 79.4% vs 67.4% (term frequency-inverse document frequency). However, Ghiassi, Skinner and Zimbra (2013b) reported the highest accuracy of 96% by using customized algorithm for positive sentiment, 89.9% - mildly negative, 95.1% for negative emotions. Singh, Shukla and Mishra (2017) reported the highest accuracy which are 90.80% (unigram feature), 74.46% (bigram feature), 86.27% (term frequency unigram feature) and 71.68% (term frequency bigram feature) with SVM classifier to classify positive and negative messages.

In Table 11, studies that used content analysis are displayed. Jabreel, Moreno and Huertas (2017) inferred using semantic content analysis that many destination management organizations (DMOs) on average use 170 different emotional adjectives

1344 times in their tweets. The more a DMO uses emotional adjectives, the more was their effort to attract tourists. Aswani *et al.* (2018) used content analytics with descriptive, network, and space-time analytics to find sentiments and emotions from tweets. Vidal, Ares and Jaeger (2016) used content analysis to study the use of emoticons and it's occurrence in positive and negative emotional expression.

Table 12 shows studies that were conducted using lexicon-based methods. Gao, Xu and Wang (2015) used emotion cause analysis, emotion classification, emotion lexicon, and multi-language features extraction; these methods helped to find emotions and their causes. Mostafa (2013) made use of Hu and Liu lexicon to find sentiment scores for mobile brands. Philander and Zhong (2016) used dictionary or lexicon based approach to study sentiments for the resorts in Las Vegas. Nisar and Yeung (2018) used lexicon based approach for stock market sentiment and prediction.

Table 13 shows other computational methods used by the articles. Nguyen *et al.* (2017) used trust ontology, event-driven trust refreshment methods. Radial layout scheme to study the sentiments during earthquakes and elections by (Nan Cao *et al.*, 2012). Sun *et al.* (2018) used single and multivariate Gaussian distribution for abnormal user emotion detection. He *et al.* (2015) used modified Chi-square feature selection and modified N-Gram model to correctly mark positive and negative messages. Computational linguistic approach for social media engagement in relation to sentiment and emotions (Leek, Houghton and Canning, 2017).

Research Question 5 – What are the limitations while detecting consumer emotions in social networking sites in the current literature?

As seen from Table 9, 10, 11, 12, and 13. Out of all the studies only 18 studies reported limitations. Abirami and Askarunisa (2017) reported that sometimes reviews were not genuine and that it created a bias with the results. Park, Jang and Ok (2016) reported that short data collection period and tweets containing advertisement affects the results. Singh, Shukla and Mishra (2017) and Chae (2015) also reported limitations regarding short data collection period in addition to the missing information regarding tweeting users. Li and Li (2013) argued that profile information or other information regarding the users were not considered similar to Vidal, Ares and Jaeger (2016). Benthaus, Risius and Beck (2016) analyzed companies that already has success with social media management tools and also reported unconscious reviewer bias. Davalos *et al.* (2015) mentioned that their study contains limitations because the study was performed only on one social networking platform similar to Aswani *et al.* (2018). One study performed analysis on retail brands within UK (Ibrahim, Wang and Bourne, 2017). Xu, Yang and Wang (2015) had problems with their own computational method stating that the algorithm used had limited in its ability. Failure to identify the sentiment topic (Mostafa, 2013) and failure to identify the true circumstances behind the tone and meaning of sentiment expressed (Tombleson and Wolf, 2017). Nisar and

Yeung (2018) used a classifier (computational method) with poor precision; accuracy was better when detecting only positive and neutral sentiment.

Research Question 6 – Where can consumer emotions be applied in a managerial context?

In the following image, several managerial applications gathered from the study are mentioned. Many of the studies contribute to various managerial themes that can be applied by understanding consumer sentiments and emotions from social networking sites.

Figure 13. *Several managerial themes that can be applied by studying consumer emotions in social networking websites.*

From figure 13 and Table 13, several studies facilitate the study on consumer emotions in various managerial contexts. There are more than thirty themes in which managers made use of different computational techniques to identify consumer emotions for business benefits and understanding. Nguyen *et al.* (2017) proposed degree of trust (DoT) to study the *'trust'* of their consumers over several events due to its dynamic nature; it can be used a basis for customer trust measurement over several events. Zhang *et al. (2016)* proposed model to detect the 'topic' and sentiment behind the topic. Vatrapu *et al.* (2016) proposed fuzzy-set based social sentiment analysis which can be used for marketing campaigns and conveyed that it can be used in crisis management for product specific context; applications include monitoring consumer behavior during marketing campaigns and crisis management. Mehmood *et al.* (2017) proposes understanding consumer emotions in distance eTeaching and eLearning to monitor the behavior of consumers with regards to the effect of a particular learning system which can enable the companies to customize their offering. Community responses at different locations were analyzed for a similar product which falls under community response management category as done by Nan Cao *et al.* (2012). It can be used in tourism industry as done by Jabreel, Moreno and Huertas (2017) who employed consumer emotion detection to find new ways of marketing for firms in tourism industry to promote tourist destinations based on emotional values in social media. Product launch feedback or consumer feedback analysis (D'Avanzo, Pilato and Lytras, 2017).

Service quality analysis by Abirami and Askarunisa (2017) who studied the use of consumer emotion in the context of healthcare industry to understand user opinion on various indicators of service quality. This would enable the hospital management to perform business intelligence and advanced decision making. Study of consumer emotion detection can be applied in restaurant industry as done by Park, Jang and Ok (2016) to analyze consumer perception and customer satisfaction of Asian restaurants. Different attributes such as restaurant environment, service quality, employee presentation and food taste can be studied. Sun *et al.* (2018) proposed a model to detect consumer emotions which can be used for consumer feedback analysis in real-time and in turn help companies to form revival strategy to neutralize negative effects by attending to the customer with displaced emotion. In supply chain analytics, consumer emotion analysis can be employed in supply chain management related problems as examined by Singh, Shukla and Mishra (2017) where several issues related to food products can be traced back to different points in the supply chain by analyzing consumer feedback; according to the authors, this could allow companies to find the root cause for customer displeasure which can lead to better use of company's time and resources. Target marketing, customer satisfaction, and customer engagement (Benthaus, Risius and Beck, 2016).

He *et al.* (2015) argued that consumer emotion analysis/study can be used in many applications such as competitor analysis, industry-specific sentiment benchmarking which can be used for decision-making, marketing intelligence and key performance metrics. Xu, Yang and Wang (2015) proposed an algorithm to detect consumer emotions in social networking context and recommend that it can be used to understand consumer trends and consumer behavior analysis. Gao, Xu and Wang (2015) provide a means to extract the cause of consumer emotions and further predicts that it could be used in precision marketing for product recommendations and tailoring products to particular customers. M *et al.* (2017b) studied consumer opinion expression in social media. According to Aswani *et al.* (2018) consumer emotion study can help to improve search engine marketing and enhanced strategy for digital marketing. Understanding consumer behavior by their emotions can help in product development, marketing, service feedback analysis and target marketing (Vidal, Ares and Jaeger, 2016).

Nostalgia-based advertisement campaign could help managers in improved marketing (target marketing) where consumers are targeted based on their social media posts and communication (Davalos *et al.*, 2015). Understanding consumer sentiment and emotions can help managers in applications such as customer engagement, customer perception management, customer complaint management, customer relationship management and brand perception management (Mostafa, 2013; Ibrahim, Wang and Bourne, 2017). Tombleson and Wolf (2017) analyzed consumer emotions in a cross cultural context and argued that it can be very helpful for cross cultural marketing, demand forecasting, product and service quality; they also think that it could be used for risk management. The concepts such as demand forecasting, product and service quality, supply chain management and operations management was discussed by Chae (2015). Public relations management and customer engagement (Leek, Houghton and Canning, 2017). Li and Li (2013) also make use of consumer emotion analysis for competitor analysis and real time consumer monitoring. Philander and Zhong (2016) employ consumer behavior, marketing intelligence and brand perception with regards to consumers in hospitality context. Nisar and Yeung (2018) also study real time consumer monitoring for stock market prediction. Other applications include stock market prediction by Ghiassi, Skinner and Zimbra (2013b) and analysis of popular events or event popularity by Daniel, Neves and Horta (2017).

Summary of the quantitative results

Two algorithms were used in detecting the sentiments. With SentiStrength, activities 'sitting' scored highest in positive (13) and negative sentiment (12) category and 'man' (9) has the highest neutral sentiment (Table 15). In VADER sentiment, 'man' is the highest in positive (14) and negative (10) sentiment category. Whereas, 'sitting' (11) has the neutral sentiment (Table 16). For emotions, 23 activities fall under *'Anger'* emotion and they are *'bed', 'black', 'board', 'clock', 'computer', 'dark', 'desk', 'front', 'holding', 'indoor', 'keyboard', 'laptop', 'man', 'monitor', 'old', 'piano', 'room', 'screen', 'sitting', 'table', 'television',* and *'white'*. Ten emotions under *'Disgust'* category namely *'air', 'bag', 'blanket', 'laying', 'pair', 'paper', 'phone', 'sitting', 'table',* and *'white'*. For *'Fear'* category, *'man', 'old',* and *'sitting'* scored the highest with 6 points each and 102 activity tags were recorded under this category. *'Joy'* emotion recorded the highest with 191 tags, *'sitting'* ranked highest with 22 points followed by *'man'* and *'standing'* with 21 points. *'Sadness'* emotion with 60 tags and it's activities *'man', 'sitting', 'small', 'table'* were all ranked highest with 3 points each followed by *'bird', 'cat', 'computer', 'indoor', 'water', 'white',* and *'background'* with 2 points each.

Under face emotion results, only 7 tweets contained images with faces and in total 10 faces were recorded. Out of the 10 faces, 7 faces showed *'neutral'* emotions and 3 faces showed *'happiness'*. 6 faces were identified as *'male'* and 4 were identified as *'female'*.

Summary of the qualitative content + quantitative results

All the activities were recorded with positive valence. For arousal, many activities fall under both positive and negative arousal. Activity *'Travel'* scored the highest valence (4.12) and arousal (4.31); both these values coming from the same tweet

"Veden lipsatus, metsän raukeus ja iholla tuntuva tuulenvire johdattelevat meditatiiviseen olotilaan aina kun olen luonnossa! #moodmetricstressinhallintakeino @Moodmetric https://t.co/amnFTBootF" which can be translated as

"Lipsatus water, forest and listlessness appreciable breeze on the skin lead the meditative state of being always when I'm in nature! #moodmetricstressinhallintakeino @Moodmetric https://t.co/amnFTBootF".

14 images were attributed to *'Travel'* category, *'Art'* and *'Relax'* came second with 7 images; followed by *'Work'* and *'Other'* with 6 images, *'Sport'* with 5 images, *'TV/Web'* and *'Dining'* with an image each. Most *'Relax'* categories were low arousal having values over as low as -4.89. *'Art'* category contained mostly neutral arousal values with only 1 outlier (2.61). *'Work'* categories contained medium arousal values with maximum of 2.61. *'Other'* category contained mostly neutral arousal values falling in positive and negative scale, but also contained one low arousal value of -4.4. *'Sport'* also scored neutral to medium arousal values with a maximum of 2.61. Only image under the *'Dining'* category also scored low arousal value of -0.148.

With regards to the attributing IBM Watson emotions to the valence and arousal dimensions. 1 image under *'Anger'* (FP) emotion and falls under *'Art'* category. 1 image under *'Disgust'* emotion and falls under *'Art'* category. 9 images under *'Fear'* emotion (*'Relax'* – 2, *'Dining'* - 1, *'Art'* – 1, *'Travel'* – 2, *'Sport'* – 2, *'Other'* – 1). 32 images under *'Joy'* emotion (*'Relax'* – 5, *'Work'* -5, *'TV/Web'* - 1, *'Art'* – 4, *'Travel'* – 10, *'Sport'* – 3, *'Other'* – 4). 4 images under *'Sadness'* emotion (*'Work'* – 1, *'Travel'* – 2, *'Other'* – 1). As seen from Figure 12 and above stated information *'Joy'* is the highest occurring emotion. Most participants tweeted images that fall under the *'Travel'* activity category.

Summary of the qualitative results (Section 3.2.3)

The CIO outlined the desire to understand consumer emotions to their product and services. The value of consumer emotions can be linked to the context that is causing this emotion which can allow to gather insight into the type of activity that causes a specific emotion. Currently, the company's app allows the users to record their emotions and activities manually. The company can only know if the consumers share it on the social media. However, there are challenges on collecting data from different social networking platforms due to arduous data collection process. On the other hand, Twitter allows for easier sharing and collection of data in comparison to other SNS. Therefore, it is convenient for the company to collect data using Twitter.

The CIO mentioned that the quantitative, qualitative content + quantitative evaluation can be helpful in designing marketing messages for the company. The positive sentiment communicated by outer world elements such as *'outdoor'*, *'water'*, *'park'*, *'grass'*, *'ocean'* can be used to convey positive messages over other tags that are very general like *'standing'* and *'sitting'*. Neutral and negative tags could not be of much use when creating marketing messages and implied that analysis on larger samples can be informative. The CIO expressed the affirmation that both the algorithms have quite similar results and indicated that both positive and negative tags can be used for marketing messages. For instance, *'Computers'* was negatively presented and that it be used to communicate the necessity for users to concentrate on recovery.

The CIO mentioned that attributing emotions to tags is valuable to their company because the consumer emotions such as *'Anger'* and *'Joy'* can now be placed into different dimensions and could help understand them better. However, the most important value for the empirical evaluation according to the CIO was plotting of activities in the valence and arousal dimensions which was similar to their own application. Additionally, the map allows user to individually witness and analyze their own situation and progress in a timely manner.

Based on the analysis and visualizations, the CIO expressed two use cases for consumer emotions. First is the development of an activity compass that can help visualize the behavior of the user, and second, a real time assessment of the discussions relating to the company which can help in matters related to communication. Similarly, this analysis is a proof of concept that the company could customize according to their business needs, foster an enhanced use in different applications such as employee well-being analysis and organizational climate surveys. Finally, CIO stated that a possibility of further understanding is possible if the same evaluation is conducted using different social media platforms.

4.2 Scientific Contribution

The systematic literature review showed the presence of consumer emotions in a social networking context. The evidence of studying consumer emotions in smaller to larger datasets, using several computational methods, software, and in different managerial contexts. Few studies measured their performance using accuracy of the computation method, which is very important to evaluate future performance and to compare benchmarks. Some studies reported limitations with regards to their study.

Out of these, there were few limitations which must be avoided when understanding consumers such as problems with the use of computational technique or method with limited features, failure to identify the topic behind the sentiment, circumstances behind the expression of a certain sentiment, and missing information about the users. Therefore, to be able to understand consumers, a certain set of important parameters like “who?”, “why?”, and “what?” must be identified. “who?” is the general information regarding the users, for example: Gender. “why?” is the reason behind (cause) the sentiment. for example: activity or a situation that caused the sentiment, and “what?” is the emotion or sentiment itself.

To address this gap, an empirical evaluation is necessary. In this case, a company that provides stress management products and services is chosen. It is an ideal selection since the important parameters to identify here is information regarding the person experiencing, battling or coping with stress (“who?”); the reason behind their emotions related to stress management (“why?”), and to identify the sentiment or emotion (“what?”). With regards to the choice of computational method, the idea is to bypass the shortcomings of lower accuracy computational problems, any sarcasm and other text limitations like language barrier; which is the reason why a face emotion detection tool is used in this empirical study along with image captioning tool to understand the “who?”, “why?” and “what?”

As understood from the summary, only 7 tweets were tweeted with a face image and 10 faces were identified. Information like gender and emotions were gathered from these face images. The positive aspect about face detection is that it provided the emotions for the faces with great accuracy. However, there was one false positive where a participant tweeted an image of a book, the detected emotion was from the face that was displayed on the book cover and not of the participant who posted the tweet. With regards to the description (captioning) or a circumstance, the image captioning algorithm provided a decent accuracy. For the images with faces, the descriptions were accurate for 5 out of 10 images.

For remaining images with no face, there were descriptions which were almost correct. For example: in the tweet,

“Hitting the gym relieves stress @Moodmetric #moodmetriccampaign @jjussila #moodmetricstressinhallintakeino https://t.co/Ymbht3wYIM” The image shows a man holding a camera and posing, but the description from the algorithm returned *“a man holding a bottle posing for the camera”.* Similarly,

“Rentoutumista mökillä, aivojen (melkein) nollausta. @moodmetric #moodmetricstressinhallintakeino https://t.co/SWg1TrAQtF” shows an image where two dogs are sitting on a person on a grass covered field to which the algorithm returned *“a dog sitting on top of a grass covered field”.* Another tweet,

“Miten hallitsen stressiäni? Metsä. Luontokuvaus. Käsityöt. Polkujuoksu eritoten pikkuisten kanssa. Aikataulutta, hitaasti ja 12 000 solmua ryijyyn ommellen. #moodmetricstressinhallintakeino https://t.co/chloX6O21u” shows a little child running down a dirt path in a wooded area, the algorithm returned *“a person riding a bike down a dirt path in a wooded area”.* These descriptions are partially correct.

Some of the other correct descriptions identified were *"a glass of beer on a table"*, *"a man standing next to a body of water"*, *"a close up of a bicycle", "a dirt path in a forest"*, *"a sunset over a body of water"*, *"a person holding a guitar", "a pair of shoes"*, *"an open laptop computer sitting on top of a table"*, *"a man smiling for the camera*", *"a group of people sitting at a table"*, *"a person sitting at a table"*.

There are many descriptions that are not correct, For instance, the tweet

"Palautumista arjessa uppoutumalla hyvän kirjan vietäväksi. Tämä kirjan lukeminen on lasten syntymien myötä jäänyt taustalle, mut nyt palautuu yhtenä rentoutumiskeinona. ~~@~~moodmetric #moodmetricstressinhallintakeino https://t.co/4QqzyevWkE" contains an image with a book; however, the API returned *"a close up of a sign"*. Another tweet,

"Syyskuu tuo mukanaan arjen monet haasteet. On kiirettä, mutta myös intoa! Mikä on sinun paras stressinhallintakeinosi? Osallistu Moodmetricin Twitter-kampanjaan - voit voittaa ~~@~~Moodmetric-älysormuksen. Kampanjan ohjeet: http://www.moodmetric.com/fi/uutiset/ #moodmetricstressinhallintakeino https://t.co/sfUNyirjjF"

shows an image where a woman is looking over a forest, however the tool returned *"a person sitting on the grass"*.

In this tweet, *"Soita Paranoid #moodmetricstressinhallintakeino #moodmetricsmuus-ikot @moodmetric @Larjovuori https://t.co/bFWF7AXKvY"* shows an image where a person is playing a piano, the returned description was different *"a person sitting in front of a computer screen"*. Likewise, there are in total 14 images that had wrong descriptions. 4 images did not return any descriptions.

With regards to the face emotion, almost 90% of the detected faces showed emotions ("what?") and gender information ("who?"). Therefore, it is beneficial for the companies to understand consumer emotions more accurately from their faces. For the description (captioning) part, further improvement with the algorithms or computational methods can ensure more accurate caption detection ("why?" or the cause of an emotion). In this scenario, it can be argued that the description or situation detection is 50% accurate and 50% not accurate. However, the above set of arguments show that the gender information, description of an image, emotions and associated sentiments can be obtained provided that these images contain faces. Further strong recommendation for using face emotion detection is explained in the following paragraphs.

Comparison of results from the two sentiment algorithms and Face API is shown in Table 19. The Face API was successful than the sentiment algorithms in many occasions to accurately describe the emotions. For example, the tweet: *"Mindful breathing keeps my anxiety and stress out while I'm working...so just inhale and exhale...#moodmetricstressinhallintakeino https://t.co/SDczQ0Gz17"* returned neutral for Face API, whereas both the sentiment algorithms returned negative emotion. This can be explained because of the word 'stress' in the tweet which inclines more towards negative polarity or sentiment. Two other tweets also contained the word 'stress' to which one of the algorithms returned negative. However, the tweets are not negative in nature and the Face API accurately returned neutral.

In Original tweet: *"Työkiireen keskellä hyvä tapa nollata päätä on järjestää hetkiä työkaverien kanssa ja oppia uutta yhdessä #moodmetricstressinhallintakeino @Moodmetric @GoforeGroup #palvelumuotoilu #muotoilupeli #neukkarinseinä kin hymyilee! kiitos @annakaisa_b https://t.co/ic6EmvtIRu"* the algorithms and the Face API were in agreement as it returned positive.

In this study, the images were broken down for activity tags and the sentiment for these tags were calculated. As seen from the results in Tables 14 most tags related to nature and outdoor activities contain more positive scores. Tags related to the external environment such as *'outdoor', 'field', 'water', 'grass', 'green', 'ocean', 'rock', 'snow', 'park', 'riding', 'river', 'rocky', 'tree', 'beach'* can be found with higher scores. In the negative column, external environment related tags occur less frequently (low scores), and some tags like *"cloud", "boat", "colourful"* have very low scores. In table 15, negative column shows external environment related activity tags such as *'walking', 'beach', 'water', 'Airplane',* and *'Tree'* having low scores. Whereas, tags like *'table', 'computer', 'laptop'* have high negative scores. From this we may conclude that that tags related to external environment provide much positive outlook on an individual's life and work life related tags may have negative effect on the participants' lives which is also backed by the CIO's interview statement

"For instance, outdoors have been largely positive by all detection methods and computers negative by all detection methods. Especially, outdoors, nature, forests are often mentioned in research reports, as well as, Moodmetric users as something that help them to recover from stress. The identification of computers as negatively associated is also not a surprise. Long hours sitting with a computer, especially if no breaks are taken, are not beneficial for health and feature also often as problems mentioned by knowledge workers in their daily life"

However, there is a problem in analysing just the activity tags because it may yield wrong results. For example, the tweet that showed a man playing a piano with an iPad in front of him returned a description *'a person sitting in front of a computer screen'* but the detected tags were *'indoor', 'computer', 'sitting', 'laptop', 'table', 'desk', 'screen', 'monitor', 'front', 'room', 'piano', 'man', 'bed', 'keyboard', 'black', 'dark', 'laying', 'television', 'holding', 'clock', 'white'.* This shows that the computational method with tags only component returns a combination of both right and wrong tags. Some tags occurred both in positive, negative and neutral columns which makes it much difficult to take the activity tag analysis seriously. The qualitative interview with the CIO only strengthened this argument.

"However, some recognized activity tags like man, sitting, standing that are often featured and associated with positive sentiment are less informative and taken out of context do not make sense."

To find further understand of this problem, the qualitative assessment can be referred. In Figure 11, many activities that were identified in the tweets and tweet images were related to *'Travel'*; meaning that majority of the participants involved in outdoor activities like travelling and sports to manage stress. Under closer examination, it is found that 3 out of 7 participants under *'Relax'* categories spent time outdoors to manage stress. 1 participant who was attributed to *'Art'*, also spent time outdoors picking berries and hiking. The qualitative assessment proves that majority of the participants prefer outdoor activities to manage stress and the quantitative assessment of the tags also show higher percentage of tags related to external environment have high positive scores. The CIO pointed out that Figure 11 provided significant insight as the tags were mapped under valence and arousal dimensions. As mentioned earlier, *'Travel'* and *'Relax'* activities that include visiting forests, and spending time near water and seas can act as recommendation to their users for stress management. With the help of their mobile application, feedbacks from the users with regards to activity, arousal and valence states over a long duration can help in customized recommendation for the users who can refer back to their ideal stress management mechanisms.

The emotion detection from the text using IBM Watson Tone Analyzer did not yield significantly accurate results. The tweet

"Hitting the gym relieves stress @Moodmetric #moodmetriccampaign @jjussila #moodmetricstressinhallintakeino https://t.co/Ymbht3wYIM" returned *'Fear'* emotion. However, there is nothing fearful about going to the gym, because it is a good feeling to work out. Similarly,

"Soita Paranoid #moodmetricstressinhallintakeino #moodmetricsmuusikot @moodmetric @Larjovuori https://t.co/bFWF7AXKvY" returned *'Anger'* emotion. The participant likes to play piano to relax. These are some of the examples which strengthen the case for accurate emotion detection because it works better for photos with faces over text aspect. Therefore, when using this type of tool can lead to false positives with regards to emotions and lead to wrong recommendations for the users.

The CIO also stated that *"The categorization by activity provides the most valuable information as it helps to describe and communicate situations that have been found important for recovery"*

This analysis helps the company to understand their consumers better as evident from the discussion with the CIO. Due to the strict data privacy laws followed by the company which inhibits the direct access to the consumer data, only social networking data can help provide better understanding of their consumers. However, this could change in the future if the company decides to create suitable guidelines for the consumers to provide data to the company directly. In that case, companies can facilitate favourable data collection by guiding the users to record their own activity during a significant stress level (either good or bad) or by taking a photograph of that situation and pinning emotions to the situation, and additionally allow customers to create custom activity tags. This type of mechanism allows customers to further enhance the quality of the data and will help the company to bypass the limitations from the existing methods.

4.3 Managerial Contributions

The most important contribution provided by this study is the evidence that consumer information, sentiments and emotions, and reason behind the expressed sentiment can be detected given the favourable data collection and analysis using Social Networking Websites. Text sentiment detection is a significant methodology and has three distinct parts (positive, negative and neutral); a manager must use the accurate algorithms (with high accuracy) to detect text sentiment. The partially correct detection of description (captions) may not be that reliant in its present condition. If a manager tries to analyse consumer emotions with the faces or text sentiments, then he/she may not have problems analysing big amounts of data. However, if any attempt to include the caption detection in its current state, then the amount of data to qualitatively analyse would be resource and time consuming.

At the same time, this study successfully demonstrated the detection of consumer emotion through an image and its advantages of understanding consumers from 8 different emotional aspects and three different sentiments. Managers must consider the above-mentioned factors when performing consumer emotion detection. They can use one method where they either analyze texts or images or can combine both these methods to understand consumers. For a company to perform such an analysis, it should identify the major source of their customer feedback for favorable data collection. These methods can be applied to different settings/industries where consumers are actively producing feedback to a product or service on SNS.

Companies related to stress management can create similar methodologies to understand their consumers. Industries in the food service can use methods in this study to create feedback analysis or complaints where consumers can provide image and text feedback for a food order on a social networking website. In this case, the “why?” factor or what causes the expression (feedback) is automatically attributed to the food, and the company can assess the emotions using the tools used in this study. Companies that have big follower bases, can use these techniques to understand their consumer opinion on new product ideas. This is a great tool among many others in a managerial tool box that would allow the company to understand their consumers' behavior. Most consumers would not be that interested in tweeting their images but in order to do so companies must enable reward systems to encourage consumers to tweet. To encourage consumers to participate in image feedback, companies must include private consumer feedback mechanisms through social networking websites which would enable consumer emotion detection.

4.4 Evaluation of the Study

Based on the evaluation criteria mentioned in chapter 2.4, the evaluation of this study is as follows.

a) Credibility: In this study, the credibility was assessed based on the above-mentioned criteria. Two methodologies were used, systematic literature review to discover methods for analyzing the sentiment and emotions, and the qualitative study to improve the usability and credibility of the study where the author worked with a person inside the case-study organization to evaluate the data; The author familiarized with the company about their social media data to get an understanding beforehand about the study; and triangulation of the qualitative results with the company representative.

b) Transferability: In this study, the transferability factors can be applied to business to consumer companies that market their products to consumers where these companies have products and services which they can track from social media.

c) Dependability: In this study, the author used overlapping methods. For example: in the analysis, several algorithms were used. These were assessed both quantitatively and qualitatively. This research did not rely on any one sentiment algorithm. In addition, the author went through the results of the quantitative and qualitative study with the CIO and another expert from the company. In some cases, when the results were questionable, the tweets were referred directly to address the problem. For example: In Figure 11, the company experts noticed that there was negative valence for three tweets. Given the nature of the campaign, it was expected that coping mechanisms would be positive and therefore by taking a further look at the negative tweets and the corresponding image. It was found that the tweets were indeed positive and that there was a mistake with the interpretation of the English translation. The results were then changed. Simultaneously, this was also applied to the quantitative results with regards to the emotion detection for the text component.

d) Confirmability: In this study, one major limitation is the small dataset size is used in this study. The use of sentiment algorithms would've favored significantly if the tweets were tweeted in English language directly because this study relied on a translator tool and this shortcoming could affect the reliability of the quantitative results of the study. The data collection could've been designed in a better way where the campaign tweet should've mentioned the importance of participants tweeting an image with their face. Due to this limitation, it only provides a small picture about consumer emotion detection despite its accuracy.

4.5 Future Research

Future research must be driven towards accurate caption detection from images. In this study, there were no dictionaries or sentiment detection algorithms that were readily available for Finnish language. Therefore, future research must create a natural language algorithm that can support Finnish language sentiment detection. Simultaneously, more computational methods must be aimed at segregating texts based on emotions in both Finnish and English language. Companies must include image-based feedback in addition to text-based feedback. With regards to the APIs and other tools, future research can evaluate different APIs and compare their usability for different contexts.

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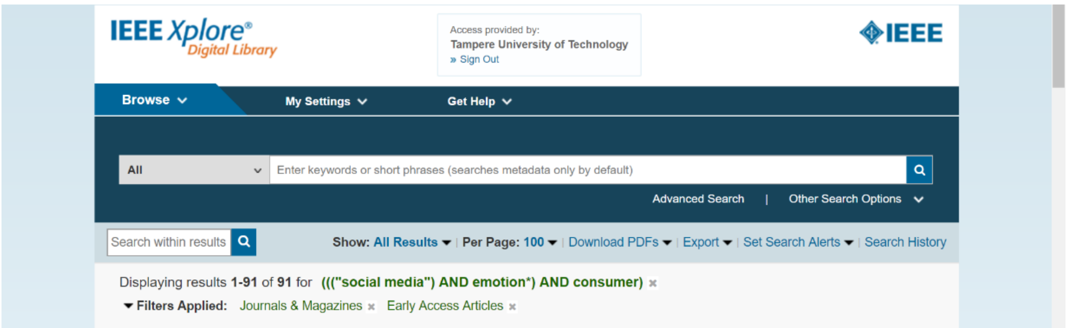
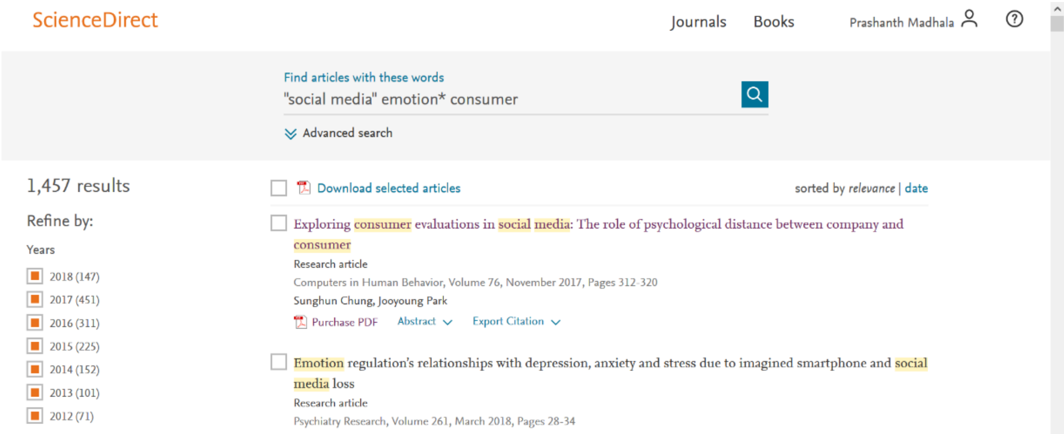
APPENDIX A: SEARCH TERMS USED FOR SYSTEMATIC LITERATURE REVIEW

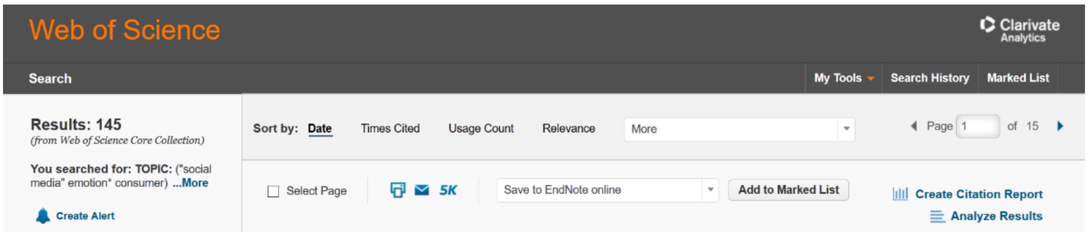
When conducting a systematic literature review, the search terms are used to search and gather articles in different databases. The search terms used in different databases are shown below.



(a) IEEE Explore search term.



(b) ScienceDirect search term



(c) Web of Science search term

Figure 14. Search terms used in the all the databases 14 (a), 14 (b), 14 (c).

The above image shows the search terms used in all three databases to gather research articles. The search terms are “social media” emotion* consumer. The search terms were used in this order at the same time.