FROM SENTIMENT ANALYSIS TO CHOREOGRAPHY OF EMOTIONS: SOCIAL MEDIA ANALYSIS FOR IMPROVED CUSTOMER RELATIONSHIP MANAGEMENT (CRM) IN THE OMANI TELECOM SECTOR

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Abstract

Across the globe telecom firms are facing fierce competition amidst rapid technological advancements; thus, in order to succeed in the telecom business and remain profitable, satisfying and retaining loyal customers is vital. The process of providing superior services to customers who are socially interconnected has changed the landscape of customer relationship management (CRM). Following a detailed review of CRM, this study has identified the constructs that are critical for customer satisfaction in the Omani telecom sector.

The literature review established that the primary reasons for organizations to implement CRM are to improve customer satisfaction, retain their customer base, obtain strategic information and enhance the value of the customer. It was also established that by collecting pertinent information on customers, such as their interests, habits and interactions, this enables organizations to provide a superior service which is specifically tailored to meet the individual needs of each customer.

The sentiment analysis (SA) is particularly useful for CRM data collection. It is an efficient tool that has evolved through machine learning algorithms to provide an efficient and robust mechanism to observe customer sentiment in real-time. This research has demonstrated that such data will help to enhance CRM in Omani telecom firms because positive, negative and neutral sentiments alone cannot be used by firms to make strategic marketing decisions; therefore, sentiment analysis has been extended to include emotional analysis. To my knowledge, this is the first time that a novel visualisation tool has been used to demonstrate the choreographic emotion of tweets in real-time. With the recent push towards Marketing 3.0 where customers are considered to be multidimensional entities, emotional scores, more than sentiment scores, can play an active role in firms' decision-making processes.

Questionnaires were developed for customers and social media managers based on the constructs identified during the literature review. Qualitative data was also collected through semi-structured interviews conducted with social media managers. Sentiment and emotional analysis were then applied to social media data pertaining to 83,981 tweets collected over one year in the Omani telecom sector. The data collected from social media managers, customers and findings of literature review were triangulated in order to arrive at meaningful conclusions. Based on this, a series of recommendations designed to enhance CRM in Omani telecom firms have been provided.

Whilst 80% of the managers interviewed confirmed that they offer interactive online customer support, customers' responses relating to their level of satisfaction with the support they received remained neutral. This shows that the effectiveness of customer support remains questionable. Female customers indicated that they were satisfied with the support they received; however, male customers were not. Similarly, younger respondents (less than 19 years of age and between 20 to 30 years of age) responded with lower satisfaction scores than the other age groups. This information has to be taken into consideration during resolution management; the implication being that telecom firms should not only implement customer-centric CRM but also enable segment-focused service delivery.

Students and government employees also provided lower scores for their satisfaction regarding the level of customer support they received. I have identified that the emotional scores of live social media data can play a big role in CRM processes, and when these data were visualised as a choreography of emotions using Plutchik's Wheel of Emotion, it was observed that the customers who received better customer service may have experienced feelings such as "surprise" and "happiness". Conversely, when customers were not satisfied, the emotions shown included "disappointment", "anger", "irritation" and/or "anxiety". These findings have been mapped on the Wheel of Emotion.

This study, therefore, led to developing a model that integrates the SA of social media data along with the CRM processes of telecom firms in real-time. This involves horizontal and vertical integration of the outcomes of emotional analyses to be shared across the organisation. I recommended the implementation of a 7-step approach to capitalise on the robustness of machine learning algorithms by choreographing emotions from live stream social media data. This can equip firms with better tools as they strive to prosper in a world of competitors and rapidly advancing technology.

Keywords

Customer Relation Management, Sentiment Analysis, Social Media.

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THANK YOU

Declaration

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed:

Contents

List of Figures & Tables

1 Introduction

In an era of growing customer-centric approaches in the service sector, satisfying and attending to customer's needs is becoming of paramount importance. Using every possible approach, organisations strive to enhance customer relationship management. The continued maintenance of high level customer relationship management (CRM) is vital for firms that are striving to prosper in a world of competitors. Ultimately, organisations' clear understanding about the three core elements of CRM, customer satisfaction, retention and loyalty, determines their economic losses or gains.

The use of social media is becoming very popular: it empowers customers to express their level of satisfaction and their views towards any products or services with a quick tweet or post. This, in turn, affects potential future customers and proceeds, to an extent, to determine the sustainability of firms. Service sectors, especially in telecoms, involve lots of customer interaction, engagement and fierce competition. More than any other industry, telecom customers are very active on social media, and share their opinions without hesitation. Thus, social media become an effective platform to observe customer behavior (in marketing, customer experience, etc). Customer behaviour affects business performance, and this continues to be widely discussed in the marketing academia (Heskett and Schlesinger, 1994, Nelson et al., 1992, Storbacka et al., 1994).

The implication of increased social media use, is that companies can insert mechanisms to automatically watch and obtain useful information from social media interactions. Tools such as sentiment analysis help organisations to effectively watch social media data, and gather information about their own, or competitors', products or services. The technological growth and explosive nature of available data (so called "big data"), reiterates the need and importance of efficient tools to extract useful information from the huge amount of data available on social media platforms. The domain of sentiment analysis is widening, owing to features such as being able to extract public opinions about products, services, brands, politics, and so on; plus the applicability and increased demand by social media fans for this type of information. (Cui et al., 2006, Mostafa, 2013). It has been reported that sentiment analysis methods underwent a "50-fold growth" in the last decade (Mäntylä et al., 2018).

This study examines present customer relationship management practices in the Omani telecom sector and reveals various gaps in computer science and marketing research. To begin I put forward my recommendations for this sector underpinned by recent studies, I illustrate technological developments in the area of sentiment analysis, and develop a broader understanding about the mechanisms of customer satisfaction, retention and loyalty.

1.1 Research context and background

The establishment of the Telecom Regulatory Authority of Oman (TRA) in 2002, announced a new era of liberalisation for the telecom sector; one that invited many foreign players and resellers into Oman, with the aim of offering not just better services but the provision of world-class telecommunications services for all customers. OmanTel, founded in 1980, was the first primary service provider established in the sector. Partially owned by the state, OmanTel is now considered to be one of the biggest telecom firms in the Middle East (Rajasekar and Al Raee, 2013). Since then, many resellers or Mobile Virtual Network Operators and telecom firms have emerged in the market. For instance, Oredoo (formerly Nawras), an Omani Qatari telecom firm, was provided with a license to operate in 2004; subsequently, they were given further licenses to provide fixed line and internet services. In addition, as per the TRA website, there are five licensed resellers in Oman in 2019, including Injaz, Majan, Mazoon, Friendi and Samatel.

During 2017, the total revenue of Oman's telecom sector was 854.58 million Omani Rial (approximately 220 million USD). Amongst this, 70% was from mobile users and 29% from fixed line users, resulting in 2% revenue growth, which is much lower than the previous year's 5.5% growth in 2016 (Daily, 2018). The average revenue per mobile subscription is now at 7.2%, which is also less compared with previous years. From 2013 onwards there has been a falling trend related to revenue. As necessitated by the TRA, these firms provide a high standard of customer relations management. There is a social media manager based in each of these firms handling transactions and following up on social media communications. While capturing information available on social media it is important to understand the relationship between service quality attributes and customer behaviour. A clear understanding of this helps organisations to know what customers think about service quality, and what to look for in the social media data.

Telecom firms in Oman are continuously improving themselves to find better ways to serve customers. There is dedicated customer service department in every firm offering services and support, and following up customers' complaints, which they aim to resolve within 15 days. Customers can contact TRA regarding any unresolved issues. To improve customer service, a recent trend entails operators opening stalls in shopping malls and hypermarkets. These stalls help customers to easily access support without visiting an operator's location. Almost all telecom firms in Oman are active in social media. Reaching out to customers through social media enables companies to track and measure their performance. Thus, customers are encouraged to use social media while contacting the company for any support issues.

Considering the case of the Omani telecom sector, the outcome of this research could cater for the rising needs of maintaining better customer relations, and also provide further insights into social media data collection with the aim of better understanding customer behaviour. Thus, the contribution of this study to existing practice and knowledge is to enable us to extend our understanding of customer behavior, and assist customer relation managers, in all sectors, to monitor and cater for the needs of their present generation of customers. The importance of this work rests, mainly, in providing an enhanced tool to collect data from social media and ways to implement this gathered information back into the system.

From this perspective, the following sections, of this chapter, provide the theoretical background of this research study by discussing the basics of two diverse fields; namely, customer relationship management (CRM) and sentiment analysis (SA). This chapter then investigates the potential applicability of the latter to the former.

1.2 The evolution of marketing theory

Following industrialisation in the 1920s, mass marketing was introduced into marketing theory as a result of the increase in large-scale manufacturing, and the availability of media technology, such as 'radio'. Mass marketing expanded throughout the 1940s and 1950s and enabled large corporations to reach a wide customer base. This boost in mass manufacturing left little chance for customization; so customisation was considered as neither economically viable nor promising. As a result, no information about customers was available to organisations because it wasn't being collected, and marketing research interactions between a firm and their customers were non-existent – especially when it comes to the customization of products. Furthermore, as there were no channels provided for customer feedback, firms were unable to accurately measure the standard of their products and services, except for within basic parameters such as functionality and durability.

It was Leonard Berry who started studying services marketing in detail and who became one of the founders of the theory of relationship marketing. Since this time, according to Google Scholar, his paper entitled "Relationship marketing of services - growing interest, emerging perspectives" has been cited more than 3000 times (Berry, 1995). Building on Berry's work, Storbacka et al. (1994) shifted the orientation of services marketing towards acquiring new customers which caused the relationship to be more profit oriented, rather than focused on building long-term relationships. However, many authors, such as Morgan and Hunt (1994) and Sheth (2002) have highlighted that the concept of relationship marketing has shifted the focus from customer acquisition to customer retention.

As stated above, unlike traditional transactional marketing, the focus of relationship marketing has shifted from service transactions or encounters to more of a focus on customer retention and enhancing relationships. Figure 1 illustrates the historical change that has taken place in the marketing arena. The shift can be seen from customer acquisition to retention and then to loyalty. On the other hand, authors like Reichheld and Sasser (1990a) and Shani and Chalasani (1992) highlight the following aspects as reasons for undertaking relationship marketing: the economy of customer retention, the inability of mass media and higher customer expectations.

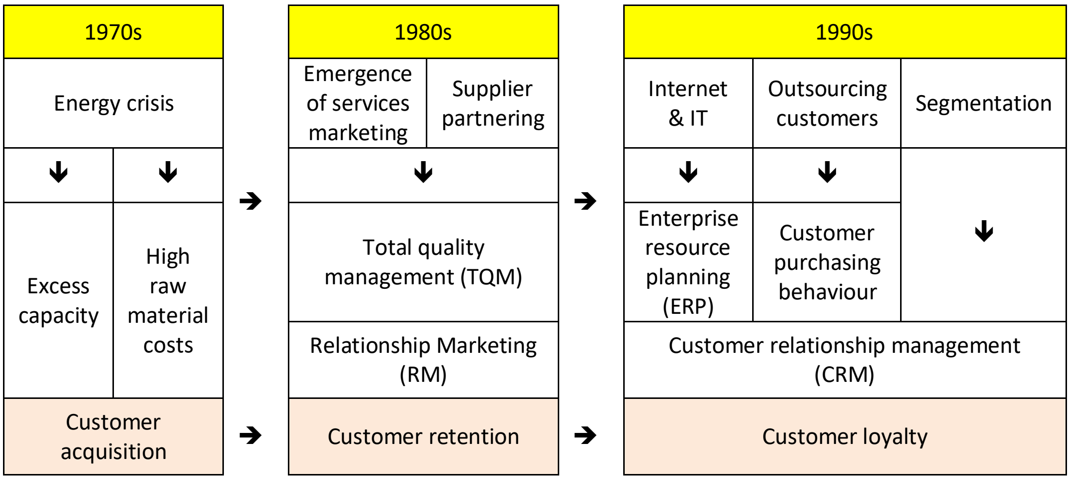

Figure 1: Approaches to marketing through the decades (Sheth, 2002)

1.3 The birth of CRM

As firms focused on finding new ways to increase their market shares they started looking for diverse ways to orientate themselves with customers' needs (Ahn et al., 2003, Bose, 2002). These attempts resulted in one-to-one customer relationship management that focused on differentiation amongst customers, and serving them accordingly. Which was further narrowed down to concentrate on how customers responded to perceived added-value services (Weitz et al., 1995). As rightly mentioned by Gummeson (2008), whilst relationship management focuses on finding new ways of marketing, customer relationship management provides practical techniques to better handle relationships. Gummerson goes on to define CRM as "the values and strategies of relationship management". This statement further emphasises that CRM is a practical application that is dependent on human action and also on information technology.

Pedron and Saccol (2009), in their literature review, identified that the definitions of CRM can be defined not only in terms of strategy, as defined by Gummeson (2008), but also as a philosophical, strategic and technological approach. CRM is considered to be many things: it is considered as a philosophy because it can affect the entire business; it is considered as a strategy because it handles processes and resources to get businesses up and running; and is considered as a technological tool because, as a process, it uses various technological or computational tools in a variety of ways to establish better CRM.

First Generation pre -1990	Second Generation Pre-1996	Third Generation Post-2002
Call Centre management Customer service/support		
	Integrated customer centric front end including marketing, sales and service	Strategic CRM
Sales force automation		Enterprise Resource Planning Customer Analytics Web integration
Goals		
Improving service operations and sales efficiency	Reducing interaction cost and increasing customer retention and customer experience	Reducing costs, increasing revenue and achieving competitive advantage

Figure 2: Timeline of the evolution of CRM (Kumar and Reinartz, 2005)

1.4 The benefits and objectives of CRM

CRM provides firms with an ongoing relationship that can provide a sense of trust, control and security (Grönroos, 2007). The studies of Xu and Walton (2005) concluded that the primary reason for organisations to implement CRM are to:

- improve customer satisfaction;
- retain their customer base;
- obtain strategic information; and
- enhance the value of the customer lifetime.

Gummesson (2008) adds that CRM enables corporations to build relationships, and to reach and maintain a prosperous market share. He places further benefits to CRM in the following two categories:

- **Retentions:** knowledge about customers including their names, habits, likes, dislikes and expectations, facilitates retention.
- **Intimacy and profits:** information technology can help firms to create intimacy with

customers. This can strengthen the mutual trust between the customer and the organisation and lead to an increase in profits.

The literature documents very well the objectives of CRM in various domains. The two most notable authors are Xu and Walton (2005), and Nguyen et al. (2007). On the one hand, Xu and Walton mention the following as the main objectives of CRM:

1. **Data collection:** all details about customers and every interaction should be logged.
2. **Efficiency:** the collected data should be efficiently used and all stakeholders should be informed of relevant information. All past and present customer records should be available at all times, and should be consulted before any communication takes place.
3. **Automation:** operational CRM processes should be aimed at improving the efficiency of existing processes through automation.

On the other hand, Nguyen et al. (2007) provide more specific objectives of CRM: increased customer loyalty (obtaining and making information about customers available across the organisation); superior data collection and sharing (keeping updated records of customers and their interactions); and knowing customers and providing a superior service (using all available information about the customer's habits and interactions with the organisation to provide information about products or services tailored to the needs of each customer).

1.5 Sentiment analysis

Sentiment analysis helps us to obtain information about a subject through text that appears in social media posts or tweets. And sentiment analysis helps us to distinguish emotions, such as anger or envy, sadness or happiness and satisfaction or dissatisfaction. An example, of satisfaction or dissatisfaction with a product, which is often cited in movie reviews, is a thumbs up "👍" or a thumbs down "👎" (Turney, 2002a). The sentiment analysis growth and importance can be seen in Figure 3.

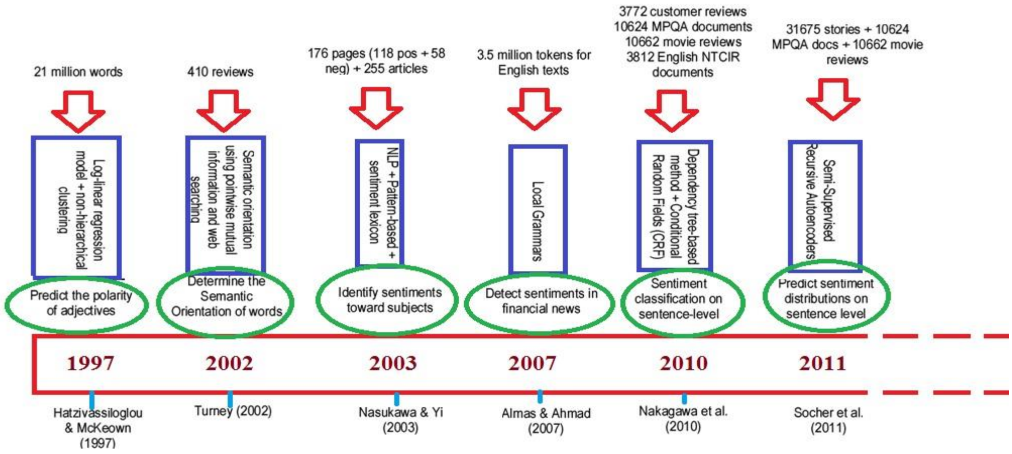

Figure 3: Sentiment analysis growth 1997 - 2011 (AlKindi, 2014)

Since 2011, there has been rapid progress in the field of sentiment analysis. For instance, Mäntylä et al. (2018) has shown that there has been an almost exponential growth in the number of papers published on topics related to sentiment analysis since 2011 (see Figure 4). They point out that the number of conference proceedings, research papers and review articles on this topic have seen an almost "50-fold increase" in recent years.

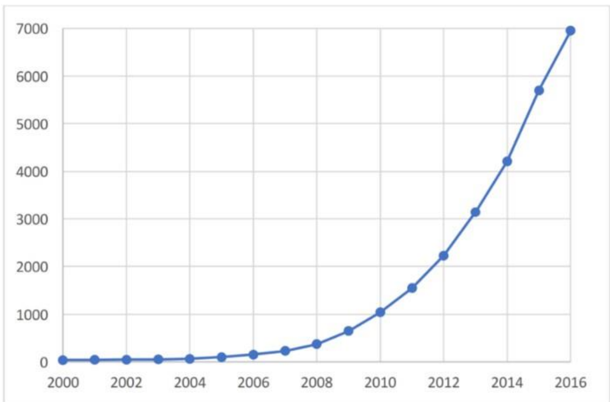

Figure 4: Number of papers published about Sentiment Analysis (Mäntylä et al., 2018)

Several such studies, including comScore and Kelsey (2007), implemented sentiment analysis as an important tool directed specifically to ease decision-making processes. Figure 5 explains the reasons why customer reviews are considered to be important when making decisions.

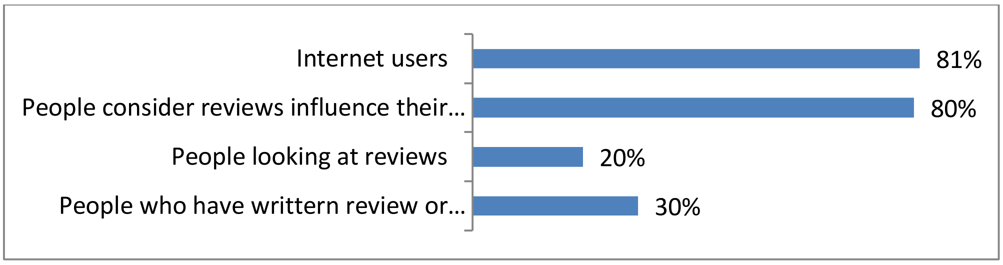

Figure 5: Impact of review on decision-making processes (comScore and Kelsey, 2007)

Aside from movies and product reviews, sentiment analysis has been hindered by bulky data which remains unlabeled on the internet. In particular, topics related to political matters produced a number of blogs which discussed crises that did not contain any substantial grade or point of view. Data mining tools, for instance, started to help sentiment analysts to obtain an average grade of an issue and to summarise users' standpoints. One such study carried out by González-Ibánez et al. (2011), illustrated how sarcasm can be identified in Twitter using data mining tools. This work seemed to enable sentiment analysts to apply automatic sentiment extractors in their sentiment analysis systems.

In recent years, there has been a steady increase in applying sentiment analysis to social media data. There is great opportunity for sentiment analysis to be applied as social media users express their opinions. Some reasons they might do so include the need to belong, the need for cognition and self-presentation and impression management (Carpenter et al., 2018). Recent studies illustrate that social media posts expose the personality traits and motivational factors of their users (Ducange et al., 2019, Goswami et al., 2019). Extraversion is a common attribute found across active users of social media, and such people show their presence through a large number of friends, posts and responses (Goswami et al., 2019). Many authors opine, that next to extraversion, another behavior: neuroticism (tense, moody or irritable people) use social media as it is a safe and controllable environment where they can self-express.

When we consider the methods adopted by sentiment analysts, we can see that diverse approaches are being used. I will refer to three instances. First, one remarkable example is the use of verb expression. Using linear regression optimised by particle methods, Jiang et al. (2019) have analysed verb expressions extracted from reviews. These verb expressions are an accurate representation of customers' opinions and a direct way for firms to improve their products. Their study has shown that without manual training their methodology of sentiment analysis worked as proposed. Such verb expression methodology is unique, and has been demonstrated to be precise and efficient beyond relying more directly on sentiment. Second, another area of progress in sentiment analysis, goes beyond word frequency and the position of terms used in the overall discourse by using rhetorical structure theory. Kraus and Feuerriegel (2019) have proposed tensor-based, tree structured neural networks, and they have also proposed two methods of data augmentation: namely, training set and overfitting. Third, another notable recent development joins visual and textual sentiment analysis. In order to extract the sentiments about events or topics, Zhu et al. (2019) argue that visual and textual information are different components. Their model incorporates a cross modality attention mechanism with an embedded semantic learning network. By using these methods, they could obtain deeper insights and a more efficient classification of the dataset.

1.6 Methods of conducting sentiment analysis

It is widely noted in the sentiment analysis literature that in order to conduct sentiment analysis it is necessary to:

- identify significant people and groups that are involved in the telecom usage of the chosen organisation;
- archive social media data, including tweets and posts pertaining to those identified in the previous step; and
- calculate a sentiment score using the most suitable tools available with the chosen sentiment analysis algorithm.

For this research study I utilised NVivo, only one of the available sentiment analysis tools, to calculate sentiment scores. NVivo is a commercial software tool that is capable of collecting, managing and analyzing, and reporting unstructured data (Miller, 2006). This software has features to import survey responses, social media discussion (tweets, Facebook posts or videos and comments); it also uses a widely-acclaimed user interface, which is similar to the one used by Microsoft, and can also be used to export data for further analysis (Miller, 2006). In addition, extended sentiment analysis has been conducted using custom written codes. There are also various visualisation tools available to visualise sentiment scores through different perspectives which will help me to explore the results.

1.7 Objectives and aims of the research

The objectives of this study are as follows:

1. Apply sentiment analysis (SA) to collected data related to CRM which pertains to the Omani Telecom Sector through social media (SM) platforms.

2. Survey SM departments to gauge their SM experience and behaviour when interacting with customers.

3. Survey customers and gauge their feedback about their experiences of using SM.

4. Develop a SM policy/model for companies to use in the Omani context.

Thus, this research aims to investigate the applicability of sentiment analysis and its potential for establishing better CRM processes in Omani telecom companies.

1.8 Research questions

The purpose of this research was to measure the impact of service attribution and how important this is for organisational performance. The literature review has enabled me to understand the factors that affect the relationship between service quality and customer satisfaction. This research study will investigate the relationship between customer satisfaction, service quality and customer behavior. As word of mouth and switching probability are very important factors, this research also tries to identify such relationships through the use social media and any similar datasets. To address the above, I will attempt to answer the following questions:

1. What are the parameters that have to be measured to understand the extent of customer satisfaction?

2. How can these factors be measured from social media discussions or any other datasets available?

3. How can the results of the sentiment analysis of these datasets be applied to developing a better CRM policy for the Omani telecom industry?

1.9 Research method

In order to realise the research objectives, the onion research methodology will be employed (Saunders et al., 2011, see Figure 23) which uses a combination of epistemology, ontology and axiology techniques. Epistemology, according to Saunders et al. (2011), is expected to draw out what is acceptable knowledge in a given field of study. This philosophical approach highlights the importance of differentiating the research being conducted with that of people and other objects of interest. On the one hand, as the research process affects the reality that is being investigated, my research is not measuring the full “reality” of every CRM eventuality in telecom sector. The research in this area is still in its infancy, it is difficult to try to quantify and measure its development; as such, an epistemological approach provides a good indication of the acceptable knowledge in the area of sentiment analysis. On the other hand, to study objectivism and subjectivism, ontology which defines the nature of the knowledge, were used. Semi-structured interviews and surveys with key stakeholders (service providers and end-users) were conducted to discuss their viewpoints and experiences. By interviewing both the service providers and end-users I aimed to increase the accuracy of the data obtained.

Axiology is a branch of philosophy that studies value (Saunders et al., 2011). Through in-depth discussion it was concurred that the use of the semi-structured interviews would add value to the research by providing a rich source of data (Adams, 2015). Furthermore, as more knowledge was gained, it was anticipated that this would add more value to the research for researchers and industry experts in the field as a CRM framework could be defined based on the results of these methods. Thus, where appropriate, I planned to submitted the results for publication or standardisation work.

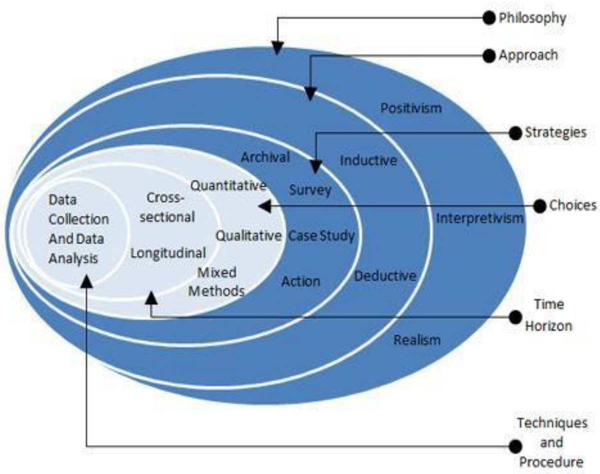

Figure 6: The Onion Research Methodology (Saunders et al., 2011)

This study is both descriptive and explorative, with reference to the parameters and factors affecting service quality, customer satisfaction and retention. I therefore proposed to collect data not only from an extensive literature review, but also from surveys and interviews conducted with Omani telecom users. Then sentiment analysis would be used to obtain key service attributes from this wide collection of data. As suggested by Bryman (2012), those surveys could include structured interviews or self-completion questionnaires via online-based surveys. Following this recommendation, my study also incorporated the use of online surveys for data collection purposes. The results were analysed with the help of suitable regression analysis, and structural equation modelling (SEM) was used to test the variables of the existing interrelationships.

To reconsider my research questions at this point, Research Question 1 will be answered by conducting a literature review on marketing and management to explore and understand the function of customer behaviour in the given business context. In order to answer Research Question 2, social media will be used to extract and collect data about key service attributes, in line with the findings from the literature review, in addition to the surveys and interviews. The collected data will be analysed using various statistical procedures including regression and structural equation modelling. The variables and constructs tested in the previous parts will be used to establish a conceptual model that can help organisations to improve their CRM initiatives (Research Question 3).

1.10 Recent studies

There have been a limited number of studies conducted during recent years, which have focused on understanding customer relationships in the telecom services industry across the world. This section illustrates a few of the studies that, in my opinion, are worth a mention here.

Through their study conducted in the Indian mobile telecom service sector, Premkumar and Rajan (2017) identified that customer retention is the key element for success in the telecom sector. This detailed study analysed how effective customer retention can be established, with reference to the chosen mobile telecom market. However, this industry is subject to heavy competition and a saturated marketing environment, and as a result customer attrition is being negatively affected by the cut-throat competition operating within this sector; in addition, during the 1990s marketing activities saw an increase in the number of customer acquisitions. Following their observations, Premkumar and Rajan concluded that customer retention is a growing trend. They demonstrated that in spite of the mutual benefits associated with customer retention, the ever-evolving marketing environment presents various challenges to telecom organisations. Furthermore, as telecom users are well-informed and are socially connected with their co-customers, these challenges are becoming increasingly complicated. In addition, the high turnover rate of customers is further increased with the introduction of new innovations into the marketplace, such as mobile number portability.

A similar study conducted by Viriri and Phiri (2017), in the Zimbabwean telecommunication industry, revealed that establishing and enhancing customer loyalty is vital for companies to grow and perform well in this sector. The study was aimed at investigating exactly what determines customer satisfaction in Zimbabwe. The study results highlighted the following:

- the customer defection rate for the telecom sector ranged from 20% to 40% globally;
- factors including competition, deregulation, privatisation and globalisation all have an impact on customer loyalty;
- various factors like price premium, competitiveness, reduced profitability and referral marketing opportunities all lead to a decline in customer defection; and
- the data collected from customers, staff and managers working in the telecom industry indicated that customers would prefer to receive reduced or varied tariff options, offers and promotions, enhanced network coverage and better service delivery.

Another recent study conducted by Mahajan et al. (2017) reviewed the communication sector following the advent of new wireless and wired technology services. They pointed out that the industry is characterised by having a better perception of customer expectations, and this has resulted in the provision of high-quality services. Mahajan et al. reviewed 75 studies from the year 2000, and the evidence demonstrates that customer churn heavily impacts the industry. By analysing the gaps in these studies, they have produced a model which addresses the primary churn factors and, consequently, have provided better churn management techniques for telecom firms.The contribution of social media to enable customer involvement is undisputable, as Corte et al.'s 2015 study on customer involvement for innovation in telecom services has shown by arguing that business processes, such as those involved in the provision of telecom services, necessitate customer involvement in the production or coproduction of service products. As there are lots of limitations in service innovation, interaction between service providers and customers (e.g. production and coproduction with customer involvement) can help firms obtain service innovations. Thus, involving customers from the beginning of the service creation process could originate in social media interaction.

To further consider the influence of social media on the telecom sector, a Kenyan study investigated the use of social media on firms' permanence. Nyambu (2013) explored how technology affected the performance of firms, and discovered that, to some extent, social media marketing impacted a firm's overall functioning. He established that promotional campaigns on social media increased firms' sales and revenue, even after the promotion period ended. In order to understand customer need and increase loyalty, Nyambu concluded that there is no medium as powerful as social media.

1.11 Learning outcome and deliverables

This study applied a novel methodological approach to understand the constructs involved in customer behaviour analysis. For the potential learning outcomes of this study, I expected to suggest a model to improve CRM; it was envisaged that this would help to understand and, hence, reduce the probability of customers switching service providers.

1.12 Research plan

The following table illustrates how the thesis is organized.

Chapter	Activities involved
Abstract	Keywords, etc.
Introduction	Background research, aims, hypothesis and outline

Literature review	Marketing theory
	  Services marketing
	  CRM
	  CRM Online
	Information science theory
	Computer mediated communication
	  Sentiment analysis
	  HCI
	  Social media interaction
	Conclusions from Literature Review

Methods	Data collection Sentiment analysis
Findings & analysis from the survey & interviews	Social media manager interviews & survey Customer survey
Findings from sentiment & emotional analysis	Basic sentiment Extended sentiment and emotion
Discussion	Results of sentiment analysis Graphical presentation of important findings
Conclusions	-
Recommendations	
Contributions to knowledge & practice	
Limitations & further research	

Table 1: Chapters and tasks involved in the writing of this thesis

1.13 Key milestones

The following table illustrates the key milestones and the anticipated timeline for the study.

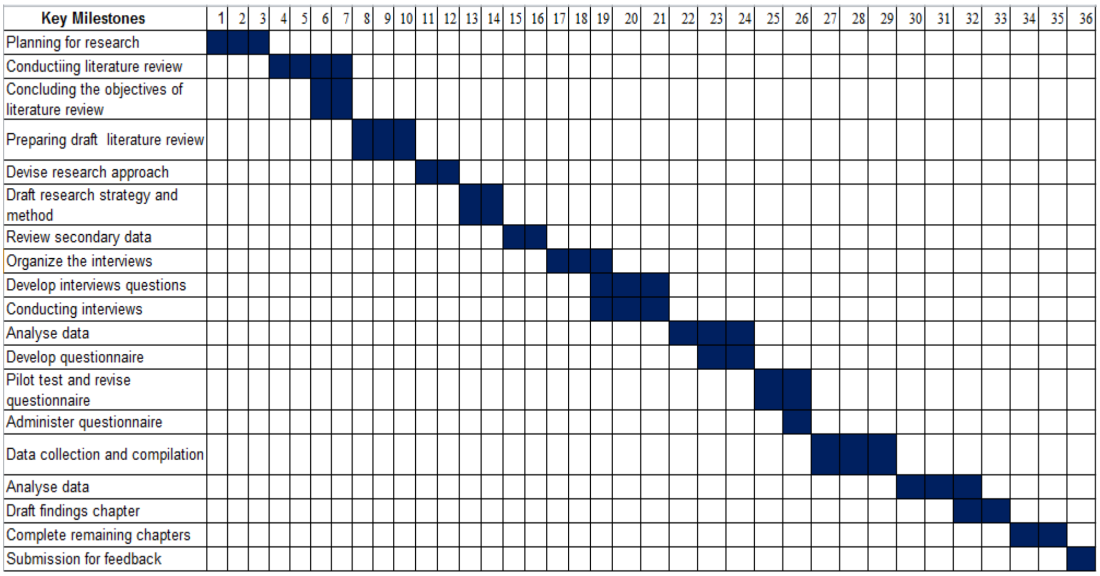

Figure 7: Key milestones of the research plan

1.14 Risk analysis and contingency plan

A risk assessment which took note of the potential site and work risks was be undertaken before conducting the research. Possible site risks included: physical, biological, chemical, anthropogenic or environmental hazards; whereas possible work risks included: travelling or safety-related hazards. However, as this study was intended to be conducted electronically, there were no such risks involved. In addition, the questionnaires and interviews were designed and structured in such a way that they did not cause site- or work-related hazards to either the respondents or the researcher. A risk analysis form was submitted to the University Ethics Committee (University of Strathclyde) prior to the data collection period.

All basic rules of safety, traffic and ethics pre-existing in the work place were followed during the data collection period. As my study is about the satisfaction and personal perception of the services received I submitted the relevant paperwork to the University Ethics Committee (University of Strathclyde) for ethical approval, so that the information obtained would not violate personal freedom or confidentiality.

As suggested by many experts, appropriate communication methods enables a researcher to mitigate potential risks. For instance, in case of emergency, a researcher should always make sure a nominated colleague and/or supervisor are informed about the whereabouts of the interview, and details such as the name of the individual they are meeting, the time of arrival and departure, and be in constant contact.

In terms of data storage, the core of the data analysis involved is a social media data-collection, which was huge and diverse. Therefore, all data were stored, tagged and backed up appropriately, as a contingency for the unlikely event of loss. Both online and offline copies of the data were stored in the system.

It was planned to use NVivo for the sentiment analysis, however, as a contingency, a working version of Semantria was also made available, so that if there were any unforeseen failures while using NVivo, Semantria could be used as an alternative. This backup plan minimised the risk of any disruption to the data analysis. I also used custom-written codes using popular statistical and data mining software R programming language; there are benefits to using R code because otherwise I would have faced difficulties in analysing the collected data using NVIVO software.

1.15 Contributions to knowledge and practice

The research plan enabled me to realise the learning outcome of the study and obtain the deliverables I aimed to achieve. As explained in the following chapters, this research illustrated the specific context of an Omani case study.

The importance of social media data is known to be a potential source of information to establish the best CRM practices on. The data analysis needed to take into account different layers of CRM, so that it resulted in suggestions which could lead to improved customer satisfaction and retention. But using such data in real-time, and feeding the outcome of such an analysis back to the various levels of an organisation has not been used so far; however, in this study I illustrate that passing strategic information in real-time to enable an organisation to provide a superior service works well.

Although sentiment analysis is employed widely for market research, I have shown that the binary nature of sentiments provides insufficient information to enable organisations to make decisions. My proposed emotional analysis transformed the results from a binary to polynomial dataset, which can better provide decision-makers with clearer and multidimensional information before making any customer-related decisions.

I consider the most important part of my contribution to knowledge to be the development of an interactive tool for visualising emotions. On realising that there was no direct way to visualise emotions in the present dataset I, therefore, created a new method to visualise this emotional insificiency. To my knowledge, based on an extensive literature review, this is the first time that a novel visualisation tool has been used to demonstrate the choreographic emotion of tweets. I name this visualisation method the 'Choreography of Emotion'. Consequently, it was observed that customers who received better customer service may have experienced feelings such as 'surprise' and 'happiness'. Conversely, when a customer was not satisfied the emotions shown included 'disappointment', 'anger', 'irritation' and/or 'anxiety '. These findings have been mapped on the Wheel of Emotion (see Figure 40).

Apart from the above contributions to knowledge, my contribution to existing practice includes developing a framework for integrating a real-time feedback system for CRM. By moving away from binary data to utilise emotional wheels, organisations can use this more robust method to read a huge amount of social media data and feed in to their improvement systems. For example, during promotion or offer periods the sales department can get a real pulse on how they are perceived by the customers by feeding back customers' emotional states of the day, the week, the month, or any particular duration, to the concerned department. A process which is expected to influence decision-making in the organisation.

My recommended 7-step approach to capitalise on the robustness of machine learning algorithms, involves the choreography of emotions from live-stream social media data. Streaming real-time information to the different levels of an organisation is expected to transform the way data is used at various levels. This can equip firms which are striving to prosper in a world of competitors and rapidly advancing technology.

2 Literature Review

This chapter of the thesis reviews the literature related to the research study, which basically covers two areas: marketing theory and sentiment analysis. This chapter reviews the literature on the evolution of marketing, and the birth of customer relationship management (CRM), where important theories and models of CRM which are applied in the service sector are discussed and critically analysed. Then, after identifying the measurable CRM parameters of this study, the strategies of CRM are discussed.

2.1. The evolution of marketing

In order to promote and sell products and services, we need a working action plan. This concept has existed for long time, Gutenberg's invention of the printer was the initial and earliest push that placed marketing at the forefront of media marketing, as this gave way to the mass production of print media (Figure 8). This mass production was followed by industrialisation in the 1920s, which was when marketing theory introduced mass marketing due to the rise in large-scale manufacturing and the availability of new media technology called 'radio'. This form of marketing expanded throughout the 1940s and 1950s as large corporations reached wide customer bases. As companies focused on mass manufacturing there was little chance for customisation which was considered neither economically viable nor promising. Moreover, information relating to customers was unavailable and, consequently, the interaction between the firm and the customer was non-existent. As no channels were provided at that time for customer feedback, firms were unable to measure exactly how good their products and services were, except within the basic parameters of functionality and durability.

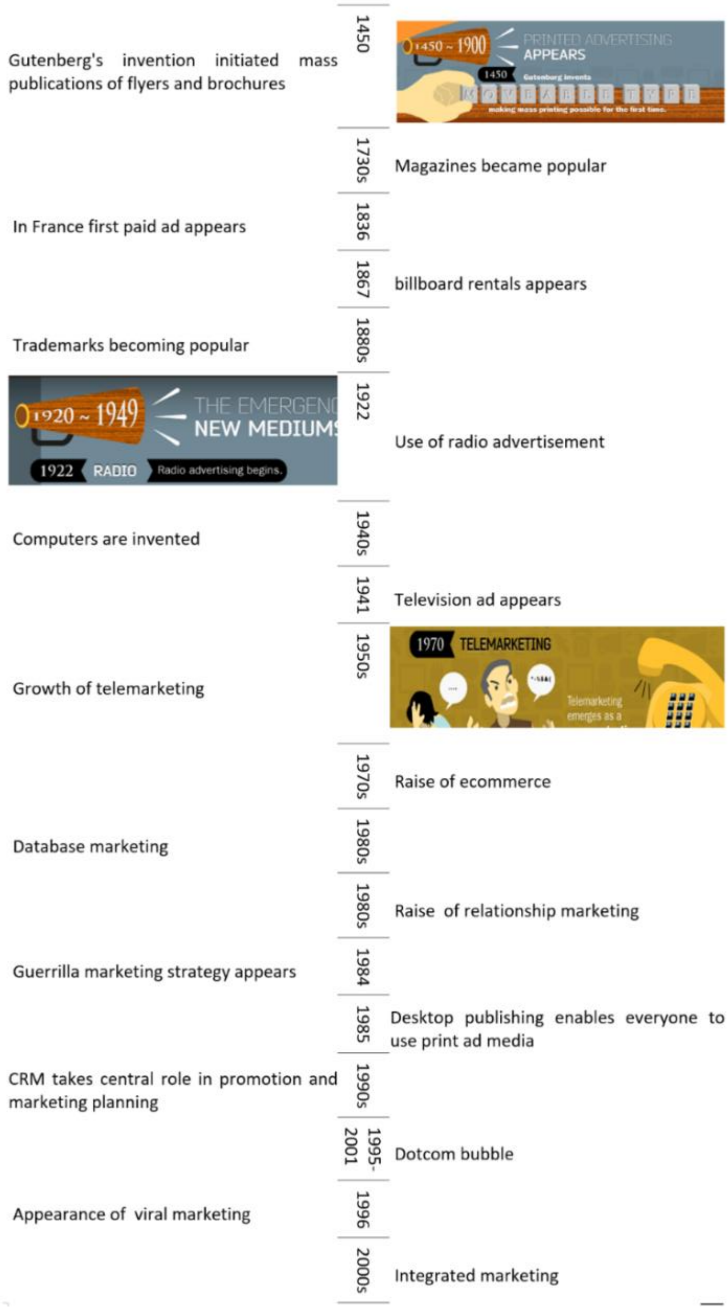

Figure 8: Timeline of Marketing (Eridon, 2012)

As rightly mentioned by Sheth and Parvatiyar (2000), it was at the beginning of 20th century when marketing began to evolve as a separate discipline to economics. However, as these authors observed, such practices can be traced back to 7000 BC. In later years the industrial revolution in the West began to introduce marketing as part of academic practice. Keefe (2008) noted that the 1935 definition of marketing is one of the earliest: "the performance of activities that direct goods and services to consumers". While this definition describes the marketing process as being as simple as taking something from point A to point B, fifty years on Keefe intimated that the definition needs revisiting and updating, so that both stakeholders and consumers are involved. Moreover, in order to think beyond the transaction and the customer McCarthy introduced his famous marketing mix in 1978 that envisaged the strategic implementation of marketing through the 4Ps: product, price, place and promotion.

In 1985, based on McCarthy's 4Ps, the American Marketing Association defined marketing as a planning process which involves conception and pricing so as to promote and distribute goods and services to meet individual or organisational objectives (Grönroos, 2007). Unlike the 1935 definition, this one not only expands marketing to include more than just transactions, but also expands its definition to include consumers and stakeholders. This definition also identifies important activities in marketing, such as pricing, promotion, distribution, goods and services.

It was Leonard Berry who first started studying services marketing in detail, and Berry is also one of the founders of the theory of relationship marketing. Kotler (1999) explains that when someone thinks of implementing theory into business operations, their thoughts are concerned with the strategic implementation of the 4Ps to realise an overall marketing strategy. In his 14th edition of one of the most popular marketing management texts, Kotler states the following in his short definition of marketing: "Meeting needs profitably" (Kotler and Keller, 2012). Kotler and Keller see marketing as a combination of art and science that involves choosing the right market and retaining and growing a customer base through enhanced customer value. They further state, that in the 21st century the definition of marketing requires two perspectives; namely, social and managerial.

Their social definition of marketing states that: "Marketing is a societal process that can help individuals or groups to obtain their needs through creating and offering products or services". At the same time, Kotler and Keller illustrate the managerial definition, simply, as "…the art of selling products/services". These authors stress that selling is *not* the important part of marketing. Citing Pete Drucker, Kotler and Kotler insist that the aim of marketing is to make selling superfluous. They justify further that all marketers may have to market as many as 10 main types of advertising that include: goods, services, experiences, events, places, persons, properties, information, organisations and ideas.

Historically, the marketing concepts introduced by Andrew Pears and Thomas J Barrat, the founders of Pears soap, are considered a famous case study. Pears and Barrat themselves are considered as advertising pioneers in advertising (Corley, 1987). They used a three-point strategy for selling their soaps, as follows:

1. Identify the gap in the market.
2. Develop the product so that it fills the gap.
3. Convince people to buy as much as possible.

These three points are still widely used today. In addition, Kotler et al. (2014) provide a holistic marketing concept that can lead 21st century firms through the various dimensions of marketing. Figure 9 illustrates the schematic overview of four important components of holistic marketing; namely, integrated marketing, relationship marketing, internal marketing and performance marketing.

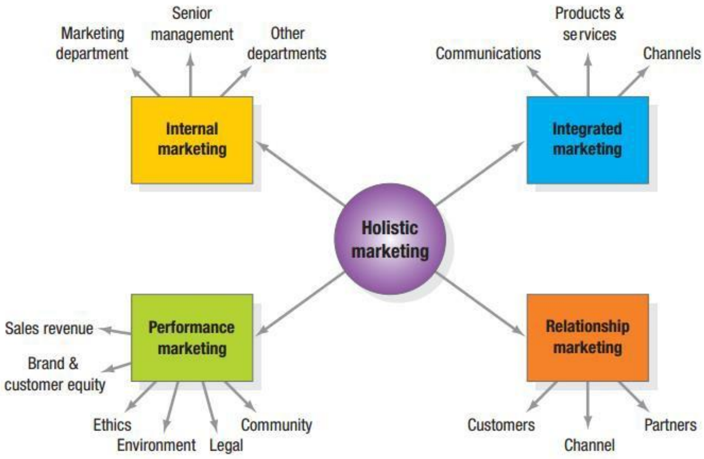

Figure 9: Holistic Marketing Dimensions (Kotler et al., 2014)

They insist that for any organisation to be successful, they have to change the way in which they market their products and services based on the changes that occur in marketplace and market space. Kotler et al. (2014) explain that the 4Ps of marketing are product, place, promotion and price. These suggestions (flexibility and the 4Ps) enable firms to position their marketing mix appropriately between the different marketing types and decide on a suitable marketing strategy.

The Lipton Tea company demonstrate a perfect example of how best to implement and utilise the 4Ps marketing strategy. Established in 1871 by Thomas Lipton, in Glasgow, Lipton remains a global leader in the beverage industry. Having purchased tea directly from gardens in Sri Lanka, Lipton sold tea packs at a low cost and used the slogan, “direct from the tea gardens to the teapot”.

The following shows the 4Ps marketing strategy used by Lipton:

- **Product:** Lipton has a range of tea products, starting from green tea, with more than 12 flavours.
- **Price:** low cost and available singly or in packs.
- **Place:** the product is available globally.
- **Promotion:** Lipton dynamically uses localised advertising strategies to sell their range of products.

Thus, for very long time, Lipton has been a pioneer of the beverage industry. Moreover, such a continued success story can be attributed to the adjustability of the product, per the customer's requirements and demand. Using a holistic view, Kotler et al. (2014) redefine the 4Ps from product, place, promotion and price to people, processes, programs and performance (Figure 10).

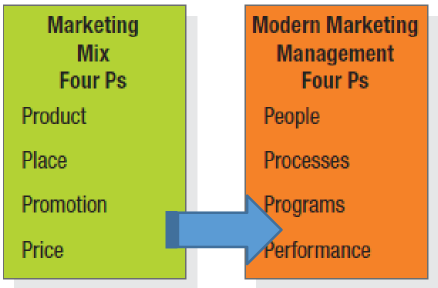

Figure 10: The 4Ps of modern marketing (Kotler et al., 2014)

They further describe the current 4Ps as:

- **People:** understanding customers as living beings, more than shoppers or consumers of products or services.
- **Processes:** creativity, structure and discipline that help marketers make decisions.
- **Programs:** activities that are planned and executed with consumers in mind.
- **Performance:** measuring financial and non-financial outcomes.

Thus, the modern 4Ps cover almost all disciplines within a firm, and necessitates the alignment of managers within the organisation (Kotler et al., 2014).

The concept of Marketing 3.0 has become popular in recent times (Kotler et al., 2019). Soon after its introduction in 2010, Marketing 3.0 enabled firms to consider customers as multidimensional entities and as value-driven people. There has been a recent shift towards customers understanding their empowerment through purchasing and decision-making power. Marketing 1.0 was considered to be product driven, and Marketing 2.0 was introduced with increased information and technology usage within organisations (Marques, 2018). Marketing 3.0 focuses on customer interaction and better relationships, even though considering the customer as a unique individual was a feature of 2.0 (Kotler et al., 2019).

In particular, Marketing 3.0 focuses more on customer engagement and data-driven decisions that can take firms to the next level. Unlike traditional marketing which pushed for marketing through print, email, etc., Marketing 3.0 gains its advantage through social media. The implication of Marketing 3.0 is far reaching in the context of my present study where social media plays vital role.

2.2 The product-service distinction

Marketing management has to handle both products and services as a part of their core business process. Furthermore, the focus of marketing has to be done deliberately on products and services as part of the extended peripheral activity. Kotler (1980) quotes that service is not a physical thing but rather, it is an energy expenditure. As early as 1983, Lovelock noted the special characteristics of services vis-à-vis products through intangibility, inseparability, heterogeneity and perishability.

Since 2003 Kotler has taken the view that the process of marketing services is different to marketing products and requires an approach that takes a different angle. While products are pre-produced, services are performed as a process (Grönroos, 2007). Thus, academia distinguishes products and services in broader categories with the wide ability to measure perception, form, shelf life, delivery, flexibility and marketing. The following table shows the major differences between product and service.

Characteristics	Produc	Servic
Product	Tangible	Intangible
Ability to measure	Objective	Subjective
Perception	Standardised	Summed
Form	Manufactured	Produced
Life	Perishable (days to	Non-perishable
Delivery	Consistent	Variable
Flexibility	Limited	Broad
Marketing	Traditional	Non-traditional
Nature of marketing	External	Mainly internal

Table 2: Product-service distinction

The marketing of goods and services vary considerably, and many authors show the differences between them; for example, Evans and Berman illustrate that there is continuum. It is worthy to note that with certain industries such as the telecom services industry; there may be products and services that are hard to distinguish.

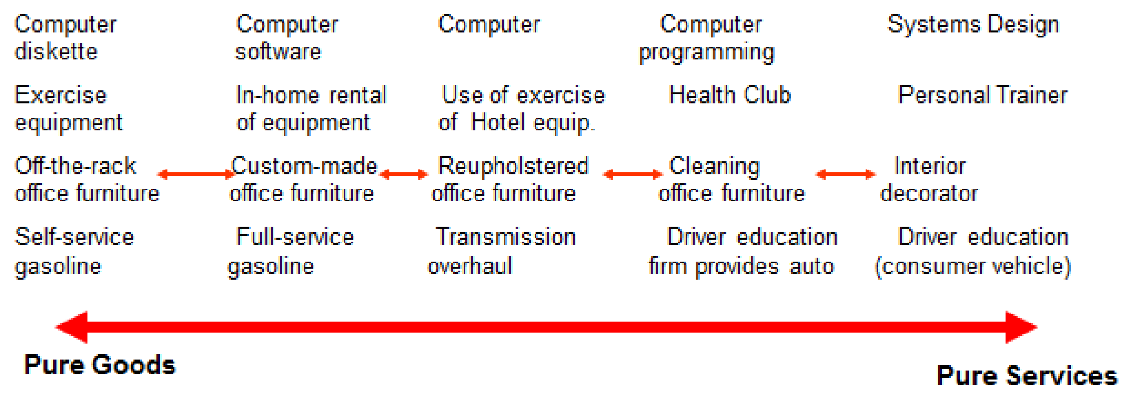

Figure 11: Goods and services continuum (Evans and Berman, 2002)

Thus, creating such a matrix for telecoms products and services will enable us to better understand the nature of the goods and services to be marketed. In order to identify whether something is a product or service, the following classifications, identified by Evans and Berman (2002), could be implemented:

Classification for products:

- By market segment
- By degree of durability
- By amount of value added
- By goal of organisation
- By degree of regulation
- By length of distribution channel
- By degree of customer contact

Classification for services:

- By market segment
- By degree of tangibility
- By skill of service provider
- By goal of service provider
- By degree of regulation
- By degree of labour intensiveness
- By degree of customer contact

At the same time, Kotler and Keller distinguish goods and services in terms of quality and evaluation. For instance, the following graph shows degrees of evaluation, on its horizontal axis, compared with quality, on its vertical axis.

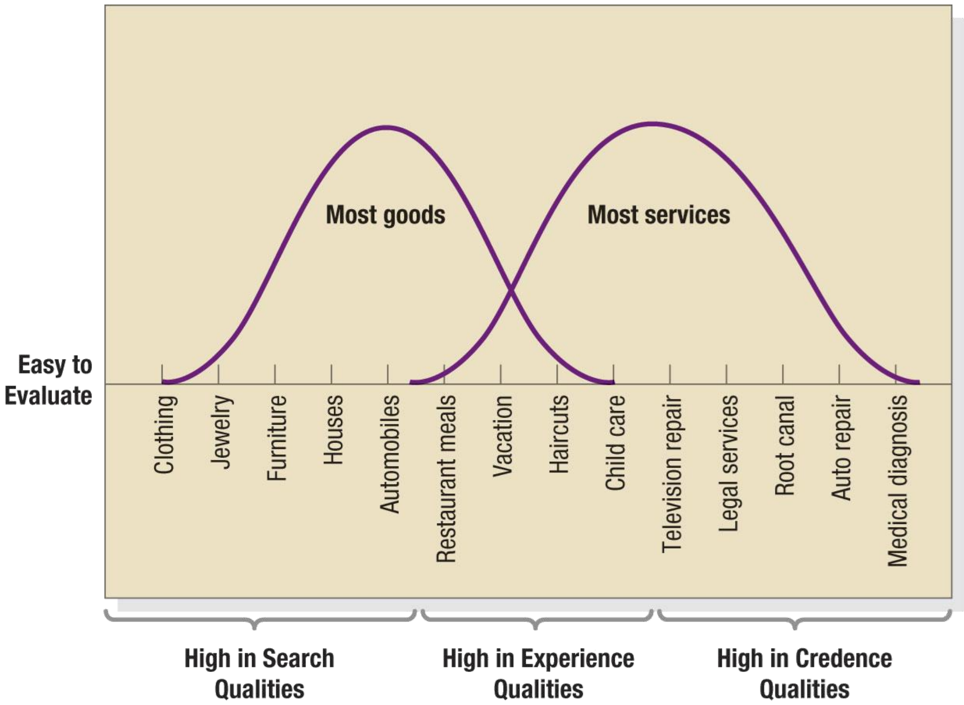

Figure 12: Kotler et al.'s (2014) product versus service distinction

Thus, by knowing the classification system one can accordingly place the output of the firm and its market. Furthermore, as each firm has its own characteristics and approach, placing the product or services in its location enables the adoption of a focused marketing approach.

2.3 Relationship marketing

It was Leonard Berry who first started studying services marketing in detail, and he is also one of the founders of the theory of relationship marketing. His paper entitled "Relationship marketing of services - growing interest, emerging perspectives" has been cited, according to Google Scholar, more than 3000 times (Berry, 1995). Storbacka et al. (1994) shifted the orientation of marketing towards acquiring new customers which caused the relationship to be more profit oriented, rather than focusing on long-term relationships. Many authors like Morgan and Hunt (1994), and Sheth (2002), indicate the transition has shifted the focus of telecom service providers from customer acquisition to customer retention.

One can observe different approaches to marketing since its inception to the present day. Hoek et al. (1996) illustrates that during the mid-1950s a production approach was at the forefront, and during the post-war periods of the mid-1950s and 1970s, a selling approach was mainly used. Later, in the post-1970s, a traditional marketing approach came into existence. Vargo and Lusch (2004) describe how relationship marketing differs from typical transactional marketing. In addition, they explain how marketing changes went through eight basic premises; explaining why relationship marketing and services became dominant over the traditional perspective when simple transactions took place (Vargo and Lusch, 2004). Although goods and services are valued by customers, in a traditional transaction the customer merely receives them. However, in relationship marketing customers become co-producers by interacting with the organisation. Therefore, the relationship is mainly dependent on collecting rich customer data, and the ability of the company to transform that data into useful knowledge about their customers. Using customer data as a basis, relationship marketing considers that customers don't just buy a product or service, but buy solutions that can address their needs and solve their problems.

Unlike traditional transactional marketing, the following conclusion applies to relationship marketing: the focus has shifted from service transactions or encounters to customer retention and enhancing relationships. Contemporary development in relationship marketing supports change in inter-organisational culture so as to facilitate relationship marketing (Larentis et al., 2019). Larentis et al. argue that developing strong inter-organisational culture is vital for better relationship marketing. Essential elements of organisational culture to support this process include shared meanings and symbols, being open to innovative ideas, interaction frequency and the quality of interaction, and an asymmetry of power. There are also some intermediate elements such as trusting available information. A commitment to the above actions play a role in the implementation of relationship marketing.

Cooperative practices, better conflict management and the integrity of organisational arenas can also influence relationship marketing at a result level. There can also be weakened elements in the system, such as the non-availability of shared symbols and meanings (Larentis et al., 2019).

2.4 The birth of CRM

As firms found new ways to increase their market shares, they started looking for diverse ways to orientate themselves with customers (Bose, 2002, Ahn *et al.*, 2003). These attempts resulted in one-to-one customer relationship management which focuses on differentiation amongst customers, and as a result identifies the different ways of serving them. This can be further narrowed down to account for how customers respond to perceived added-value services (Weitz *et al.*, 1995). As rightly mentioned by Gummeson (2008), whilst relationship management is focused on finding new ways of marketing, customer relationship management provides practical techniques to handle relationships more efficiently and effectively. His definition of CRM states: "Customer Relationship Management is the is the set of tools that help us to establish values and strategies of Relationship Management". This definition further emphasises that CRM is a practical application that depends not only on human action, but also on information technology.

Kumar and Reinartz (2005) provide a timeline of CRM to show how its practices shifted from transactional marketing to relationship marketing to raise the economic value of a customer for the firm. They reiterate the importance of customer value which emphasises the value of long-term customer relationships instead of short-term sales goals.

First Generation Pre-1990	Second Generation Pre-1996	Third Generation Post-2002
Call centre management Customer service/support	Integrated customer -centric front end practices including marketing, sales and services	Strategic CRM
Sales force automation		Enterprise Resource Planning Customer Analytics Web integration
Goals		
Improving service operations and sales efficiency	Reducing interaction cost and increasing customer retention and customer experience	Reducing costs, increasing revenue and achieving a competitive advantage

Table 3: Timeline of evolution of CRM (Kumar and Reinartz, 2005)

Pedron and Saccol (2009), in their literature review, identified that CRM can be defined in terms of strategy, as defined by Gummeson (2008), and via a philosophical, strategic and technological approach. The following table illustrates how literature defines CRM under these three approaches.

Approach		Justifications by Pedron and Saccol (2009)
CRM is a:	Philosophy	"The idea that the most effective way to achieve loyalty is by proactively seeking to build and maintain long term relationships with customers."
	Strategy	"Resources destined for relationship building and maintenance efforts should be allocated based on a customers' lifetime value to the firm."
	Technological tool	"The role that technology plays in CRM initiatives can have detrimental effects on a firm's relationship management efforts."

Table 4: Justifications of CRM in three approaches (Pedron and Saccol, 2009)

In the above table, CRM is considered as a philosophy because it can affect the entire business; it is considered as a strategy because it handles processes and resources to get businesses up and running; and, finally, CRM is considered as a technological tool because, as a process, it uses a variety of technological and computational tools with the aim of establishing better CRM.

2.5 The benefits and objectives of CRM

CRM provides firms with an on-going relationship with their customers that can provide a sense of trust, control and security (Grönroos, 2007). The studies of Xu and Walton (2005) conclude that the primary reason for organisations to implement CRM are:

- improved customer satisfaction;
- customer retention;
- obtaining strategic information; and
- enhancing the value of the customer lifetime.

Gummesson (2008) adds, that through relationship building CRM enables corporations to achieve and maintain a prosperous market share. Furthermore, he divides the benefits of CRM into the following two categories:

- **Retention:** acquiring and retaining knowledge and pertinent information about customers, including their names, habits, likes, dislikes and expectations will increase retention.
- **Intimacy and profits:** information technology can help firms to create intimacy with their customers. This can increase the level of mutual trust between the customer

and organisation, and ultimately lead to an increase in profits.

In earlier studies, Zeng et al. (2003) identified that smart IT enabled CRM, because as such technology is based on customer requirements it provides increased customer satisfaction. They also indicated that this process can result in information to be used in future sales. Such additional information can help firms to deliver customised services. Most importantly, CRM that enables firms to be flexible in leading and meeting customer needs.

The above literature effectively documents the objectives of CRM in various domains. Two notable objectives include Xu and Walton (2005) and Nguyen et al. (2007). Xu and Walton mention the following as the main objectives of CRM:

1. **Collecting information:** all details about customers and every interaction should be logged.
2. **Efficiency:** the collected data should be efficiently used and all stakeholders should be informed. All information relating to both past and present customers, and relevant contacts, should be available at all times, and should be consulted before communicating with customers.
3. **Automation:** the operational CRM should be aimed at improving the efficiency of existing processes through automation.

Nguyen et al. (2007) provide more specific objectives, such as increased customer loyalty (obtaining and making customer information available across the entire organisation); superior data collection and sharing (keeping an updated history of customers and their interactions); and knowing customers and providing a superior service (using all information about customers' habits and interaction with organisation to provide information about products or services tailored to the needs of each customer).

2.6 Theories and models of CRM

The previous section illustrated the benefits and objectives of CRM for organisations. As previously demonstrated, the chosen CRM solution should, ideally, link various departments to other business units to get the front office up and running. This information should provide an organisation with the information they need for planning and defining future strategies.

The literature regarding CRM strategies revolves around the concepts of interaction and customer values, and consider CRM as a continuous process. Therefore, this section illustrates these concepts under the exponents of CRM. In addition to measuring the performance of customer relation management, this section also provides an overview of the models and frameworks of CRM development.

2.6.1 Interaction

Chen and Popovich (2003) reiterate that touchpoints provide an effective link for interaction to occur across departments. They further identify that these touchpoints are "places where the customer comes in contact with the organisation". Davids (1999) concluded that one of the primary concerns of CRM is to replicate various access points in the organisation, access points which transmit single pieces of information to customers at every point of interaction. Xu and Walton (2005) go further by explaining that one of the goals of CRM is to integrate all interaction points, thus enabling firms to understand and work specifically towards enhancing customer experience. Peelen (2005) classifies these interaction points as media (TV or radio), websites, email, phone calls or 1-1 contact by sales or service employees.

2.6.2 Customer value

Any firm which wants to employ a long-term strategy should start by looking at how their customers' values change over the course of time. As customers may hold different values over time, it is important that a modelling process is used to study an ever-changing context. Therefore, this modelling should be equipped with prediction and probability parameters. There are various control measures available in the literature which describe exactly how to start this process. For example, Lifetime Value (LTV) is one of the generic parameters that can be used to measure the long-term financial value of a customer.

Kurma and Reinartz (2005) illustrate that the LTV is subject to the type of product or service being promoted, as well as the data and capability of the analysis involved. Therefore, only suitable analysis can provide useful information for managers to devise an appropriate strategy to handle any given situation. Kurma and Reinartz suggest that along with a company's acquisition costs, it is the *recurring* revenues and *recurring* costs that contribute towards calculating the lifetime profit and the lifetime value of a customer (as shown in the figure below).

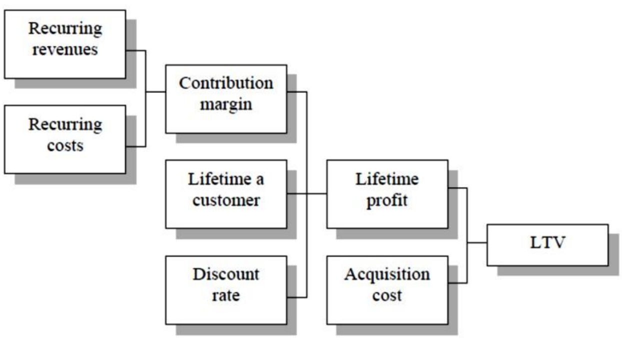

Figure 13: Lifetime Value calculation (Kurma and Reinartz, 2005)

Wailgum (2007) cautions that CRM cannot happen just by buying and installing some software. And can be effective only if firms realise the value of customers with respect to retaining them over the long term. Nguyen et al. (2007) advise that CRM initiatives should start by building an effective model for every customer's profitability. One that can be developed further as and when required.

Prior to implementation, the following equation given by Wreden (2004) is worthy of consideration. It takes the following form:

```
Customer Profit = (gross revenues) – (customer allowances) – (credits and
    rebates) – (product costs) – (channel costs) – (cost to serve) –
                      (administrative costs)
```

At the same time, Nguyen et al. (2007) insist that any adopted strategy should ensure that no customer costs more than they are actually worth. Thus, the literature provides an extension to this methodology called Customer Lifetime Value (CLV). This parameter is simply defined as:

```
CLV = present value of all future generated profits
```

(Gupta et al., 2006)

This approach enables firms to distinguish between potentially profitable customers as well as those who may potentially cause losses. This CLV also helps organisations to have an idea about the financial value of each customer and the maximum amount to invest in them.

There many ways to calculate CLV and, according to Gupta and Lehmann (2003), such formulas should be customised for each firm. There are some general points that should be considered while calculating CLV: these include sales margins, investment costs, discounts and loyalty, among others.

Zikmund et al. (2003) also reiterate the following as the key drivers that accelerate customer lifetime value: profit margin (given by the formula: *profit margin = annual profit – cost to serve*), retention rate (calculated from the *total number of customers making repeated purchases*), discount rate (equivalent to the *current cost of capital*) and time (*obtained from the period that the customer stays with the company*).

There are various formulae available in academia. They include:

1. Simple customer lifetime value formula:

$$CLV = 52\times(Avg\ customer\ value\ per\ week)\times Avg\ customer\ lifespan\ Avg\ customer\ value\ per\ week = expenditures\times visits$$

2. Custom CLV formula:

$$CLV = Avg\ customer\ value\ per\ week\ (52\times(Avg\ customer\ expenditures\ per\ visit)\times\#of\ visits\ per\ week\times Profit\ Margin\ per\ customer)$$

3. The traditional CLV formula:

$$CLV = Avg.gross\ margin\ per\ customer\ lifespan(customer\ retention\ rate 1 + rate\ of\ discount - customer\ retention\ rate).$$

The margin is calculated by the revenue minus the annual expenses of every customer; whereas the retention rate is obtained from the probability of a customer quitting using a product or a service from an organisation (Gupta and Lehmann, 2003).

Gupta and Lehmann (2003) are very positive about the CLV model and advise that once a firm develops its own CLV, the value for each customer can easily be calculated in segments because of IT systems which are equipped to handle large databases and conduct powerful queries.

Xu and Walton (2005) are also of the view that the extensive profiling of customers enables firms to instantly obtain their value to the firm. They list the following as measures to find potential high CLV customers:

- Cost of the product
- Acquiring cost
- Serving cost
- Retaining cost
- Probability of retention and loyalty

Their profit-cost matrix shown below enables us to classify customers according to their value to the firm.

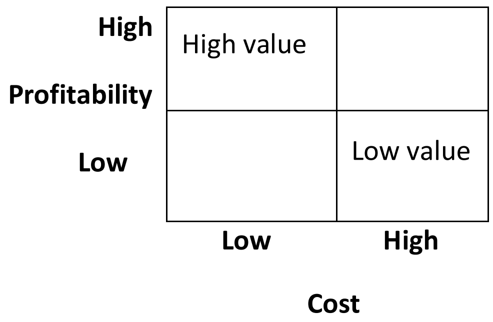

Figure 14: Profit-cost matrix (Xu and Walton, 2005)

The above matrix illustrates that a customer may not be of high value, even though he or she may be buying high volumes of goods when low costs are involved. Therefore, firms should evaluate customers individually in order to obtain detailed knowledge about the associated costs of keeping them and guaranteeing continued profitability.

2.9 Measuring customer relationships

The literature illustrates various means to define and measure customer relationships. Curry

and Kkolou (2004) illustrate that measuring the performance of such processes is very important, not only to understand how it works but also to further improve CRM. The outcome of any CRM initiative is to see changes in customer behaviour; therefore, it is essential to establish a measurable benchmark and desired objectives. Greenberg (2004) further adds that such measurable figures provide data that can be presented to the stakeholders to understand what is going on in the organisation as a whole.

Kotler and Keller (2012) illustrate that failure could be creeping into CRM in various dimensions: for instance, in the process, the people or the system. The following figure identifies the causes of failed customer relationships.

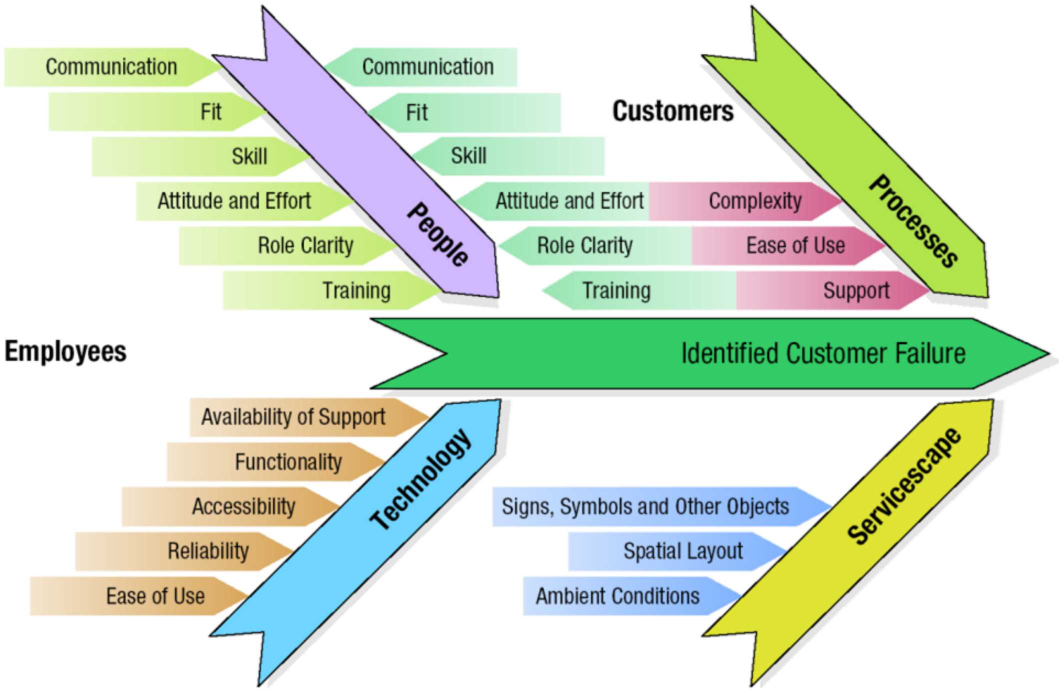

Figure 15: The root causes of customer failure (Kotler et al., 2014)

Having the right metrics to understand which components and/or processes need to be addressed during focused marketing efforts is crucial. Kotler and Keller suggest that such identification enables firms to redesign processes, as well as redefining the role of customers.

They also propose using the right technologies to foster good relationships between employees and customers. In addition, Greenberg (2004) divides such processes and metrics into three categories; namely: customer, performance and diagnostics. Customer metrics could involve understanding the customers' desires, willingness and potential. Performance metrics involve measuring revenue, lifetime value or response rate increase, etc. Diagnostic metrics focus on the number of employees, customers and actions, etc.

As proposed by Hyung-Su and Young-Gul (2007), scorecards are another notable method used to measure CRM initiatives in an organisation. A score card takes various perspectives to diagnose different factors. In addition, it provides both subjective and objective instruments to identify the importance of CRM within an organisation. The main perspectives include: organisational performance, customer experience, process and infrastructure on which these diagnoses where conducted.

Hughes (2009) integrated the Balanced Score Card along with Six Sigma. He suggested that the following measurements could help to effectively measure CRM:

- Number of customers leaving
- Number of orders per customer per year
- Number of product categories bought
- Number of expensive products bought
- Number of returning customers

He, thus, concludes that the purpose of CRM is similar to marketing: to enhance the profit, rather than increase the costs.

Zarah and Kimiloglu (2009) add additional effective CRM measures to those listed above. These include brand awareness, trustworthiness, a robust customer support system, a sophisticated customer database, problem resolution and website clicks or interaction, etc. Thus, organisations need to design a better CRM system, but also employ appropriate, measurable parameters, so that the entire process can be monitored, measured and guided.

2.10 Measuring the effectiveness of CRM in the service sector

When I examined the existing service-marketing literature, I obtained the following factors that measure or define the customer relationship: the customer Satisfaction-Retention-Loyalty Chain (SRLC), the behavioural and financial consequences of service quality, customer satisfaction (CS) and customer retention (CR). Thus, this section reviews the literature surrounding these factors.

2.10.1 Satisfaction-retention-loyalty chain (SRLC)

SRLC is one of the most important concepts that relate CRM to profitability. Since 1990, this concept has been popular and companies have relied on this tool to obtain a measure of satisfaction (Heskett et al., 1994). Mousavi et al. (2001) mention that the primary goal of such a tool is to improve service performance attributes that can lead to satisfaction; a high level of customer satisfaction can retain more customers and lead to increased profit (Anderson and Mittal, 2000, Rust and Zahorik, 1993). Although clear and positive links exist between CRM and profitability, Zeithmal's empirical evidence shows otherwise mixed support (as will be discussed in the section below).

2.10.2 The consequences of service quality

Many authors reiterate that a better quality of service is vital for an organisation to survive in the competitive business arena (Parasuraman et al., 1985, Reichheld and Sasser, 1990b). Indeed, as early as the 1980s organisations started to align their service quality to meet customer expectations (Parasuraman et al., 1985) and, as a result, various management frameworks have been proposed. Zeithmal et al. (1996) list the following such tools:

- Total quality management (TQM)

- Quality function deployment (QFD)
- Failure modes effects analysis (FMEA)
- Six sigma or zero defect
- Plan do check act (PDCA)
- Deming cycle

Although there were no measures of correlation amongst customer service relationships, measure of service quality and financial performance, Zeithmal (2000) concluded that the relationship between satisfaction and profitability ranges from positive to no effect. While Anderson and Mittal (2000) identify three generic relationships between service attribute performance and satisfaction (as discussed below).

2.10.3 Customer satisfaction (CS)

Heskett et al. (1994) insist that customer satisfaction results from how a customer perceives the service quality that they received in relation to their expectations. According to Looy et al. (2003), customer satisfaction is about feelings; specifically the gap between "what is expected and what is perceived by the company, product of service".

Many authors, including Anderson and Mittal (2000), have showed that improving customer satisfaction leads to increased intention – what consumers look for at a specific moment and/or where they seek it – and results in more profit. Using his comprehensive model, Storbacka et al. (1994) successfully linked service quality with the attitude and behaviour of the customer, as illustrated by the following figure:

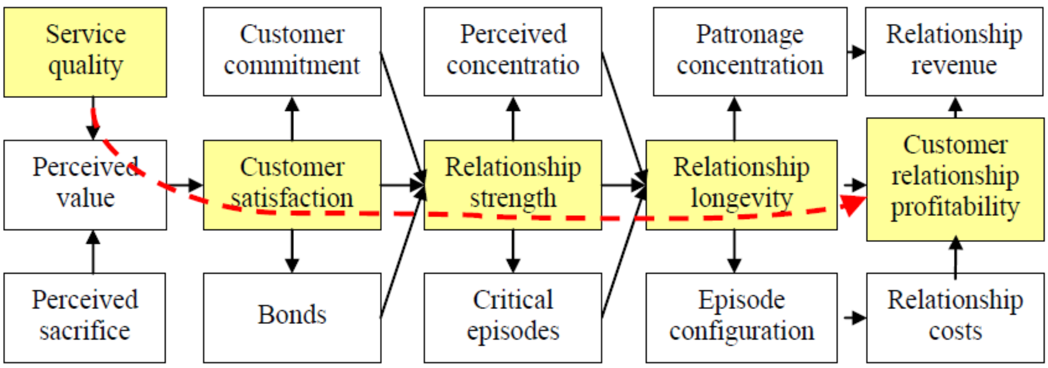

Figure 16: Service quality to customer satisfaction to profitability (Storbacka et al., 1994)

For a long time, the relationship between customer satisfaction, customer retention and financial performance has been the centre of attention for organisations in CRM. Here, I examine the literature concerning the financial implications of customer retention. This literature makes two assumptions: firstly, authors like Anderson and Mittal (2000), and

Reichheld and Sasser (1990a), illustrate that obtaining new customers is costlier than retaining prevailing customers; secondly, prevailing customers may lead to more profit through word-of-mouth (Rose, 1990). In her study, Rose (1990) established that if a customer can be retained for longer than ten years then they will be three times more profitable for the organisation than a customer of five years.

2.10.4 Customer loyalty (CL)

A wide variety of descriptions of customer loyalty are mentioned in the marketing literature. Literature which also includes a multitude of other generic terms, such as retention, switching, strength of relationship and commitment of continuance. In addition, the terms relationship continuance, cross-selling, word-of-mouth, customer recommendation and upselling are other terms which are used to describe loyalty. Wallin Andreassen and Lindestad (1998) define loyalty as an "intended behaviour triggered by the service" while operational loyalty is "a re-purchase intention" and a "willingness to provide positive word-of-mouth" recommendations. Thus, from the many equivalent descriptions of loyalty, one can clearly see and understand that they all result in increased revenues, lower costs and obtaining new customers, all of which leads to increased profitability.

Customer loyalty is also influenced by customer satisfaction on a greater scale. Yet, although there are a great many studies on loyalty, scholars are not in agreement about the most suitable way to measure loyalty. In spite of the diverse definitions, the inability to agree how to measure it, and the resulting limitations for further study, the following points are commonly found across the literature:

1. Repeat purchases indicate loyalty (Liljander and Strandvik, 1993)
2. There is a combined aggregate of patronage and attitude (Dick and Basu, 1994)
3. Psychological prospects, such as attachment towards the provider, commitment, etc. (Czepiel, 1990)

2.11 Marketing intelligence or business intelligence?

It has been established by many authors that organisations need to foster a long-term relationship with their customers. This is only possible by creating a systematic process in which information is appropriately gathered, analysed, supplied and applied, in both the internal environment and the external market. Lee and Trim (2006) illustrate that this process can be facilitated only with the help of business intelligence. They further reinstate that marketing intelligence plays an important role in formulating and implementing appropriate plans to realise the goal of establishing long-term relationships with customers.

Cornish's (1997) definition of marketing intelligence states that "It is the process of acquiring and analysing information to understand the market in order to find the present and future needs, preferences, attitudes and behaviours" of customers. Therefore, for better decision-making that can facilitate the growth of business performance, organisations have to pay attention to marketing intelligence. The analytical results obtained during this process should not only provide organisations with competitive differentiation, but also help firms to evaluate the efficiency of current processes in place.

A recent study from Watson et al. (2013) illustrated that although consumers use smartphones extensively, any marketing-related communications are often disregarded. Consumers remain resistant to any marketing-related texts or calls and see them as intrusive (Watson et al., 2013). The study enunciated further that only through proper permissions, trust-building measures and providing something useful for the customers would customer satisfaction and retention be accomplished.

Another notable point regarding smartphone usage for online shopping is evident through a study by Holmes et al. (2013). Their study demonstrated that mobile phone usage remains lower than the use of computers for shopping. Interestingly, consumers do use mobile phones for searching and shortlisting, but final purchasing is done only through computers – which is a very important point (Holmes et al., 2013).

2.12 CRM and database marketing

The growth of information technology and faster internet speeds has led to improved manufacturing and outsourcing facilities. In this scenario it is imperative to understand each customer's needs, as this knowledge has the potential to become a determinant of a firm's profitability. Traditional databases enables the assembly of different sets of data about customers in ways that can be easily queried and reported. As such, a dataset enables the team responsible for database marketing to identify and analyse their customer population; by taking advantage of the rich data contained in the database about different segments of the customer population. Therefore, many authors suggest CRM be used to maximise the potential use of database marketing techniques in order to reach customers and ultimately strengthen customer-firm relationships (Holmes et al., 2013, Watson et al., 2013).

Kumar and Reinartz (2005) explain how customer data can be, potentially, collected to maintain a repository of information in the data warehouse of an organisation. Kumar and Reinartz (2005) further advise that customer data could contain information like demographics, transactions, sales details, campaign details, etc. This data then enables segmentation to be used regarding customers, sales and time bound calculations, etc. Moreover, by accessing this information it is possible for decision-makers to select the most appropriate products, costs and offers, etc., for each customer. Information which can be sent to the data warehouse for later use.

All the above methods are aimed at shifting firms from using transactional marketing towards relationship marketing, and will ensure that there is an increase in the long-term economic value of customers, rather than only increasing short-term profits. Rowley (2016) insists that the information marketplace is evolving, and every organisation has to adopt new strategies, alliances and identify new market segments in order to keep growing. Under tight competition, an organisation needs to use plethora of tactics to ensure success and survival. Introducing new products or employing marketing approaches all help organisations to face an ever changing dynamic environment (Rowley, 2016).

2.13 Customer segmentation

In their study on the Korean mobile telecommunications service industry, Ahn et al. (2006) established that a traditional marketing strategy will not be able to meet the demands of a modern business scenario. This is the case, because in order to tackle the issues of competing with an ever-increasing number of competitors, such as reducing the switching rate of customers and retaining customers, it is important to serve each individual customer in accordance with their individual needs. Thus, organisations need to prioritise their customers so that they have the required capabilities, processes and infrastructure to cater for customer demands. This is possible only with the help of segmentation, as without such processes firms will never be able to recognise the individual needs of their customers.

Customer segmentation is generally classified as the process used to categorise customers into smaller groups or market segments, and this step assists managers to focus on profitable segments and choose appropriate winning strategies to retain high-value customers. Bounsaythip and Rinta-Runsala (2001) define customer segmentation as “The process of dividing customers into groups with similar, shared or common attributes”.

DeSarbo et al. (1997) categorised customer segmentation into two distinct groups: general variables involving customer demographics and lifestyles, and product specific variables, such as the purchasing behaviour of customers. According to Kamakula(1998), customer segmentation is the process of classifying customers into different groups, to view the entire database as a single picture, thus allowing the firm to treat customers differently according to their classification, and pursue marketing that is suitable to each classification.

Studying customer profitability reveals that there is not always a positive correlation between customer revenue and customer profitability (Kaplan and Narayanan, 2001). Foster *et al.* (2001) states that "… each dollar of revenue does not contribute equally to net income" because customers from different segments contribute differently to a company's financial performance. In other words, some customers bring more income to the firm than the others.

2.14 The continuing process

Xu et al. (2002) characterizes a firm as a successful one when it has a system that uses its customer database wisely in order to deliver what the customer wants every time. Nguyen et al. (2007) explain that such a process is continuous, and the process of digitising the employees of the Telecom service provider is vital, because employees handle and manage the provider's relations with customers using the latest technologies, including Sentiment analysis. They give the following example how CRM can be modelled or how it can be implemented.

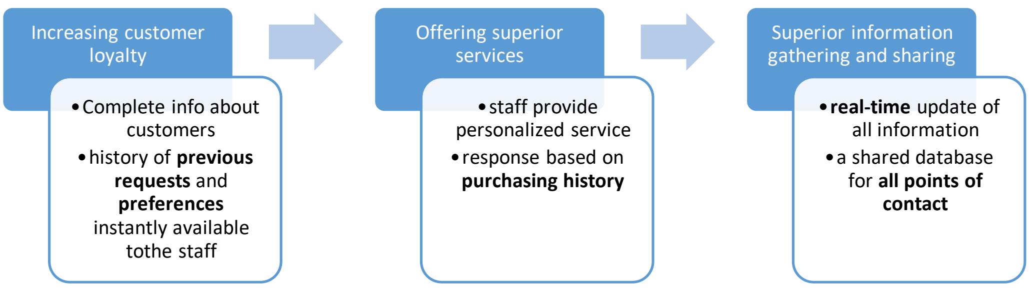

Figure 17: Process Integration (Nguyen et al., 2007)

Therefore, it is very clear from the above discussion, that building tools to obtain useful information from the data play a vital role in the CRM process. Such an awareness can be reached after areas of knowledge are classified as done by Xu and Walton (2005) in their Analytical Customer Knowledge Acquisition Model (Figure 18).

	Existing (Internal)		
Profiling (who's who)	Existing segment who are loyal & strategically important	Existing behaviour pattern with satisfied and loyal customers	**Pattern (How)**
	Demographically segmented prospective & new customers	Observed defecting pattern, loyal to competitors	
	Prospects (External)		

Figure 18 : Analytical Customer Knowledge Acquisition Model by Xu and Walton (2005)

In addition to the associated purchasing costs of each customer, firms should also know about their customers' purchasing behaviours and patterns. This will then provide information about defecting customers, such as when, why and even where they go to; in addition to providing information relating to the acquisition of new customers, and when, why and where they come from. These patterns and behaviour will enable managers to keep abreast of any common and recurring problems that the company is facing.

According to Xu and Walton (2005), to identify potential customers, such processes are essentially continuous, analytical and strategic and should be built-in and proactively integrated within the processes of the business. Such rich information will enable firms to cater for different customer segments which results in increased profitability (Leventhal and Zineldin, 2006). Such information can also be used to develop effective and targeted marketing strategies as well as to identify the learning limitations of competitors, and capitalise on this information to attract new customers. Leventhal and Zineldin (2006) point out that the main use of CRM is to engage in defensive marketing strategies. This could involve firms gaining an understanding of why their customers are leaving, and consequently implementing suitable customer retention programmes. They further suggest that such retention programmes not only improve customer retention rates but also increase the level of customer satisfaction and increase profitability.

2.15 Strategies for CRM

It is worthwhile to examine some different strategies in addition to defensive marketing. Peelen (2005) illustrates some different types of strategies which he describes as being either defensive or offensive. The following figure illustrates his classification and their definitions.

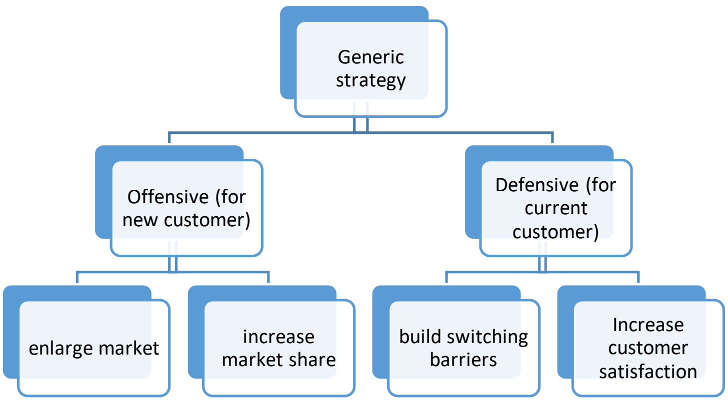

Figure 19: Offensive vs. Defensive Strategies (Peelen, 2005)

It is clear from the above classification that an offensive strategy focuses on increasing a firm's market share by beating the competition and acquiring new customers, while a defensive strategy focuses on retaining existing customers and building barriers that prevent customers from defecting. Peelen (2005) illustrates that such strategies have different measures of success; for example, firms may focus on re-acquiring previous customers and reducing customer turnover.

Leventhal and Zineldin (2006) add to this by insisting on the importance of giving special recognition to long-term customers as well as those that are highly profitable. This is possible only by welcoming feedback and resolving complaints promptly and satisfactorily; thereby giving customers a second chance to receive a positive experience and feel satisfied with the service.

Greenberg (2002) cautions that one of the most overlooked and undervalued component of CRM is the culture of the organisation. He illustrates that firms may not realise the necessity of a suitable working culture which focuses on customers to exist, and he concludes that culture is the "lynchpin" of CRM in an organisation. Thus, it is very clear that for organisations to be competitive it is necessary for them to focus on their social, physiological, emotional, organisational and personal culture.

Another problem experienced by organisations relates to customers that do not want to engage in a relationship with them. Even when a relationship is imposed for their benefit customers may still decide to leave permanently (Xu and Walton, 2005). In order to mitigate this, it is necessary to understand the different types of relationships that can exist within organisations. Rao and Perry (2002) have studied relationships and classify them into six categories:

1. **Single transaction** associated with price.
2. **Repeated transactions** that encourage multiple purchases through building commitment and increasing loyalty.
3. **Soft relationship** when repeated buying occurs without any obligation.
4. **Hard relationship**, long-term contractual relationships built through an intimate social bond.
5. **Strategic alliance**, a comprehensive relationship that can occur because of legality.
6. **Networks** that are complicated and involve more than three factors.

Xu and Walton (2005) insist that organisations should be aware of the types of relationships that exist with their customers, and then provide a specifically targeted level of service that adds value to them. Mintzberg's (2003) solution is to integrate customers at the various levels of the supply chain. His ideas involve providing standardised and customised solutions at each stage of the production or service.

The following figure illustrates how standardisation and customisation can be accomplished at various levels.

Pure Standardisation	Segmented Standardisation	Customised Standardisation	Tailored Customisation	Pure Customisation
Design	Design	Design	Design	Design
Fabrication	Fabrication	Fabrication	Fabrication	Fabrication
Assembly	Assembly	Assembly	Assembly	Assembly
Distribution	Distribution	Distribution	Distribution	Distribution

Figure 20: Continuum of strategies, standardization (in blue) versus customization (in red) (Mintzberg, 2003)For example, ***pure standardisation*** does not incorporate adaption as it is for a general market. When there are individual segmented customers then ***segmented standardisation*** is applicable. ***Customised standardisation*** enables firms to use various sets of components that best fit customers. When a firm's design fits its customers' use then ***tailored customisation*** is used. When the customers' input is involved from design to delivery, ***pure customisation*** is utilised.

2.16 An overview of two CRM models

Curry and Kkolu (2004) proposed Customer Management Activity as a model that uses the customer's life cycle as the process under consideration. Customer Management Activity is categorised into three main parts, namely: acquisition, penetration and retention. Each one, according to Curry and Kkolu (2004), consists of a number of stages. For example, acquisition begins with targeting, identifying, converting, capturing and distributing, whereas penetration consists of data collection, data analysis and retention, which involves problem management and the win-back of customers.

Another model worthy to note here is Peppers' and Rogers' (2001), based on the 'IDIC' view which stands for identify, differentiate, interact and customise.

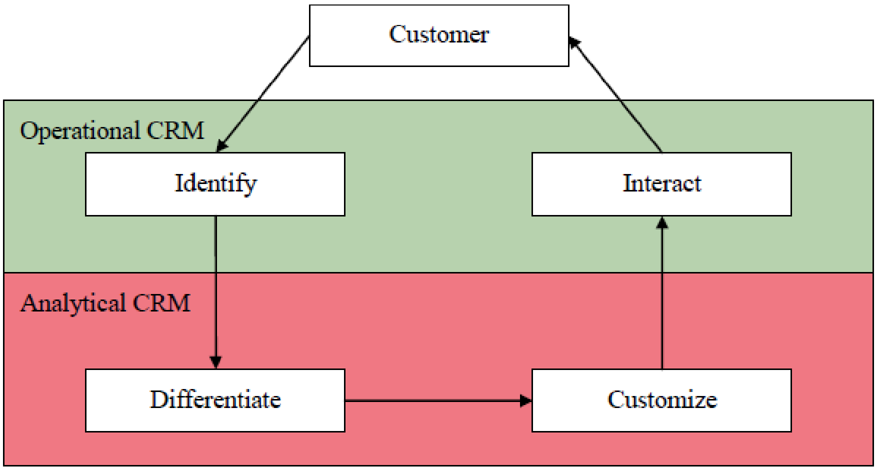

Figure 21: IDIC model (Peppers & Rogers, 2001)

As is clear from the above flow chart, the customer has to be identified and differentiated in order for a product or service to be customised. Based on the level of customisation, CRM can interact with customers specifically in relation to their needs and wants. It is important to note that both identifying and interactingare part of the operational CRM process while differentiating and customising consitute the analytical part of CRM.

2.17 Chapter two summary

The literature review of this chapter covered evolving marketing theory, and how this gave birth to an important branch of marketing called CRM. The benefits and objectives of CRM were discussed above in detail; in particular, Xu's and Walton's (2005) conclusions which highlighted the primary reasons for organisations to implement CRM. These reasons included improved customer satisfaction, retaining the customer base, obtaining strategic information and enhancing the value of customer lifetime. Also, Nguyen et al. (2007) have provided specific objectives of CRM through increased customer loyalty, superior data collection and sharing, knowing customers and providing a superior service. Hence, Research Question 1 has been addressed through the section of the literature review focused on marketing and management which explored the function of customer behaviour in the given business context.

In order to see how CRM works in the service sector, we started by studying the product-service distinction. In addition, we have tabulated how academia distinguishes products and services in broader categories with a wide ability to measure, perception, form, shelf life, delivery, flexibility and marketing (Evans and Berman, 2002). This then creates a matrix, recommended specifically for telecom products and services, which enables us to understand the nature of the goods and services to be marketed.

We have also reviewed how CRM and database marketing are related, and this has established how potential relationships pave the way for a greater focus on customer segmentation. In particular, Xu et al.'s (2002) characterisation of a successful firm being one which has a system that uses its customer database wisely in order to deliver what the customer wants, every time. With this in mind, Nguyen et al. (2007) expanded this idea to take into account that a continuous process of digitising the employee's knowledge is vital.

The use of all possible technologies, such as mobile phone marketing, is essential to effectively implement CRM. At the same time, we should make sure such an approach does not become intrusive (Watson et al., 2013), so, for instance, obtaining the proper permissions from customers, incorporating trust-building measures and providing something useful for customers are worthy procedures. Some limitations exist, as despite the extensive use of smartphones, customers tend to use mobile phones during an early stage of shopping, but often only purchase a product through computers (Holmes et al., 2013).

Firms also need to take into account Marketing 3.0, a marketing method that insists firms consider customers as multidimensional entities who are value-driven (Kotler et al., 2019). This holistic framework necessitates organisations to consider customers as unique, and thus strive for better interactions and relationships (Marques, 2018).

Relationship marketing is also experiencing a recent change when we consider the bigger role of inter-organisational culture (Larentis et al., 2019). Social media expressions, that consist of shared symbols with characteristic openness, provide customers with an interactive channel. In turn, an organisation can make use of this information to serve its customers. Cooperative practices, such as better conflict management and the integrity of an organisation (in all areas) can also influence the success of relationship marketing at a result level. Consider, also the limitations, such as the existence of weakening elements such as the non-availability of shared symbols and meanings which might cause confusion in communications between a company and its customers (Larentis et al., 2019).

3 Research Methodology

This chapter justifies the research methods used in the study in order to obtain data to solve the research questions. The first part of this chapter describes the research philosophy, approach and strategy, followed by experiment and survey methods. The second part of this chapter reviews the literature on human-computer interaction, and, in particular, sentiment analysis. This part attempts to identify the tools and/or methods that can be potentially used for measuring the parameters of CRM in the service sector. The third part of this chapter discusses cross-sectional and longitudinal methods. Saunders et al. (2015) ask an important question prior to designing a research strategy; which is, "Do you want your research to be a snapshot of a particular time, or is it a diary or series of snapshots to represent specific events over a given time period?". While the snapshot time horizon is known as cross-sectional, the diary perspective is often called longitudinal (Saunders et al., 2015). So, as well as choosing appropriate research strategies, it is equally important to acknowledge that every research study should define its time horizon.

Saunders et al. (2015) propose a research process that incorporates forward planning and backward reflection based on the following various steps: formulating the research topic, conducting the literature review and choosing the appropriate research philosophy, approach and strategy.

Considering this in more detail, the following flowchart illustrates the research process that this study adheres to (Saunders et al., 2015):

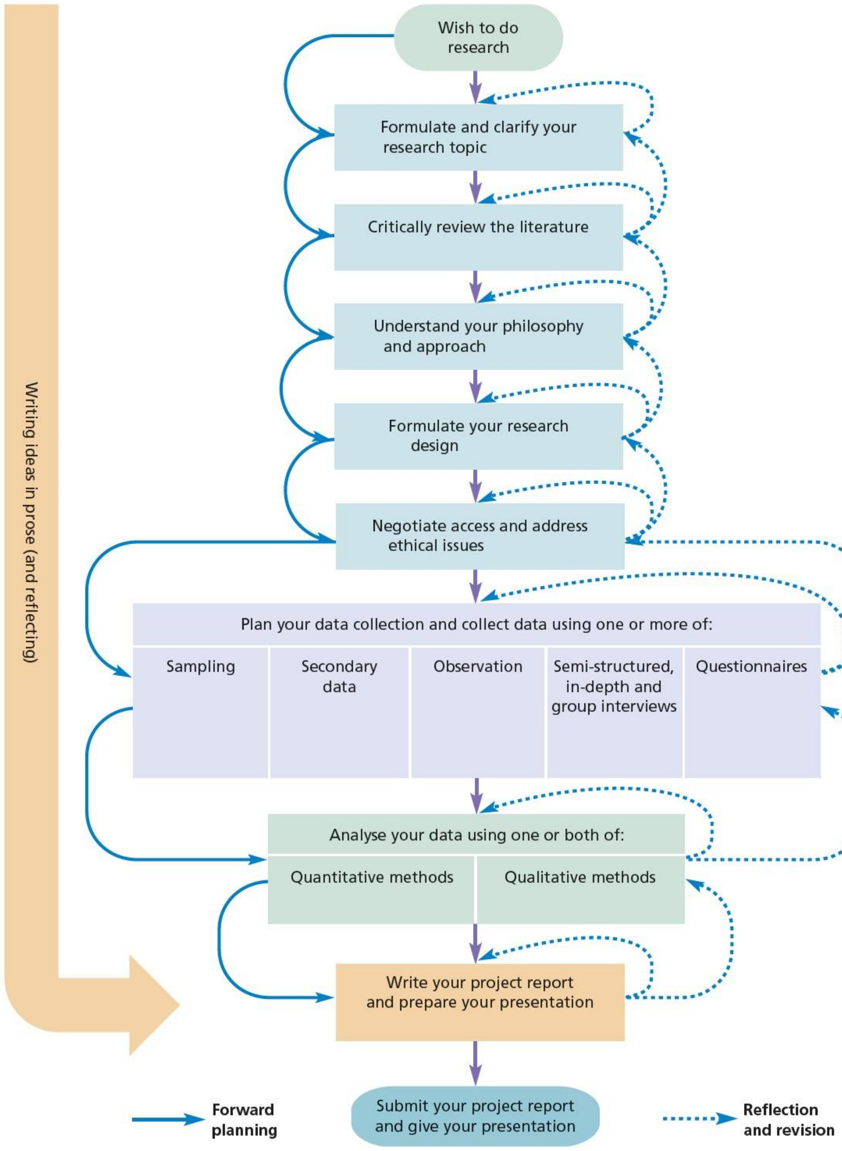

Figure 22: The Research Process (Saunders et al., 2015)

Saunders et al. (2015) also proposed using The Research Onion (Figure 23) which illustrates the wide number of choices available for a researcher to use when conducting his or her research. The research onion encompasses different layers, consisting of philosophy, approach, methods, strategy, time horizon, data collection and analysis. And I have used this structure to organise this methodology chapter.

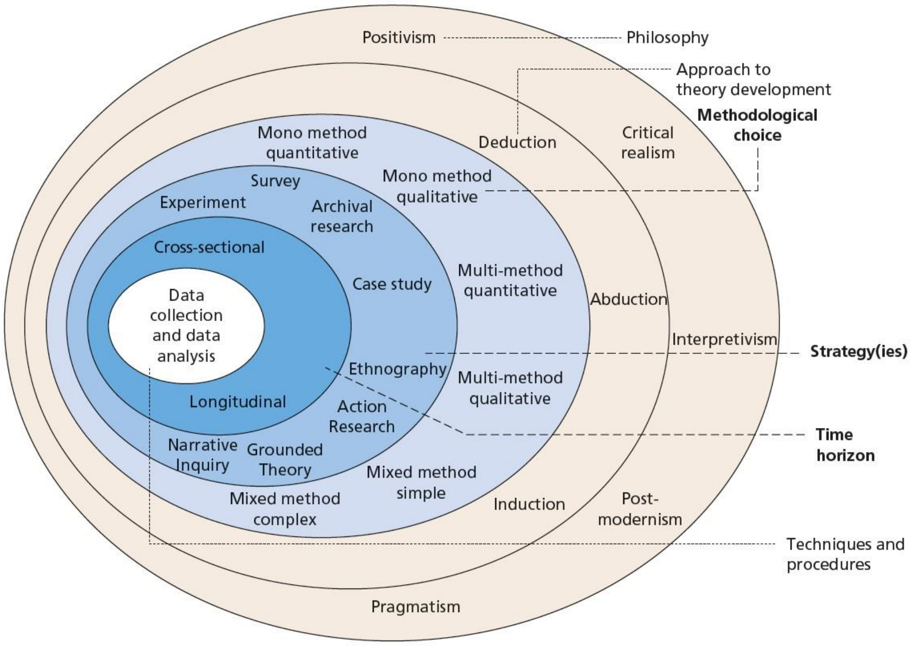

Figure 23: The Research Onion (Saunders et al., 2015)

As justified in this chapter, this study gathered data from Omani telecom customers (through a questionnaire and social media data, viz. tweets) and from social media managers based in telecom firms in Oman (through a questionnaire and semi-structured interviews). This social media data and interview texts are subjected to sentiment analysis, and customers' and social media managers' survey responses were analysed using quantitative and qualitative statistical analyses.

3.1 Research philosophy

Research philosophy enables a researcher to guide how data should be gathered, analysed and applied. What is known to be true (epistemology) or what is believed to be true (doxology) covers the research philosophies used in a research approach (Quinlan et al., 2019). Therefore, any adopted philosophy should transform from doxa, what is believed and what is generally known, into episteme, understanding a subject area in detail.

In general, researchers in computer science either use positivist or interpretivist philosophies. A positivist approach which is often called scientific philosophy relies on the fact that reality is stable and objectivity oriented, while the interpretivist approach is anti-positivistic and demands intervention to subjectively interpret an issue. In other words, interpretivists rely on the fact that a phenomenon can be understood only in terms of its own context (Quinlan et al., 2019).

On the other hand, phenomenology, which is also called non-positivism, is a variation of interpretivist often employed in business research studies as this type of research focuses on people's experiences of events, such as customer satisfaction.

Saunders describes research philosophy as "… a system of beliefs and assumptions about the development of knowledge" (Saunders et al., 2015). The chosen research philosophy of the current study is positivism or phenomenology. Bryman and Bell (2015) consider positivism as an epistemological position that advocates the application of natural science methods to study social reality (Bryman and Bell, 2015). It is important to abide by the principles of positivism, especially in the case of society-related research, then any such research outputs become well-defined constructs, similar to that of a physical or natural researcher (Saunders et al., 2015). Thus, adopting this philosophy ensures that the researcher is completely independent of the research subject; the researcher neither affects the research subject nor is affected by the subject.

As in the case of the present study, business situations are complicated and unique; and hence, a question arises concerning whether it is possible to theorise about business concepts through scientific laws. Saunders et al. (2015) propose that interpretivist researchers *should* take account of such complexities by collecting only what is meaningful to their research respondents; thus, studying the experiences and recollections of respondents (Saunders et al., 2015). Bryman and Bell (2015) demonstrate that phenomenologists view human behaviour as a product of people's interpretation; that is, simply seeing things from *that* person's point of view.

Several authors agree that no single research methodology befits all types of research, rather they advise using a combination of different philosophies (Horkheimer, 2018). This could be owed to the nature of the real world which is diversely rich and complex. At the same time, some authors opine that there is no philosophy that is incapable of being used; on the contrary, any method could be valid and/or useful if it is applied appropriately (Horkheimer, 2018). So, taking this into account, it is better to opt for a combination of philosophies for maximum benefit and guidance. As employing a mixture of two philosophies can enable better results from each of the philosophies used (Saunders et al., 2015), for this study, therefore, I have employed a mixture of positivism and phenomenology. I will now define the different types of research used in this study (as classified by Saunders et al., 2015): exploratory, descriptive, explanatory, or a combination of some or all of these. We shall see briefly what each one stands for in Sections 3.1.1 to 3.1.3.

3.1.1 Exploratory research

As evidenced in the literature, research studies that conduct interviews with experts are exploratory in nature. Exploratory study enables researchers to ask open questions and discover what is happening in addition to gaining insights about the topic being researched (Saunders et al., 2015). Such research questions start with 'what?' or 'how?'.

The advantage of this type of research is that it is flexible and adaptable. This method enables the researcher to alter the course of the research as and when the results of new data are ascertained and new insights occur. Although exploratory research, usually, commences with a broad focus, in the course of the research process the focus becomes narrower. Exploratory research enables the researcher to formulate problems and hypotheses with precision and clarity so as to achieve practical results (Bryman and Bell, 2015).

3.1.2 Descriptive research

According to Saunders et al. (2015), descriptive research is an extension of exploratory research: in the sense that it acts as a forerunner for explanatory research. The purpose of descriptive research is to gather a precise profile of events, persons or situations. The research questions are of a descriptive nature and start with or include either 'who?', 'what?', 'where?', 'when?' or 'how?'.

Therefore, descriptive research is stricter than exploratory research, as unlike exploratory studies it defines research questions, decides what people to involve and the methods of analysis. Such descriptive design enables the researcher to propose a theory, detect problems with the present scenario and justify their reasoning. In the context of the current study, the aim of the research is to understand existing practices of social media usage and their justifications.

3.1.3 Explanatory research

Studies which establish causal relationships between variables fall under explanatory research (Saunders et al., 2015). Most questions of this type of research start with or include: 'why?' or 'how?'. Moreover, there are various statistical analyses available to establish the relationship between variables. My study follows this approach by including many such variables which are qualitative in nature.

3.2 Research approach

Malhotra et al. (1996) reviewed the three research methods above, and listed their objectives, characteristics and methods (Table 5).

	Exploratory	Descriptive	Explanatory
Objective	Discovery of ideas and insights	Describing the characteristics or functions	Establish cause and effect relationships
Characteristics	Flexible as well as versatile. The forerunner of overall research design	Marked by prior formulation of tentative hypothesis and research questions. Pre-planned structured design	Manipulating and controlling one or more independent variables
Methods	Pilot surveys Secondary data Qualitative research	Surveys	Surveys Experiments

Table 5: Comparison of research types (Malhotra et al., 1996)

As illustrated by Saunders et al. (2015), many research studies are often designed with more than one purpose in mind, and as such a single research type is insufficient. Often these studies, such as the present study, need to engage multiple types of research designs. My research purpose and questions illustrate that the research method is, supposedly, descriptive and explanatory. Yet, the purpose of my pilot study was to find causal relationships, thus the adopted research method could also be classified as exploratory. Such exploratory research in the pilot phase enables us to modify the subsequent research model as required.

Many types of research can lead to the development of a theory, however, in the case of a deductive research approach, in addition to theory hypotheses are also developed, and in the case of inductive research, in addition to theory hypotheses are tested as a result of the analysis of the collected data (Saunders et al., 2015). While the deductive approach arose from positivism, the inductive approach relies on phenomenology. In my study research questions were developed, research strategies designed and as a consequence questions are answered. Thus, the research approach is deductive in nature.

Researchers often utilise quantitative and qualitative approaches in order to realise their overall research strategy. Guba and Lincoln (1994) illustrate that the most important difference between these methods is the use of numbers and the application of statistics. The nature of the research problem and the characteristics of the data (required to solve the problem) decide what research methods are most appropriate. Whenever processes and their outcomes are measured through quantity, amount, frequency or intensity, the method employed is quantitative. Conversely, when processes and their outcomes are not measured through quantity, amount, frequency or intensity, then a qualitative research method is employed.

On one hand, a qualitative method enables the researcher to obtain a deep, contextual understanding of the phenomenon they are investigating (Guba and Lincoln, 1994). Qualitative research also enables the researcher to understand the social constructive nature of their chosen topic. Additionally, qualitative methods also assist researchers when there is less theoretical support for the case under study; as it may be difficult to develop appropriate hypotheses, precise research questions and definitions, qualitative research provides assistance as it is exploratory in nature.

On the other hand, quantitative researchers identify causal relationships between variables by the use of numerical measurements. It is possible to measure attitudes and behaviours using quantitative methods (Malhotra et al., 2013). It is also possible to develop a model to predict future observation as this method is driven by the principle of statistical analysis.

Cochran and Dolan (1984) distinguish qualitative and quantitative research methods through exploratory research that is qualitative in nature, and confirmatory. Taking all of these comparisons into consideration I selected a quantitative approach to explain all the possible links in my research questions. At the same time, I included qualitative methods in the pilot test to ascertain the factors involved in the study.

3.3 Research strategy

Saunders et al. (2015) define the research strategy as a plan of how the research questions will be answered, in other words how a researcher intends to carry out their study. It is therefore a methodological link between the research philosophy and the methods used for collecting and analysing the data (see Figure 25). While the choice of an appropriate strategy for this study was guided by the research questions, the research strategy also depends on existing knowledge in the field of study, the availability of time, and/or resources and data.
Bryman and Bell (2015) remind researchers that understanding each element of the research strategy will enable a researcher to gain insights into the different methods they could potentially use. It is important to note how methods are applied and analysed, and how they relate to different theories and research design. This, in turn, enables researchers to know how, where and why certain methods are useful, and the range of choices available that might suit their research study (Bryman and Bell, 2015).

Thus, in order to perform a research study, an appropriate research strategy should be followed. It is the research strategy which informs the researchers whether to use experiments, surveys or case studies, so I consider what methods to use for my experimental design in more detail below.

3.3.1 Experiments, surveys and interviews

Saunders et al. (2015) describe natural science laboratory experiments as the "gold standard" as their procedures express to researchers how rigorous other strategies are. A natural science laboratory experiment is a form of research that studies the probability of a change in an independent variable causing a change in a dependent variable (Saunders et al., 2015). Different experiments handle different types of variables. The following table lists some of the important types of variables that could be encountered during experimental design.

Variable	Definition
Independent Variable (IV)	A variable that is being manipulated or changed to measure its impact on a dependent variable.
Dependent Variable (DV)	A variable that changes in response to other variables.
Mediating Variable (MV)	Variables located between independent and dependent variables (IV→MV→DV). They explain how IV and DV are related.
Moderator Variable	A variable that affects the nature of the relationship between IV and DV.
Control Variable	Variables remain constant to compare with the experimental group(s).
Confounding Variable	Extraneous variables that are difficult to measure.

Table 6: **Types of variables in experiments (Saunders et al., 2015)**

Every standard experiment consists of two opposing types of hypothesis; namely, a null and an alternative hypothesis. A null hypothesis predicts that there is no significant relationship between the variables being tested, whereas an alternative hypothesis states that there is a relationship (Bryman and Bell, 2015).

Saunders et al. (2015) explain that experimental design can include methods like classical experiments, quasi-experiments and within-subject designs. On the one hand, in classical experiments a sample population (of participants) is selected and randomly assigned to two groups: the experimental or the control group. In the experimental group an intervention and/or manipulation will be tested, whereas in the control group no interventions are made.

Bryman and Bell (2015) remind us that the purpose of the control group in such experiments is to control or eliminate the effects of causal findings.

On the other hand, a quasi-experiment – apart from using similar control and user groups – does not randomly assign participants to each group. Analyses such as matched pair analysis enable researchers to study the difference between participants between the groups. This minimises the effect of extraneous variables (Saunders et al., 2015).

Considering survey research, in which data are collected through the use of questionnaires and/or through structured interviews, Bryman and Bell (2015) categorise this type of research as being cross-sectional in design as it is used as both an exploratory and descriptive research tool. Saunders et al. (2015) describe the survey strategy as one of the most common deductive research approaches; with one advantage being that the researcher can include 'what?', 'who?', 'where?', 'how much?', etc., into their experimental design.

Surveys use questionnaires for the following reasons (Saunders et al., 2015):

- They allow the collection of standardised data from sizeable populations.
- They are highly economical.
- It is easy to compare data.
- They are generally trustworthy.
- They are easy to explain and to understand.

Surveys allow researchers to collect quantitative data and to statistically analyse possible relationships between variables. In addition, the models of these variables of interest and their interactions can be obtained through experimentation (Bryman and Bell, 2015). Furthermore, as well as providing complete control over the research process, a survey strategy enables researchers to generate findings from the sample instead of attempting to obtain the same information from the whole population (Malhotra et al., 2013). It is therefore more manageable; however, care should be taken to ensure that the sample chosen for the survey is representative and towards these aim researchers should make sure that they receive a good response rate.

Some drawbacks regarding the use of questionnaires:

- Preparing and analysing data is time consuming.
- Data collected in the survey may not be as varied as for other research strategies.

- Survey questionnaires cannot be lengthy and comprehensive.
- The goodwill of the respondents cannot be presumed.
- The use of a questionnaire provides an opportunity for the respondents to do badly.

Due to the drawbacks above, it is reassuring to know that the questionnaire is not the only data collection technique available. A survey strategy can also incorporate the systematic assessment of activities to improve human and other resources in an organization, as well as structured interviews (Saunders et al., 2015). I chose to include structured interviews in my study in an attempt to avoid any possible pitfalls associated with using questionnaires alone.

Different types of interviews include highly formalised, structured or standardised (see Figure 24). Based on the level of the formality and structure involved Saunders et al., (2015) categorise interviews as being either:

- structured;
- semi-structured;
- unstructured; or
- in-depth.

Using typology, interviews can be further classified as being either: standardised and non-standardised. While, based on Watts' and Ebbutt's (1987) topology, interviews can also be described as being either: respondent or informant.

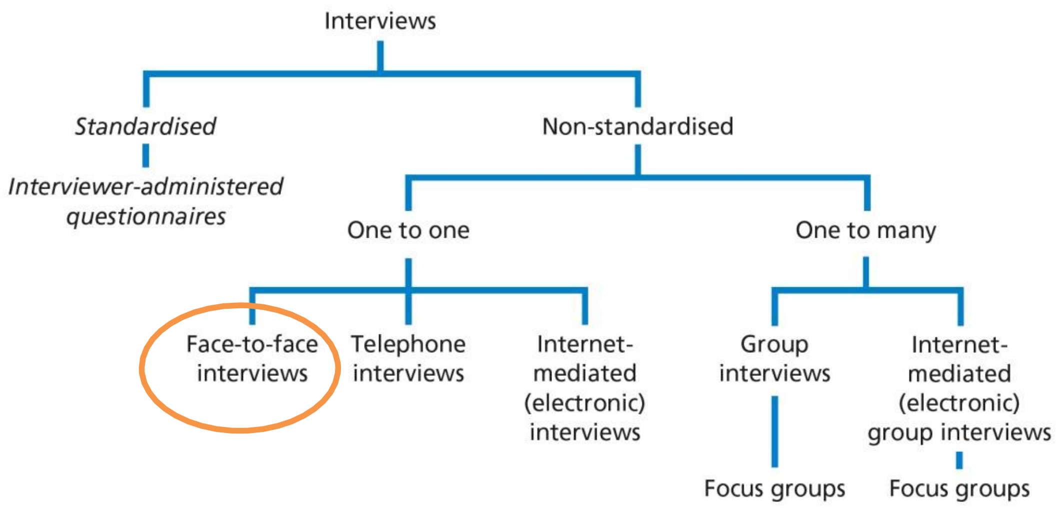

Figure 24: Types of Interviews (Saunders et al., 2015)
(highlighted to indicate the semi-structured, non-standardised interviews chosen for this research)

I employed semi-structured interviews to collect qualitative data from my respondents about their social media usage in terms of CRM. The following list provides the justifications for choosing semi-structured interviews over other methods for this study.

- Interviews lead to rich and well-detailed information being received from respondents.
- The process is flexible and interviewees are allowed to give their own opinions, as social media usage is relatively new with much to discover from a research perspective.
- Interviews can be arranged with members of staff responsible for maintaining the social media relations of a company, as data collected from them will help us to understand how social media company-customer relations support CRM.

I developed an interview guide to conduct semi-structured interviews. According to Bryman and Bell (2015), an interview guide should include a list of research themes and it is useful to prepare an interview guide to help researchers to maintain the same level of consistency between different interviews (Bryman and Bell, 2015). Despite using a guide, the respondents involved in this study were allowed to discuss the themes I was interested in throughout the course of the interview. The interview guide prepared for this study is provided in the appendix (please refer to Appendix 1: Interview Guide (Social Media Managers) for semi-structured interviews). All the interviews were audio-recorded and transcribed for further verification and analysis.

3.3.2 Information science theory

This part of the chapter discusses information science theory before proceeding to a particular focus on computer-mediated communication (in Section 3.3.3) and, importantly, sentiment analysis tools are reviewed (in Section 3.3.4) for the purpose identified in the earlier part of the literature review; that is, with the intention of using them for real-time CRM analysis and decision-making. Then I discuss human-computer interaction followed by social-media interaction (In Sections 3.3.5 and 3.3.4).

Living in today's world, we live amongst a vast array of IT and social media related systems and activities. Systems and activities that encourage the masses to search for, collect, and retrieve information. What is information? Surely even the earliest definition of "information" has had to be rapidly adapted following the superfluidity of modern technology that exists today: for example, forms of information range from collections of texts, images, sounds and even videos, and there are a plethora of algorithms which have been specifically developed to extract people's cognitive contents from these rich sources of information.

Information science became a popular discipline during the 1950s. It appears that the term 'information science' was first mentioned in Farradane's paper titled 'Professional education of the information scientist' in 1955 (Robinson, 2009). In his paper Farrandane proposed that information science is a prototype for methods of documentation. In addition, he used the term to reference those who handle scientific and technical information: thus, information scientists emerged.

Robinson (2009) explains how the discipline of information science evolved during the 'documentation movement' influenced by social, technical, and economic factors. At the same time, there is little agreement on the nature of information science amongst scholars, and, Robinson notes, the following question is a hot topic of discussion:

Information science
or
Science of information?

The former, the information of science, handles scientific or technical information whilst the latter, the science of information, is an academic study of information. This unanswered question, according to Robinson (2009), is whether information science is a discipline or just a practical art. A scientific discipline is supposed to have laws, hypotheses and speculations; in order to be considered a scientific discipline, however as Heilprin (1989) comments, without an adequate scientific and epistemic basis how can information science exist as a discipline? Robinson (2009) also highlighted the various claims that label information science as: a social science, a meta or postmodern science, an interface, a superior science, a rhetorical or nomad science, or even a liberal art.

As this is beyond the scope of my study, I adopt Zins's (2007) description of information science: "although there are different approaches and traditions representing different knowledge domains, they all imply different fields of information science; all of which, in essence, represent the same thing called information science".

The following section gives the definitions of the important terms, in the context of this thesis, relating to information science, and is proceeded by the theories of information science.

3.3.2.1 Definitions of important terms

3.3.2.1.1 What is information?

Bateson's (1979), earliest, definition of information states that: "Information is said to be conceived when there is perceived difference that causes a difference within a conscious human mind." Belkin's (1978) definition adds to this description: memory traces, objects, ideas and knowledge from other minds. Johnson (1997) goes on to state that anything that causes changed patterns of matter and energy around us can be defined as information. Further, Case (2007) adds that information is whatever appears important to humans, whether it is from the external, physical world or the internal, psychological world. Ingwersen and Järvelin (2006) further relate information science as a solution to human information problems that can resolve the states of cognition and knowledge. For instance, there have been many studies on social cognition and in particular, a study by Beer and Ochsner (2006) has highlighted the fact that the perception of others, self-perception and interpersonal knowledge all describe what social cognition actually represents. They further state that every user of social media perceives social stimuli with various degrees of difficulty and orientation (Beer and Ochsner, 2006).

3.3.2.1.2 Information behaviour

Information behaviour refers to all sorts of human behaviours related to information gathering. For example, Kuhlthau (1993) states that information is a process that coordinates an individual's cognitive state, knowledge level and individual understanding to result in a coherent series of activities. This could even be an unintentional or a passive process, such as glimpsing, as purposeful behaviours can include avoiding information (Case, 2007). Many authors also include behaviours such as the conscious or subconscious, the overt or covert, and the voluntary or involuntary. Information behaviour is ubiquitous behavior that interleaves and interweaves with everyday activities; thus, for this study, I include the whole-life context in my definition, so that we incorporate how information behaviour interacts and informs every moment of our daily lives.

3.3.2.1.3 Information searching behaviour

This term plays a very important role in understanding information science. According to Spink (1997), information searching behaviours are exhibited during the process of searching and locating information. Spink and Dee (2007) further add that information searching behaviour includes non-observable, internal, cognitive orientation that takes place within the mind. Therefore for my study, I use information searching behaviour in a similar way to Spink and Dee's broader term, rather than focusing separately on behaviour itself.

3.3.2.1.4 Information use behaviour

Information use behaviour is the process of incorporating information into one's existing knowledge base (Spink et al., 2006). Savolainen (2007) is of the view that this process follows information seeking, and the usefulness of the information is perceived based on how effective it is at solving a particular problem, or making sense of a situation.

I incorporate both of the above approaches, existing knowledge and the usefulness of the information, in my study; in addition to the manipulation, suppression and dissemination of information by a person or people during acts of information use behaviour.

3.3.2.1.5 Information organising behaviour

Taylor and Joudrey (2004) reiterate the importance of organising behaviour by stating that: "We organise because we need to retrieve". Information organising behaviour is a process that involves analysing and classifying information into various categories; this could be with one's own organisation methods or schemas.

3.3.2.2 Theories of information science

Both the generation and collection of information can become complicated. And enforce further problems associated with retrieving useful information, which involves various variables including cognitive, situational, affective and social interactions. Spink (2000) illustrates that information is not merely a technical process, but, rather, it is a cognitive, situational and social process. The growth of computers and telecom technology enabled information collection mechanisms to become robust, and more information gathering provided more scope for effective interactions between humans and their data.

Information theory is, therefore, a mathematical-related discipline which involves quantifying data with the goal of storing and/or transferring information. Information measurement is often described by information entropy, and defined as the average of number of bits required for storing or communicating information.

Various theories of information science have established Human Information Coordinating Behaviour (HICB) as a binding process pivoted around information seeking and retrieval. During such a process it is commonly accepted that there are number of elements involved. Information behaviour theories and models have so far focused on the following:

1. Information finding: that involves seeking and searching for information, thus foraging and making sense of information.
2. Information organising: this involves organising and storing information for later retrieval.
3. Information using: the outcome of the whole process.

3.3.3 Computer mediated communication (CMC)

Any communication that takes place between two or more networked computers is considered as Computer Mediated Communication (CMC). The term CMC was coined as early as 1978 by Hiltz and Turoff (1993). At that stage the world had limited ideas about what computers could do, in the present day Thurlow et al. (2004) extended the context of Hiltz's and Turoff's work beyond computers to mobile phones. Given the current prevalence of social media, Erickson Erickson and Herring (2007) describe CMC as a persistent conversation that takes place in a digital medium. They point out that "persistence" can be achieved through various modes; available through digital channels, in addition to textual or verbal conversations. These new digital channels provide the opportunity for conversations to be recorded, saved, browsed, searched, replayed and retransmitted; a ready-made dataset.

Taking into account the various communications this generates, Kelsey Fragoso et al. (2008) define CMC as "a form of communication that presents or exchanges by means of a computer. The information thus transacted could be with oneself to another person or group or even to some imaginary audience". They also pointed out the following characteristics of CMC:

- one to one or one to many;
- synchronous (real time) or asynchronous (time delayed), even super synchronous (with multiple parties in real time);
- containing text, visual, audio or audio visual messages; and
- various software enables CMS such as email, chatting, social networking sites, wikis, RSS feeds, blogs, etc.

3.3.3.1 The nature and scope of CMC

As communication technologies continue to grow rapidly, CMC's popular definition sets aside the defining of specific forms, but instead describe it as a process. Therefore, various definitions, including that stated by Jones (1995), move CMC away from a technological focus towards a social one: Jones' states that "CMC of course, is not just a tool; it is at once technology, medium, and engine of social relations. It not only structures social relations, is it the space within which the relations occur and the tool that individuals use to enter that space."

Figure 25 illustrates how communication between a source and a receiver is established. It is important to note, that although the worldview of the source and the receiver is different and exclusive, due to the fact that they have a shared linguistic background, an information exchange effectively takes place. Furthermore, although the technology used by the source and the receiver may be different, the transaction will still take place via the transmission of relevant information.

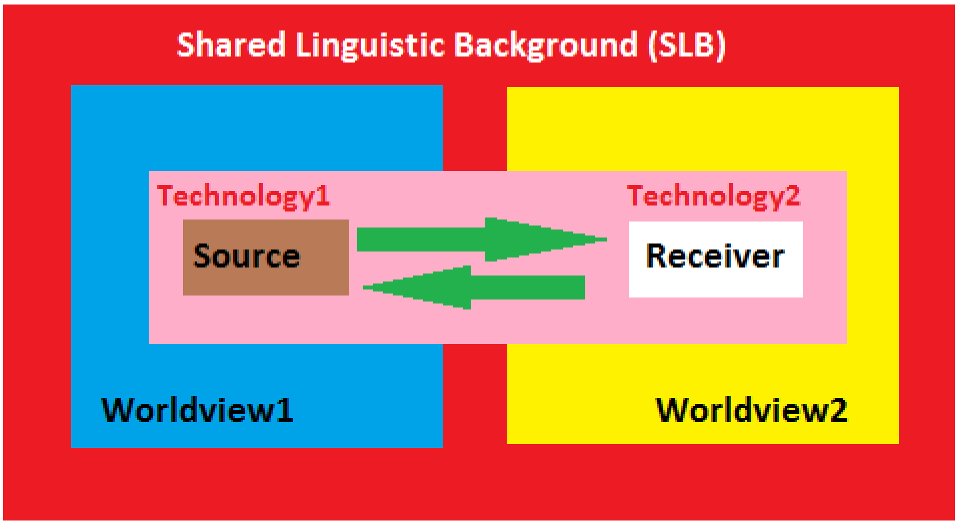

Figure 25: Schematic diagram of computer mediated communication

3.3.3.2 Constraints and affordances

In order to understand the theories of CMC it is important to identify its constraints and affordances. Authors Clark and Wilke-Gibbs (1986), Clark and Brennan (1991), and Clark (1996), examined CMC and determined eight important constraints:

1. **Co-presence:** when interactants communicate within the same physical environment.
2. **Visibility:** when interactants see each other during the communication.
3. **Audibility:** when speech is used for communication.
4. **Cotemporality:** when production and comprehension take place in synchrony.
5. **Simultaneity:** when both production and comprehension are simultaneous.
6. **Sequentiality:** prevents confusion because it involves the way that several pieces of information are arranged, so that the reader understands the sequence and their implications.
7. **Reviewability**: when senders are able to review their communication before sending.
8. **Revisability:** when senders are able to review communications privately.

3.3.3.3 The theories of CMC

The literature on CMC classifies the theories of CMC into two major dimensions. One is through online interaction, and the other is through the adoption, appreciation and uses of communication technology. Oni (2013) reviewed and classified these theories, as shown in the following figure (Figure 26).

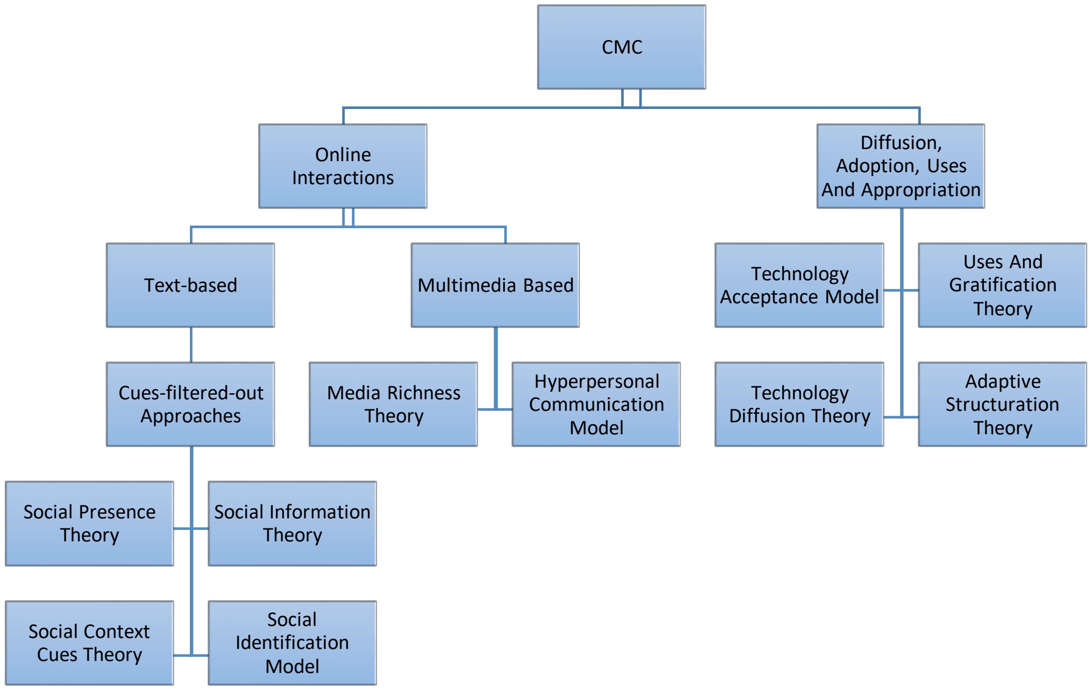

Figure 26: Fundamental theories of CMC (Oni, 2013)

In his review of the fundamental theories of CMC, Oni (2013) concluded that they are shuttling between two paradigms; namely, mass media effects and technology adoption/acceptance approaches.

3.3.3.4 Content management

During the mid-1990s, several corporations discovered the need to manage web content, using in-house built information systems (Jablonski and Meiler, 2002). Yet, at the time, managers were unable to keep track of what was created, edited and updated by their webmasters. The solution took the form of content management as a functional web-based application that helped even a non-technical user to create, modify or delete content on web pages.

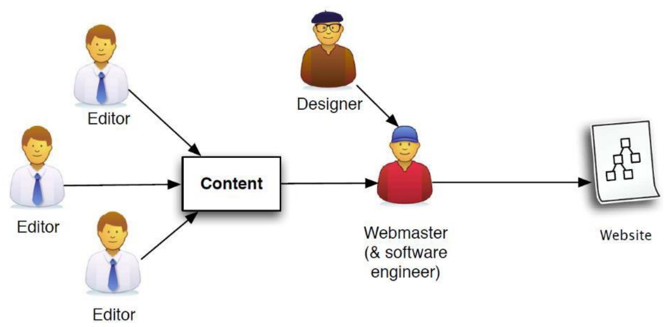

Figure 27: Earlier content management for websites (Jablonski and Meiler, 2002)

Since then, technological progress has resulted in better content management systems which use a variety of robust development platforms. The capabilities of these content management systems have increased over the years to produce better authoring and administration tools, and straightforward ways of managing documents and defining roles with the workflow, amongst others. These advancements have resulted in better websites that offer RSS feeds as well as popular systems like Facebook, YouTube and Twitter (Grossniklaus and Norrie, 2002).

Thus, the modern content management systems of today go beyond the legacy management systems of yesterday. For instance, well-established standards of interchange exist which use XML (extended mark-up language), that provides the option of integrating multiple web pages and utilising multiple devices through large organisational databases.

Modern content management systems are efficient web-based applications with an enterprise architecture that provides a robust interface for users. These systems have converted simple website management to a multidisciplinary, complex development process. One that enables non- technical users to offer and share their opinions quickly and easily. In addition, these websites have well-defined data structures with easy interfaces that offer content management activity for companies to create and manage digital content.

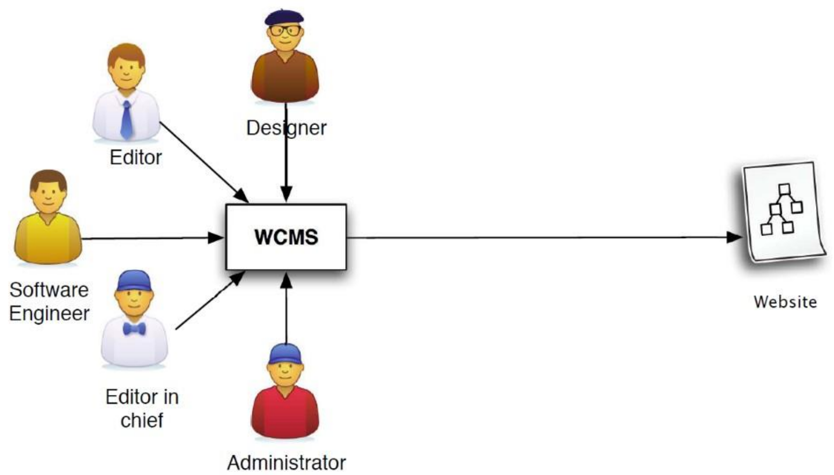

Figure 28: A Modern Web-based Content Management System (WCMS)

Paivarinta and Munkvold (2005) define the following as the core aspects of efficient content management solutions.

1. The structure of the content, and how it can be viewed and presented
2. The content life-cycle

3. Metadata
4. Corporate taxonomy

Owing to the holistic nature of content management, experts describe the development of such systems as web engineering. Kappel et al. (2005) define web engineering as being "… the application of quantifiable systematic approaches in designing, analysing and implementing high-quality web applications". This definition establishes that all websites, such as Facebook, Twitter, YouTube, etc., that host content are sophisticated, web engineered systems.

Therefore, modern content management systems are economically important assets for corporations. These systems have facilitated users and customers to become writers, and have thus enabled corporations to quickly and easily find ways of extracting useful information from their data (Pullman and Baotung, 2017).

3.3.4 Sentiment analysis (SA)

The quest to ascertain 'what do others think?' might have started simply by listening to people when the voice alone was the medium of communication; however, when the medium was further widened by books, blogs, posts, statuses and tweets, this necessitated the use of special tools specifically designed to establish exactly what others know. These tools are known as brand monitoring, online anthropology and consumer intelligence.

The aim of this part of the thesis is to review the methods of sentiment analysis from its inception to the current era of social media. After defining the relevant related terms, Section 3.3.4.2 introduces the early history of sentiment analysis with a note on the justification of need. Section 3.3.4.5 illustrates the classification of the available methods of sentiment analysis that can work in unison with data collected from social media. The developments and the applications of sentiment analysis (Sections 3.3.4.3 – 3.3.4.4) illustrate how its tools have been improved to handle large amounts of data. Then, after reviewing the basic characteristics of social media we observe that most of the methodology relied on machine learning algorithms (Sections 3.3.4.5 – 3.3.4.6). As there is a clear connection between offline (the "real" world) and online (social network) interactions, the results of utilising sentiment analysis on social media is wide and multidimensional.

Everyone is so curious to know 'what do others think?' that the human race, possibly, started asking this question when we first learnt to distinguish ourselves from others and listened to what others said and, equally, did not say. But today we reach beyond hearing, and this is evident through buzz words, such as brand monitoring, online anthropology, influence analytics and consumer intelligence.

In the current era of the widespread availability and use of digital information, there is a, seemingly, inexhaustible wealth of information about existing and potential customers that may be the key for companies to make decisions. There are many ways, as identified in the literature review, to detect the sentiments underlying these digital sources. Each of these techniques has their pros and cons, and there is no singular, universal method that suits all situations, thus forcing more and more methods to be developed.

In Oscar Wilde's words, sentiment is not the starting point but it is the destination of the journey that is guided by science: "Romance should never begin with sentiment. It should begin with science and end with a settlement" (Oscar Wilde, An Ideal Husband).

3.3.4.1 Definition of terms

The following terms are considered in this study:

- **Subjectivity:** Quirk et al. (1985) define subjectivity as: "…states that are not open to objective observation or verification". Liu (2006) broadened and improved this definition by taking into account the overall contextual polarity of opinion, so that it could include various different types of textual analysis to be evaluated.
- **Opinion mining:** the earliest definition of the term "opinion mining" is given by Dave et al. (2003) as "processing a set of search results with a list of attributes and aggregating opinions". The attributes they mention include quality, features, etc.; while opinions refer to judgments, which could be classified further into poor, mixed or good.
- **Sentiment analysis:** The authors like Das and Chen (2001), and Tong (2001) who have expressed a great interest in analysing market sentiment, have been using the term sentiment analysis to mean the "automated analysis of text" and the "tracking of predictive judgments".

3.3.4.2 Foundations of sentiment analysis

When making decisions, most people often seek the opinion of others. Indeed, many people discuss politics in forums, read consumer reports before buying appliances, read restaurant reviews or obtain verbal recommendations prior to choosing where to dine. In addition, access to the Internet also enables anyone, even novice users, to obtain the opinions of experts, as well as other millions of users, almost instantly, on practically every subject.

The Internet has now become an active platform for discussion, and a major provider of information for many users. Moreover, it has been established that more 22% of Internet users' online time is spent using social media sites and 65% of adult users are always logged onto one or more social networking sites (Nielsen, 2015). Therefore, sentiment analysis has become increasingly popular for companies over the last decade to understand what their customers are thinking and feeling.

Experts in computer science, linguistics, data mining, psychology, and also sociology, work in symphony to create a better sentiment analysis system. Natural Language Processing offers various tools to extract information from a given source. Sentiment analysis is one such tool. It extracts one's view on a particular topic through comments, requests, questions and replies in a given dataset. The basic thrust in the research of sentiment analysis has been to find emotions, such as happiness, sadness and anger, etc., and to decide whether the outcome of the results/output is positive or negative.

The American media measurement and analytics company, comScore partnered with Kelsey to establish the need for sentiment analysis (comScore and Kelsey, 2007). They demonstrated how such analysis enables common users to make decisions or, at the very least, eases their decision-making process. In addition, they highlighted how novice users are able to access the information and experiences of others, thereby assisting them with their decision-making and preventing them from having to "reinvent the wheel".

The following chart details how Internet users effectively use the opinions of others in their decision-making processes.

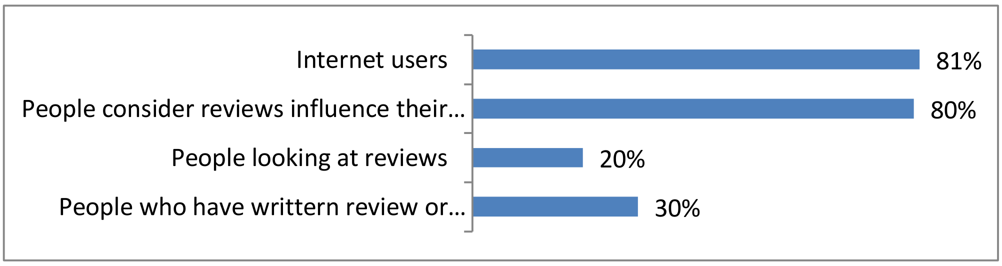

Figure 29: Decision-making influenced by the opinions and experiences of others (comScore and Kelsey, 2007)

When we look beyond movie reviews and product experiences, we are met with voluminous amounts of data which are available on the Internet that lack an appropriate index or structure for ease of use. Consequently, this makes the task of searching for information arduous, and in order to obtain a suitable graded point of view from this information improved tools are required. Data mining tools are available which can help sentiment analysis to handle bulk data. González-Ibánez et al. (2011) show how data mining tools can be applied to obtain sentiments from Twitter, which established sentiment analysis as a method which could be conducted automatically and in real-time.

3.3.4.3 Recent developments in sentiment analysis

In recent years, there has been a steady increase in applying sentiment analysis to social media data. The users of social media express their opinions for many reasons, including the need to belong, the need for cognition and self-presentation and impression management (Carpenter et al., 2018). Some recent studies illustrate that social media posts expose the personality traits and motivational factors of their users (Ducange et al., 2019, Goswami et al., 2019). Consequently, it has been shown that extraversion is a common attribute found across active social media users, and such people show their presence through a large number of friends, posts and responses (Goswami et al., 2019). Many authors opine that next to extraversion, people with neuroticism (tense, moody or irritable people) use social media as a safe and controllable space to express themselves.

It is very clear from these points that the sentiment analysis of data that merely shows positive, negative and neutral sentiments is no longer beneficial to organisations. There is a need to move beyond these aspects to capture emotions from social media datasets.

When we consider the methods adopted by sentiment analysis, we can see that diverse approaches are being used. One remarkable use, as detailed in Section 1.5, involves using verb expression and linear regression optimised by particle methods (Jiang et al., 2019). Another recent progression goes beyond the frequency of words and takes the position of terms in the discourse into consideration (Kraus and Feuerriegel, 2019). By using rhetorical structure theory, Kraus and Feuerriegel have proposed tensor-based, tree structured neural networks. They have proposed two methods of data augmentation namely training set andoverfitting. Another notable recent development joins visual and textual sentiment analysis. In order to extract the sentiments about events or topics, Zhu et al.'s (2019) model incorporated a cross modality attention mechanism with an embedded semantic learning network. Such methods provide deeper insights and obtain a more efficient classification of the dataset.

3.3.4.4 Applications of sentiment analysis

As the main goal of sentiment analysis is to extract emotions from text, there are number of areas where sentiment analysis can be potentially applied: political blogs, product reviews, financial news, and brand tracking. I will discuss the application of sentiment analysis to each of these areas in turn.

3.3.4.4.1 Political blogs

This is one area that brought more attention to sentiment analysis. As a result, various news channels started using sentiment analysis in the following areas:

- to track people's opinions about various issues;
- to track burning, emotionally discussed topics; and
- to understand the subjectivity of various active bloggers.

Word Clouds, for instance, enable us to understand the most frequent words used by speakers and also the orientation of words to one another. Such charts are essentially the outcome of sentiment analysis. However, there may be potential challenges when applying sentiment analysis to political blogs. Tan et al. (2011) identify a number of issues including the difficulty of detecting opinion holders, association opinions and issues, public figures and legislation.

3.3.4.4.2 Product reviews

The next area where sentiment analysis can be effectively applied is for product reviews. Such analysis enables novice users to review the experiences of others so as to influence their decision-making process. Cui et al. (2006) predict that this could be an area where the general public can benefit from the principles of sentiment analysis.

Some criticisms and concerns associated with the application of sentiment analysis include identifying various aspects of the product, linking customer opinions with these aspects, identifying fake reviews, and avoiding canonical forms. Despite these criticisms and concerns, sentiment analysis still remains one of the most successful applications of analysis for the general user.

3.3.4.4.3 Financial news

Financial analysts use sentiment analysis to predict the rise and fall of stock prices to provide better advice on portfolio management. Devitt and Ahmad (2007) reviewed such applications, and illustrated the potential applicability of sentiment analysis in this domain. The following figure illustrates the link between news trends and their stock price.

Most financial news services pay special attention to these kinds of alternative approaches in an attempt to gain competitive advantage over their competitors, as this kind of analysis enables potential investors to make informed decisions relating to buying or selling.

Although it is well known that news items can affect stock prices, the research undertaken by Nagar and Hashler (2012) provides a good example of the application of sentiment analysis. They predicted stock market trends based on published news, such as blogs, online news stories and streaming data sources for their research, and created a corpus of financial data from Google Finance. Their research, openly, utilised a popular natural language processing algorithm, to break this financial corpus into sentences. In addition, they counted all of the positive, negative and neutral scores in the data to produce a corpus score for the data using the following formula:

```
Corpus score = positive instances/total instances
```

From their results, Nagar and Hashler (2012) demonstrated a strong correlation between stock price movement and sentiment score. The following figure compares the output of their sentiment analysis which reveals striking similarities between news headlines and the movement in the stock market.

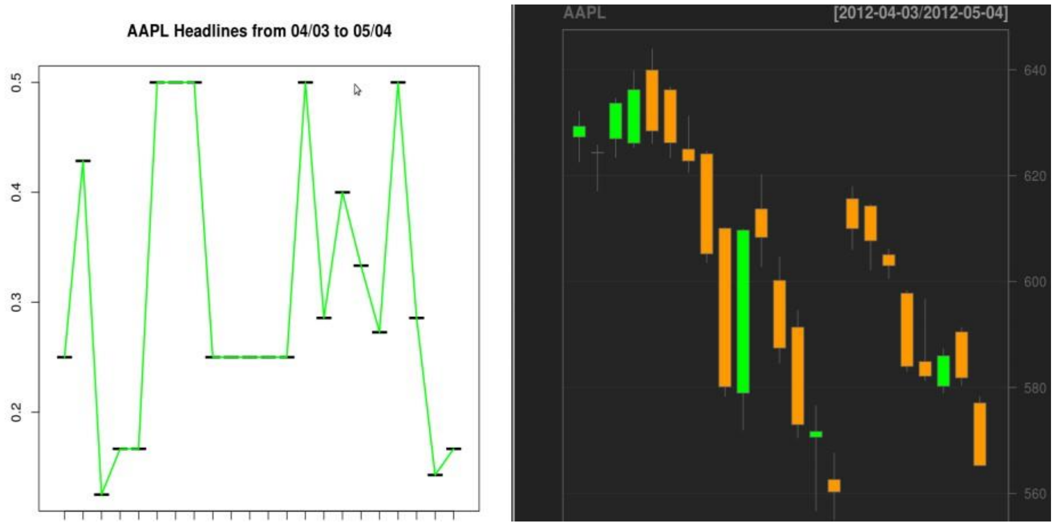

Figure 30: Correlation between stock movement and news headlines (Nagar and Hashler, 2012)

Such analysis, however, has the following limitations:

- analysts may not be able to identify the equity of the stock/commodities;
- they need access to the sophisticated word bank of terminology used in the finance sector; and
- most of the news items will reflect only one article of concern.

3.3.4.4.4 Brand tracking

This is another area where sentiment analysis helps corporations to track the image of their brands (Mostafa, 2013). By monitoring the discussions taking place on social media, such as in Figure 31, it is possible to implement sentiment analysis to obtain an overall perspective of customer opinions relating to the health and perception of a brand.

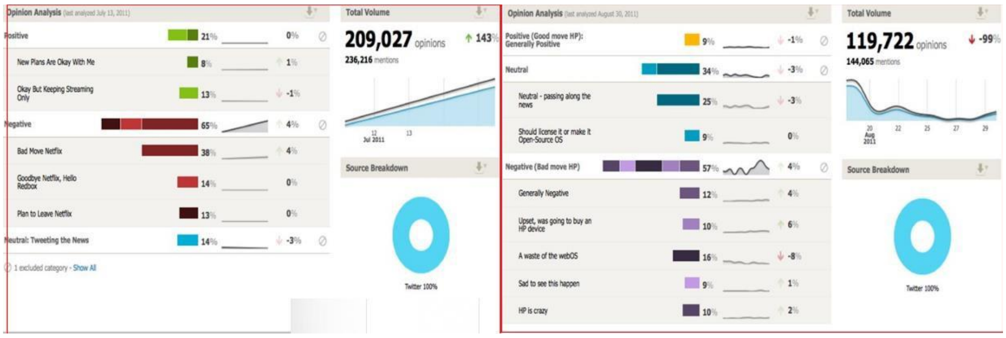

Figure 31: Sentiment analysis for gauging brand health

The above charts illustrate brand health for NetFlix which has been estimated using sentiment analysis on the 13th July 2011 and the 30th August 2011. NetFlix's brand health became better after the withdrawal of some of its products (Mostafa, 2013): 65% of negative customer sentiments decreased to 57% after withdrawal of the products.

Even over the past decade, one can see an increased availability in simple analysis software tools based on sentiment analysis methodology. For example, IBM SPSS[1] enables users to conduct quantitative sentiment analysis, and produce a brand perception summary using data from news media. Another popular software package, LexisNexis[2], enables users to correlate consumer confidence and brand perception. This too has the facility to import data from news media. OpSec[3] also utilises user-generated data obtained from social media sites to data-mine information about brand perception. All these tools use the principles of sentiment analysis. Even websites like tweepularity4 provide real-time reports on popular topics with sentiment scores. The following figures show the outputs for Obama (the former US president) and Modi (an Indian PM) who scored +149 and -48, respectively.

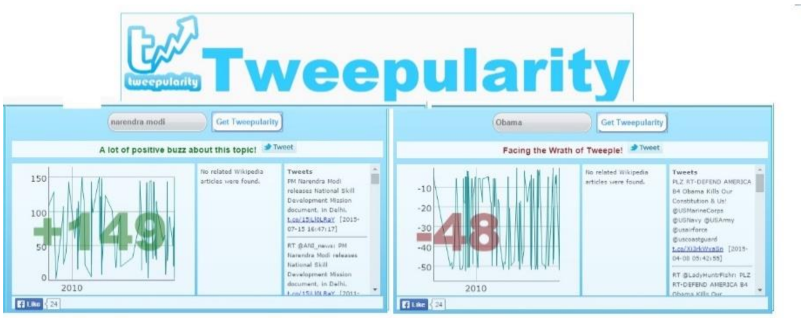

Figure 32: The sentiment scores of Barack Obama and Narendra Damodardas Modi from real-time streaming data.

[1] (http://www.01.ibm.com/software/analytics/spss/)
[2] (http://www.lexisnexis.com/risk/data-analytics.aspx)
[3] (http://opsecsecurity.com/brand-protection/online-brand-protection/sentimentanalysis)

One of the important challenges that sentiment analysis has to overcome is in defining its object of study. Subjectivity is the term widely used by linguistics to describe this. Related to subjectivity, Quirk (2000) defines the term known as "private state" as something which is not open for observation or verification; for example, emotions, speculations and opinions are areas which are considered as private states. Bruce and Wiebe (1999) are two prominent natural language processing researchers who use a narrative tracking point of view which is similar to private state.

Turney (2002b) mentions that the most cited sentiment analysis symbols relate to movie reviews by using either a thumbs up "👍" or thumbs down "👎" icon to show how they are perceived. Indeed, the applicability of sentiment analysis is more than just for the classification of texts, as it often concludes to what extent the text is positive. Many authors classify sentiments into various categories; these include, negative or positive states and reasons, such as the facts customers share about particular products. The following figure illustrates this:

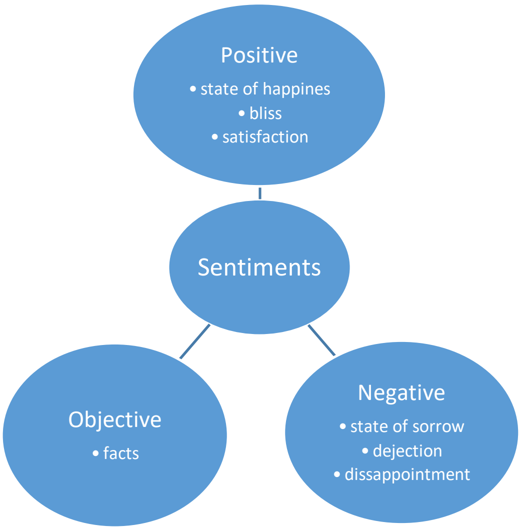

Figure 33: Classification of sentiments

Some researchers also use pre-determined lists of phrases with different groupings that correspond to various emotional states; for example, Linguistic Inquiry and Word Count (LIWC) and the Profile of Mood States (POMS). However, many critics argue that *opinions* can't be *facts* and therefore the results of sentiment analysis should be considered with caution. Pang and Lee (2008) illustrate their reasoning by listing the following issues with sentiment analysis:

- most sentiment analysis algorithms seem to be influenced by sentences at the start and end of articles;
- irrelevant sentences can change the sentiment outcome of the documents; and
- the order of appearance, valence, can shift the sentiment completely; for example:

- ✓ The car is reasonable but there are far better ones for this price.
- ✓ The dinner could have been better though still yummy.

The above sentences might have been classified by the sentiment tool in the wrong perspective; and, finally,

- Sentiment orientation can be changed by the use of special words in the text that is being investigated. Although special words themselves have no sentiment, they can present sentiments along with other phrases that a human might understand but an algorithm would miss. Keeping interpretations consistent is a difficult process. Many naïve methods, like the bag-of-words model, may fail here.

3.3.4.5 The evolving methods of SA

The research areas of sentiment analysis and opinion mining are becoming an active research activity in recent times. This could be attributed to the steady undercurrent of research studies which have been conducted for a very long period of time.

3.3.4.5.1 The early history of SA

Some forerunning investigations that started this burst of research interest in sentiment analysis could have been instigated by the studies carried out by Carbonell (1979), and Wilks and Bien (1984). Carbonell's project proposed a computer model for a belief system, whereas Wilks and Bien extended this belief system model to incorporate the perspectives of multiple environments. There was then a shift in the research focus, mostly towards interpreting metaphors (Huettner and Subasic, 2000), explaining narratives (Huettner and Subasic, 2000, Wiebe, 1990) and "evidentiality" which is the speaker's assessment of the evidence for his or her statement (Wiebe et al., 1999).

After 2001, according to Pang and Lee (2008), marked the beginning of the "burst" in sentiment analysis and opinion. They provide the following reasons for such a "land rush":

- this was the beginning of the extensive use of machine learning algorithms;
- the increasing availability of huge datasets; and
- the intellectual challenge and potential application areas for the research.

Thus, in an earlier period, sentiment analysis was seen as an extension of web analytics and as an integrated field of web analysis – most of the algorithms in this early stage were focused on various extraction patterns and remained largely academic. In addition, this extension was linked with knowledge extraction, and associated the term "opinion mining" with sentiment analysis. As can be seen in the reference section of this work, most of the papers appear in the Access Control List (ACL) or the World Wide Web (WWW).

3.3.4.5.2 *Contemporary methods of SA*

Current methods of sentiment analysis involve various techniques including machine learning, lexicon-based learning, statistical or rule-based methods. First, the machine learning method involves using learning algorithms to determine the sentiment of the textual data, and usually involves training with an earlier recognised dataset to test its validity (Allwein et al., 2000). Second, sentiment orientation is the key tool used in lexicon-based learning; in this method the data's sentiment polarity is calculated to measure subjectivity and customer opinion (Ding et al., 2008). Third, identifying words of opinion and classifying them with respect to positive, negative or neutral sentiment is the methodology employed in the rule-based approach. There is are set of rules which use dictionary definitions and negation emoticons to understand the data. Poria et al. (2014) have recently reviewed approaches where sets of rules that use dictionary definitions and negation emoticons are employed to understand the data; the available statistical methods make use of latent aspects and ratings of the data, and use multinomial distribution by clustering them into sentiment scores (Moghaddam and Ester, 2011).

The above three classifications are based just on techniques; however, some authors, such as Wiebe et al. (1999), and Wilks and Bien (1984), classify sentiment analysis methods in terms of how text is extracted from the data. This could be either at a document-level, a word-level or even a sentence-level. Various rating methods also exist by which an analysis can be conducted at a global level. For instance, a polarity/scale schema (e.g. positive, negative or neutral), or a detailed rating schema (e.g. one to five stars) can be put in place for calculating the overall sentiment score of a dataset (de Albornoz et al., 2011).

The following figure illustrates the broader picture of contemporary SA methods.

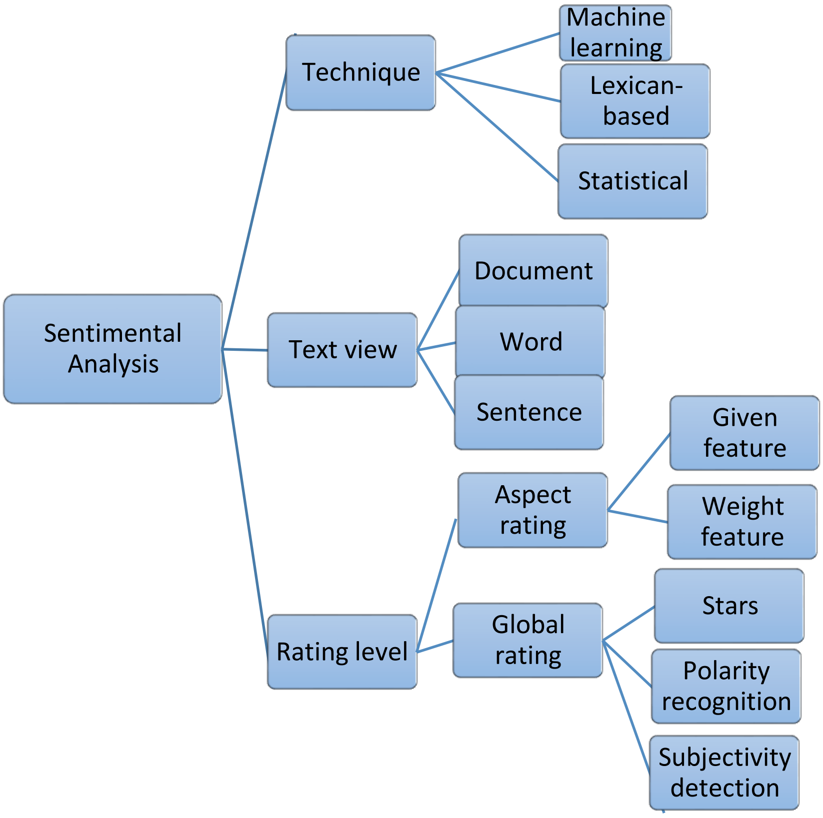

Figure 34: Contemporary Methods of SA

3.3.4.5.3 *Towards social learning*

Social media, or "social networks", are defined by Scott (2010) as being "… a social structure, formal or informal, comprising a group of people or organisations, together with their respective views". Yu and Kak (2012) go further by considering social media as virtual platforms "that allow common persons to create and publish contents", and share content, which, in turn, are generated by their users. This is the point of difference between traditional media and social media where anyone who owns a mobile phone with an Internet connection can post their views.

With all its capabilities, sentiment analysis possesses a great advantage as it is able to mine useful information from these raw sources of data. Sentiment analysis has just started to acknowledge that data mining "belief systems" have to grow and be equipped to analyse huge amounts of social media data, which is increasing exponentially and, as such, necessitates the use of real-time analyses. Consequently, sentiment extraction approaches become more compelling due to the array of such highly complex data contained within social media.

Today's social media is comprised of blogs, forums, social networking sites and wikis, to name a few. Twitter has, in recent years, become a prominent, powerful micro-blogging portal which houses millions of data points, tagged with rich information. Tagging can include temporal, special and communal information that are required for further classification (Bollen et al., 2010). Although each tweet is only 140 characters in length, there are still approximately 95 million tweets recorded per day. Therefore, it is beneficial and worthwhile for sentiment analysts to exploit Twitter as a reliable source for the sentiments of a wide range of people (Lai, 2011).

Most sentiment analysis employed with Twitter employs machine learning techniques. For example, Pak and Paroubek (2010) conducted a study aimed at classifying tweets based on the polarity of their sentiments. They constructed a simple binary classifier to identify tweets as positive, negative or neutral. Moreover, they attempted to go further and detect sarcasm in tweets (Reyes et al., 2013, Tsur et al., 2010). In fact, their study was able to report the sarcasm in tweets at a level of 70-80% accuracy.

3.3.4.6 An overview of the techniques of sentiment analysis

This section takes a closer look at contemporary methods used in sentiment analysis which enabled me to choose the appropriate tools for this study.

3.3.4.6.1 An introduction to natural language processing (NLP)

Natural language processing is the basis of sentiment analysis. Often referred to as computational linguistics, this discipline mostly depends on frequency counts, and these frequencies become statistics for "meaning reasoning" or finding the polarity of sentiments. Although there could be some flaws with the statistics, NLP is still useful as a preliminary tool for conducting sentiment analysis (Nasukawa and Yi, 2003).

In NLP, stemming is often used to combine words with the same root. In order to find the frequency of a word, all the words and stem words are counted as being the same; for example:

$$\left.\begin{matrix} Running \\ runner \\ runs \end{matrix}\right\} run$$

As indicated above, the endings of words are dropped and similar words are counted as being in the same group to calculate their frequency of use; although, there is a category of words called "stopwords" – such as: a, the, an, is, could, there, be, etc. – as these words may not give any polarity to sentiments; thus, most of the NLP algorithms ignore or remove these words while counting (Nasukawa and Yi, 2003).

In addition, alongside stemming and stopwords, “parsing“ is another technique commonly used in NLP. There are a number of approaches to parsing, including shallow parsing, dependency parsing and part of speech (POS) tagging. Parsing is used to understand the structure of the sentence by treating it in the same way as programming languages; the sentence is then converted into a tree- or branch-like structure for further interpretation (Nasukawa and Yi, 2003). For example, the sentence, “John hit the ball” can be grammatically broken down to a tree structure, as shown in Figure 35 below.

WordNet is another NLP tool which is very useful for sentiment analysis. As there are many similar words that have the same meaning, WordNet is a hand-created technique designed specifically to identify sets of words with the same meaning. This is useful for identifying semantic orientation (Nasukawa and Yi, 2003). Figure 36 gives an example of such an ontology showing synonyms and antonyms.

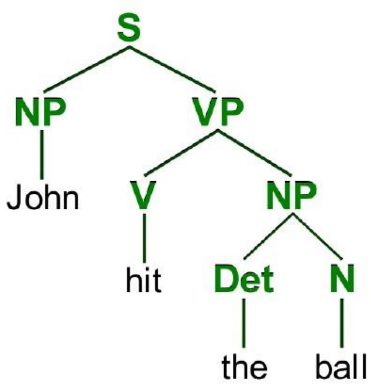

Figure 35: Parsing in NLP (Nasukawa and Yi, 2003)

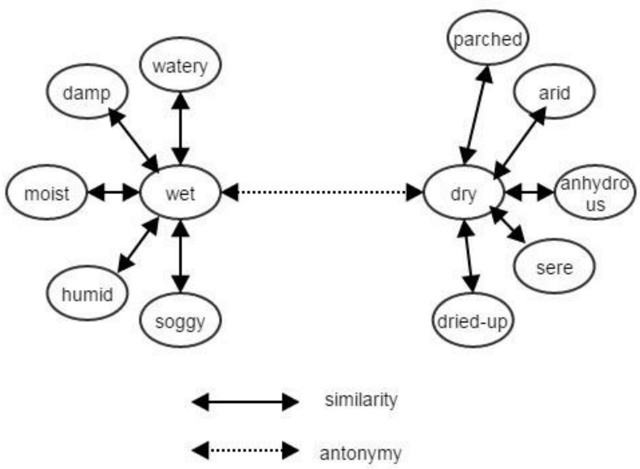

Figure 36: WordNet synsets Sentiment definitions and approach (Nasukawa and Yi, 2003).

Esuli and Sebastiani (2007) define customer opinions as a "vector denoting an opinion with either positive, negative or neutral values. Therefore, an " opinion holder" is an agent whom an opinion belongs to. In the case of political analysis, which was discussed briefly in an earlier section, this aspect is heavily dependent on the opinion holder.

The facets of the objects studied that are readily available, are known as "item features" (Wong and Lam, 2008). Once we subscribe an opinion to the facets of the objects it is then called a "sentiment feature". These features are usually difficult to extract from texts.

Tsytsarau and Palpanas (2010) propose the following seven step technical approach to conduct sentiment analysis:

1) **Collect a seed set**: there are many opinion corpora available from sources like Wiebe's corpora (http://www.cs.pitt.edu/mpqa/) – this comes with scores of subjectivity as well as sentiments. Sentiwordnet (http://sentiwordnet.isti.cnr.it/) is an auto-generated, good quality collection, and one can even develop personal dictionaries. The content could be handpicked and, although small, could be of good quality for its intended use.

2) **Study sentiment of unfamiliar words**: this could be supervised or non-supervised. In the case of supervised learning, obtain a good expanse of collections and label them to use when required. In the case of unsupervised learning, one can either use Turney's method, calculated by using pointwise mutual information (PMI), or the WordNet approach, as previously explained.

3) **Simplify the document by applying rules:** rules enable us to make words independent and rewriting them help us to correctly classify a given phrase.

4) **Detect opinion phrases**: identifying opinion phrases is an important step where one can parse documents into chunks, as per the tree-like structure previously described. During this stage we can also remove any chunks which are neutral.

5) **Apply sentiment to phrases or documents**: As the final objective is comprehending the sentiment of phrases and sentences, the sentiments of individual words can be used only as priors. The effective sentiment score should be the net value of the sentiment across words in a given phrase. Models introduced by Naïve Bayes or Markov (qtd in Preety et al., 2015) are useful for this purpose.

6) **Aggregate sentiments:** phrases can be grouped by entities, topics, sentiment features, item features or even users.

7) **Generate a report or summary**: this is the supposed outcome of the entire process, that provides only relevant information which is rated based on readability, with all classified charts and sentiment vectors available for users to easily interpret.

3.3.4.6.2 Methods for conducting sentiment analysis

As widely noted in the sentiment analysis literature (Greene et al., 2012, Max, 2013), in order to conduct sentiment analysis we should:

1. Identify the significant people and groups related to the telecom usage of the chosen organisation.
2. Archive the relevant social media data, including tweets or posts pertaining to those identified in the previous step.
3. Calculate the sentiment score by using the suitable tools available with the chosen sentiment analysis algorithm.

I used NVivo, a potential sentiment analysis tool, for calculating the sentiment scores in my study. NVivo is a commercial software tool that is capable of managing and analysing unstructured data (Miller, 2006). This software has features which enable a user to import survey responses and social media discussions (e.g. tweets, Facebook posts or videos and comments). In addition, having a widely-acclaimed Microsoft-like user interface, it can be used to export data for further analysis (Miller, 2006). There are various other visualisation tools and methods available which will enable us to visualise the sentiment scores of the data dynamically, through different perspectives to explore the results.

Based on many needs and demands, robust data collection mechanisms and rapid analysing tools have been developed over time. Certainly, the sentiment analysis tools of today cater for the needs of much more than linguistics alone. Sentiment analysis started as a simple belief system and has grown and developed into a learning system that can contribute to decision-making; whether that is buying a product or electing a president. On one hand, new algorithms have been developed and, on the other hand, the availability of rich data, both of these aspects makes this area of research exciting and challenging. Thus, from belief systems to social learning, the journey of sentiment analysis is multi-folded.

3.3.5 HCI and User experience

User experience or usability is the area of information design where human-computer interaction is studied. Diaper and Sanger (2006) illustrate that Human Computer Interaction (HCI) started as early as 1959 with a paper by Shakel called "*The ergonomics of a computer*". Another seminal paper, by Liclider in 1960, called '*Man-computer symbiosis*' explains how man and computer can live together. In 1969, the launch of the first specialist journal called *"The international journal of man-machine studies"*, reopened the subject as an active study. Since then, the terms "usability" and "HCI" have become interchangeable. The goals of HCI during this time, according to Diaper and Sanger (2006) were to develop and improve the following areas:

- the safety of users;
- the utility of the program;
- the effectiveness of the application;
- efficient processing; and
- usability.

Another review of the literature on HCI from a technological perspective by Myers (1998), indicated that HCI started moving towards graphical objects as early as 1960. University research projects on HCI, according to Myers (1998), turned towards commercial production usage. Myers highlights the following as potential areas of research, at that time:

- understanding gesture: pen-like input device;
- multimedia rich, multiple windows;
- a three dimensional, location-sensing system;
- virtual or augmented reality;
- computer aided work, remote collaborative working; and
- speech recognition.

3.3.5.1 The theories and principles of HCI

Although various definitions of HCI are available in the literature, I used the following definition for my study: "HCI is a discipline concerned with the design, evaluation and implementation of an interactive system between a human and a computer in two-ways to understand phenomena surrounding them" (Dix et al., 2004).

In addition, with the above related discipline, there is a research trend towards developing adaptive interfaces, speech, gesture and face recognition. The literature provides thousands of rules for better usability and complacency. Nielsen (1994) and Baker et al. (2002) illustrate that consistent efforts have been made to make the huge set of rules easier and more manageable. Nielsen (1994) outlined 10 rules called "usability heuristics" that can solve a large number of problems which occur during efficient HCI. They include:

1. **Natural and simple dialogue**: unnecessary information overrides vital information and this can cause the purpose of HCI to fail.
2. **User friendly language:** all communication should be carried out in such a way that it is user friendly rather than operator or system friendly.
3. **Avoid forcing users to remember too many details:** never expect users to remember everything. Instead, establish a system where the user can get all the necessary information they need, and make robust help links available.
4. **Consistent usage**: use terms and definitions that are consistent across the board.
5. **Appropriate feedback:** users should be able to see where they are and how to proceed in a timely manner and without any ambiguity.
6. **Easy exits:** users should be allowed to exit at any time and not be stuck with annoying warning dialogues. There should be an easy emergency exit.
7. **Usage of shortcuts:** expert users may look for shortcuts and these should be diligently used without affecting novice users.
8. **Error messages:** appropriate error messages should be displayed in lucid language for the user to know what the problem is and what possible solutions they could follow.
9. **Error-free processes:** careful designs may lead to fewer errors during usage.
10. **Help and documentation:** although the best designs work without help and supporting documentation, thinking about the diversity of the users there should always be a handy help tool with detailed documentation which provides step-by-step explanations and instructions.

Baker et al. (2002) investigated the above heuristics and subsequently devised a reduced set of rules consisting of eight points called the “eight groupware heuristics”. The following list provides a brief explanation of Baker et al. (2002) groupware heuristics:

- better means of intentional and verbal communication;
- use gestured communication – both implicit and explicit gestures enhance HCI more effectively;
- provide hierarchical communication mechanisms to share artefacts;
- protect users from inadvertent interference;
- manage transitions with appropriate coupling;
- help users to coordinate their actions;
- facilitate collaborations by connecting people appropriately; and
- linking collaborators by establishing appropriate contacts.

3.3.5.2 HCI models

Similar to the theories of HCI, there are various models that position HCI theory in a given context. Examples of such models, include Norman's Interaction model, Abowd's and Beale's model, and the Audience Participation model (each of which I will discuss in turn).

3.3.5.2.1 Norman's interaction model

This is one of the most influential models of interaction, since it is based on human intuition (Dix et al., 2004). In short, this model relies on the formulation of a plan of action which is carried out on the interface. Norman divided this approach into seven stages which are: establishing goals, forming intentions, specifying actions, executing, perceiving, interpreting and evaluating.

Figure 37 illustrates how the gulf of execution and gulf of interpretation connects people's interpretations of the world to their intentions to act, in order to achieve goals.

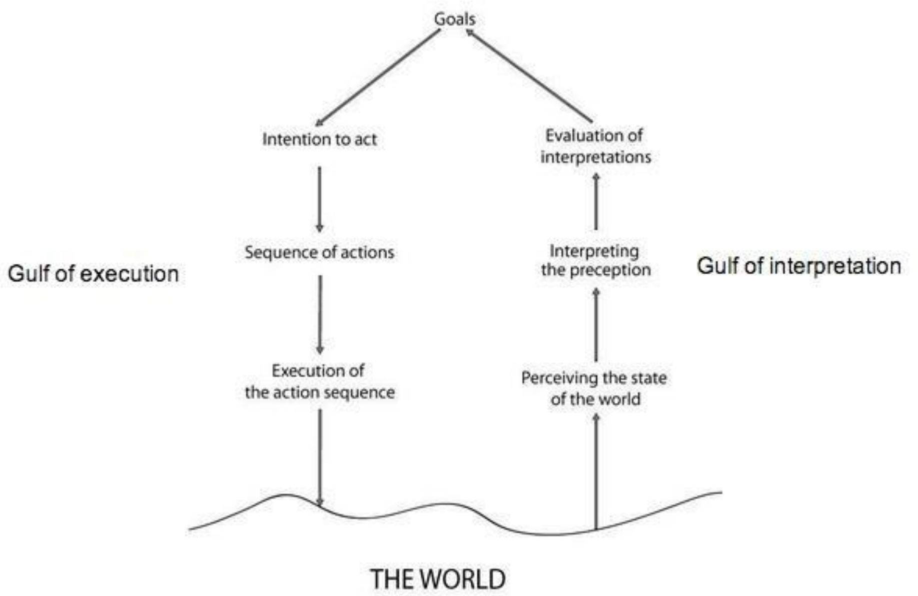

Figure 37: Norman's Model of Interaction (Dix et al., 2004)

Although this model helps us to understand how interaction connects the user with the system it was not a realistic model because of its non-practicality.

3.3.5.2.2 Abowd and Beale's interaction model

Unlike the previous model, this model is more realistic, and is considered as a better framework. It was built based on Norman's model (Dix et al., 2004), and consists of four main parts; namely, system, user, input and output. The interface sitting between the user and the system allows a four-step cycle which is represented by the arrows in the above figure: the presentation of a core system enables outputs, and provides users with an observation; the user then inputs information into the system, and improves the system's performance.

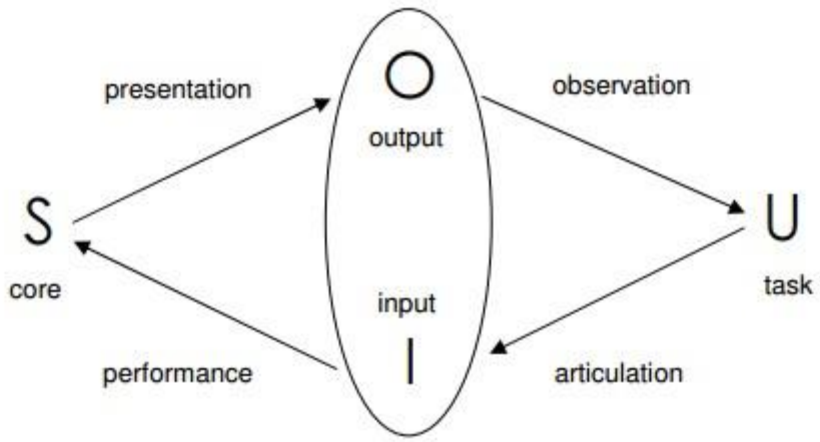

Figure 38: Abowd's and Beale's Interaction model (Dix et al., 2004)

The state of the system changes when the goal is achieved and the user and the system understand each other. Rogers et al. (2007) established the fact that HCI designers involved in designing social media interactions should have a good knowledge about perception, attention, memory, speaking, learning listening, reading, reasoning, planning, solving and decision-making. They further stated that the knowledge acquired from the physical world can indeed be applied to the digital world which what makes this model the most suitable theory for this thesis.

3.3.5.2.3 The audience participation model

Nemirovsky (2003) criticises the traditional view of considering computers as deterministic boxes, and following them blindly without being able to change the course of commands. Furthermore, he opined the view that conventional models consider users to be entertained, rather than being creative. Even being creative is taken as a mistake in the absence of an appropriate framework.

Thus, Nemirovsky provides a framework to allow users to be creative, as well as being able to modify, exchange or perform tasks using multi-media, such as audio or video. He recommends a framework of three layers: at the input level with an interface for sampling, at a structural level with a neural network for control and at a perceptual level for media modification.

On reviewing the above three theories of HCI, it appears that they are highly fragmented and available without a single method or approach. Therefore, an approach should be tailored to the specific needs of the demands and situations where they are applicable. After studying the three models of HCI, Abowd and Beale's interaction model is the most refined and appears to be the most suitable methodology for this thesis.

3.3.6 Social media interaction

Kaplan and Haenlein (2010) duly point out that the major driving force of social media is sharing and interaction. In today's world, social media is becoming the driving force which gives the younger generation ample opportunity to be proactive, to contribute and share information, and to share knowledge with their families and society without any physical constraints. Palfrey and Gasser (2010) point out that software developers are utilising every available opportunity to break new grounds and deliver new services. Consequently, today's social media is similar to the movie industry as its technology rapidly adapting.

New breakthroughs are continuously emerging to attract new users and to find a new usage for social media. This pushes forward the development of human computer interaction (HCI) to enable growth. At present, social media is becoming a diverse field which includes various environments, such as games and other sources of entertainment, as well as social networking sites. In this scenario HCI is struggling to cater for the needs and demands of social media. A divide now exists between HCI scientists and developers.

3.3.6.1 The future of HCI: social interaction design

Harper et al. (2008) justify social interaction design as the next step, the future of HCI. At the same time, they are concerned that the adoption of HCI remains in its initial stages and is operating without appropriate social interaction; in other words, feedback from users. Thus, social interaction designers should anticipate and provide features and facilities that may be beneficial when rolled out to the general public.

Jakobsson (2006) goes further and detaches social interaction design from conventional, computer-mediated communication approaches. This provides further insight into the very basic principles of HCI, and highlights that HCI should also take inputs from disciplines like psychology and sociology which most research into social interaction revolves around.

3.3.6.1.1 Social media

Social media provides a robust platform to facilitate social communication that evolves social interaction. The most suitable definition of social media for this study is the one given by Kaplan and Haenlein (2010) which states that: "Social media is a group of Internet based applications that is built on the ideology and technology of Web 2.0 and allows users to create and exchange user generated content".

Social media is, in fact, the most common form of communication between communities, organisations and individuals. Person-to-person communication has changed since the advent of social media. Social media keeps encroaching on almost every field, with the use of blogs, micro blogging, social networking, video-sharing, games and virtual worlds, to name but a few (Kaplan and Haenlein, 2010).

The findings of Poynter (2010) are particularly relevant for the purpose of this study. He stated, “This huge potential of expanding domains of social interaction becomes the driving force for organisations that see the opportunity for better marking and profit making”. Thus, by understanding and analysing people’s identity, conversations, shares, relationships and reputations in social media, it is possible that organisations can implement a sophisticated social media strategy (Kietzmann et al., 2011).

There has been a continuous reporting of social media success stories in the business arena. Unlike word of mouth, an unsatisfied customer can inform millions of people about his or her experiences with an organisation by simply clicking a button. Keegan and Rowley (2017) evaluated social media marketing techniques and discovered some significant findings. They developed a framework named the Social Media Marketing Evaluation Framework. They six stages of this framework involve: evaluating key objectives, identifying KIPs, collecting data and analysing their metrics, reporting and decision-making (Keegan and Rowley, 2017).

Rowley et al. (2016) investigated how social media can bring brand awareness. They examined how Facebook and Bebo can influence young customers’ brand recognition. Their three stage study used focus group discussions, observations and interviews. They found that discussions on social media about brands mitigate the development of advertising and marketing. Rowley et al. (2016) proposed a framework calledOnline Brand Communications (OBC); a literacy framework that conceptualises online branding, including its overt and covert forms. Their research has established that online consumers may, indeed, act as brand promoters (Rowley et al., 2016).

3.3.6.1.2 Issues facing social media

Many authors consider the social networking site Friendster as one of the most successful networking sites in that it that sets standards for many to follow. Recently, however, Friendster.com has ceased operating, supposedly due to issues relating to software mismanagement, which is evident from messages published on the Friendster.com website, as shown below.

Figure 39: An example of software mismanagement in social media

Over the past 50 years there have been numerous studies which have made recommendations and suggestions on how social media should interact (e.g. with health, education, telecom services, and even changes in traditional media). If the founders of Friendster.com had considered the recommendations made by Boyd (2004) this may have prevented the problems, they experienced from ever occurring. According to Boyd (2004), the HCI community should adapt their technology (co-evolve it) with their social community. However, Friendster.com only enabled users to see other users within four degrees of separation. This action, undoubtedly, restricted people from reaching out and finding their friends or soul mates which could have contributed to some of the issues and problems they encountered.

Another issue affecting social media usage is the dysfunctional relationship between HCI and developers. Fogel and Nehmad (2009) illustrate that many social service networks ignore or underestimate the potential risks and privacy concerns associated with signing up. Consequently, there have been various reports of users suffering from personal, financial and psychological damage while using social media sites.

It is commonly accepted in the literature that although there are great benefits associated with the application of such new technologies, one should not ignore or neglect the use of appropriate, scientific and guided software designed to enable effective social media communication.

3.3.6.2 Beyond sentiments: emotions

Information from sentiments are polarised with either positive, negative or neutral orientations. Hence, in order to extract more meaning from user content we need to look for these orientations. The capabilities of machine learning algorithms offer robust tools to extend these analyses.

I found that after sentiments, emotions are the construct that illustrate the affect and mood of the content. Various experts (Izard and Kobak, 1991, Roseman, 1984, Scherer, 2000) define emotion as a complex phenomenon illustrating an organism's different functioning. Such functions include cognitive, physiological expressions and feelings.

The componential theory of emotion focuses on its cognitive domains, and draws conclusions from theoretical and empirical facts demonstrating the interdependency between cognition and emotion. Such theories, model emotions as a response elicited by personal and subjective evaluations of feelings. This argument actually leads to an infinite number of emotions but many psychologists, as shown by Scherer (2000), agree with the existence of a family of emotions or prototypes. In his model of emotion, Scherer (2000) proposed frequently occurring patterns of emotions.

Furthermore, Plutchik (1980) proposed the popular "psycho-evolutionary theory" to classify emotional responses from subjects. He included eight emotions: anger, joy, fear, surprise, disgust, trust, sadness and anticipation. He further stated that these emotions exhibited by humans are "primitive".

The Wheel of Emotions has been used by psychologists for a long time to illustrate emotions in a compelling and nuanced way. For example, the emotions associated with bipolar individuals are arranged opposite to each other in a 2-dimensional wheel model, as shown in Figure 40 which illustrates the Wheel of Emotions. In addition to this, the colour wheel illustrates the connection between the emotion circle and the colour wheel. Similar to a colour chart, this wheel helps us to visualise emotions of different intensities and their combinations with other emotions.

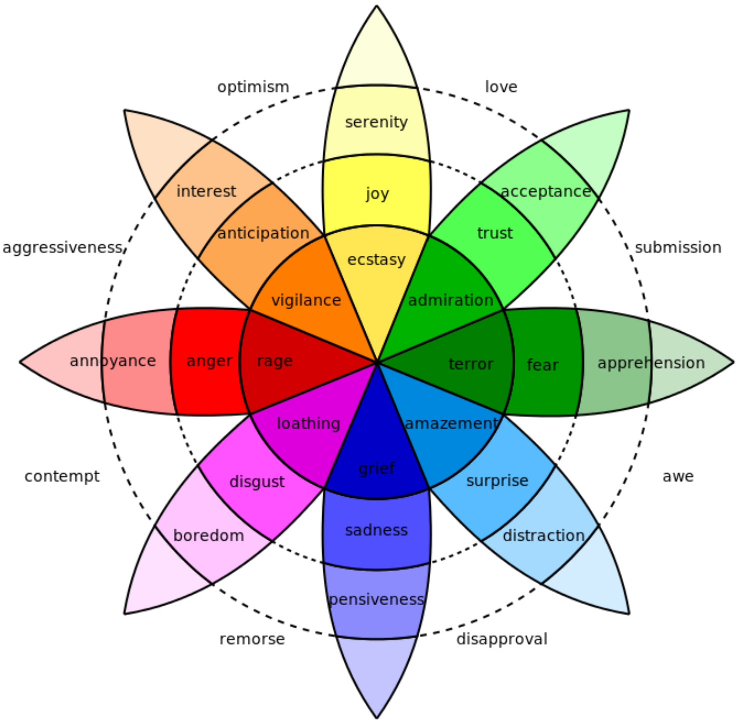

Figure 40: The Wheel of Emotions (Plutchik, 1980)

The above Wheel of Emotions classifies the primary emotions in the centre along with secondary and tertiary emotions radiating outwards. The primary or basic emotions in the above Wheel of Emotions include: Joy (with the opposite being Sadness), Trust (with the opposite being Disgust), Fear (with the opposite being Anger) and Surprise (with the opposite being Anticipation). The mix of these basic emotions gives rise to others; for example, Joy and Trust lead to Love (with the opposite being Remorse). Similarly, the combination of Anticipation and Joy leads to Optimism (with the opposite being Disapproval).

To illustrate this further, the following emotional equations explain further relationships (combinations and their opposites):

Anticipation + Joy	=	Optimism	(X	Disapproval	)
Joy + Trust	=	Love	(X	Remorse	)
Trust + Fear	=	Submission	(X	Contempt	)
Fear + Surprise	=	Awe	(X	Aggression	)
Surprise + Sadness	=	Disapproval	(X	Optimism	)
Sadness + Disgust	=	Remorse	(X	Love	)
Disgust + Anger	=	Contempt	(X	Submission	)

I will talk more about emotion, later in "The need for a new visualizing method".

All of the research strategies discussed above then enables a research to proceed using either a cross-sectional or longitudinal study.

3.4 Cross-sectional and longitudinal study

Continuing our journey through the various layers of Saunders et al.'s (2011, 2015) research onion brings us to contemplate time horizons. While the "snapshot" time horizon is known as cross-sectional, the "diary" perspective is often called longitudinal (Saunders et al., 2015). Saunders et al. (2015) suggest researchers ask an important question prior to designing a research strategy: "Do you want your research to be a snapshot of a particular time, or is it a diary or series of snapshots to represent specific events over a given time period?" So, as well as choosing appropriate research strategies, it is as equally important to acknowledge that every research study should define its time horizon.

Longitudinal and cross-sectional studies can involve both qualitative and quantity research strategies (Bryman and Bell, 2015). The following table compares and contrasts these two research designs in terms of research strategies.

Research Design	Research Strategy	
	Quantitative	Qualitative
Cross-sectional	Social survey or structured observation on a sample at a single point in time. Content analyses which are conducted on a sample of documents also come under this category.	Qualitative interviews of focus groups at a single point in time.
Longitudinal	Social survey research on a sample on more than one occasion. Can also include content analysis of documents obtained during different time periods.	Ethnographic research conducted over long periods with qualitative interviews and qualitative content analyses conducted over different time periods.

Table 7: Research Designs versus Research Strategies (Bryman and Bell, 2015)

Although both designs involve survey research methods, the cross-sectional approach is useful to study specific time frames, usually more condensed, while the longitudinal approach is useful for studying change and development over time. To conduct research for the present study about people's social media engagement in the Omani telecom sector during this particular period of time (one year between 1.12.2016 to 31.12.16), I obtained a snapshot of data through questionnaires and interviews;. Thus, the present study is cross-sectional in nature.

3.5 Data collection methods

The following subsections discusses the details for this study: my sample selection, pilot study, gaining access, choosing appropriate measurements, structuring the interviews and questionnaires, before proceeding to the statistical results of the pilot study.

3.5.1 Selection sampling

It is often impossible to collect data from the entire population (in the form of a population census) and hence, selective sampling is advised. Saunders et al. (2015) suggest selection sampling as the best option because

- it is almost impossible to survey the entire population;
- budget constraints will hamper surveying the entire population; and
- there are time constraints involved in administering, collecting and analysing a massive amount of data.

Various studies have demonstrated that a sampling survey and a population census can both produce same results – within some reasonable degree of error (Crano et al., 2014). Barnett and Bown (2002) argue that sampling even makes it possible to achieve greater accuracy than a census. They explain that this is because to handle a smaller number of data researchers spend less time designing and piloting their research. At the same time, Barnett and Bown (2002) caution that careful sample selection is crucial to enable the researcher to answer his or her research question(s). Yet, sampling should also be undertaken with efficiency and economy. According to Crano et al. (2014), efficiency involves balancing the research costs with precision.

Many sampling techniques attempt to devise a means of reaching precision without resorting to using samples which are unmanageable in size. Saunders et al. (2015) divide sampling techniques into two types; namely: probability or representative based sampling and non-probability sampling. As the names imply, in probability sampling each selected case has the same probability of being selected from a known target population; this enables a researcher to statistically estimate the characteristics of the target population from the sample and this leads to the research questions being answered. Non-probability sampling is used when the probability of each case being selected from the target population is not known because the entire sampling population for the study is unknown.

The following figure illustrates various types of sampling classified under probability and non-probability sampling.

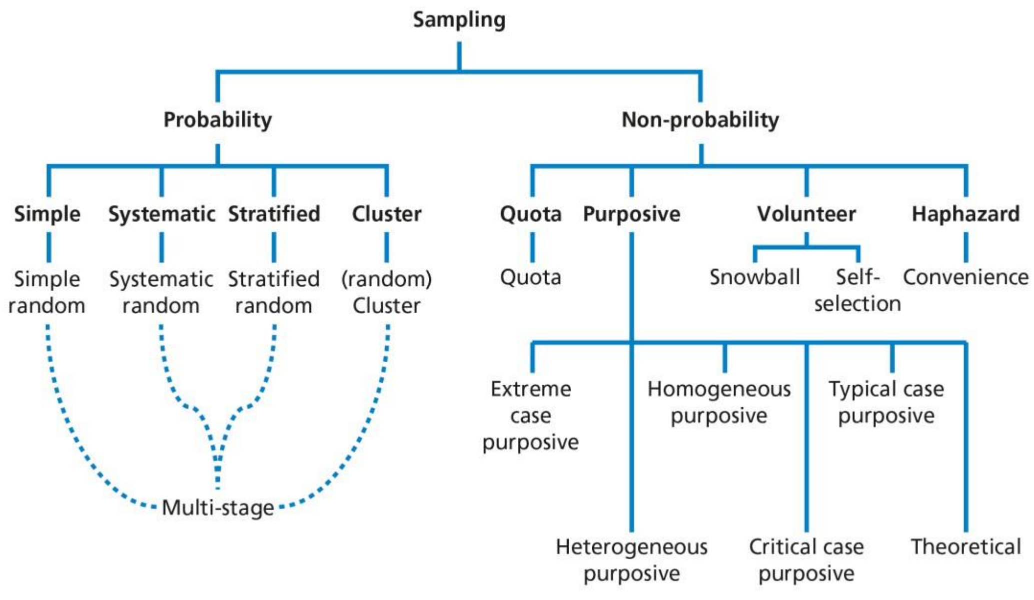

Figure 41: Types of sampling (Saunders et al., 2015)

The population of interest for my study included two groups. The first group consisted of top managers and social media managers who provided telecoms services to Omani citizens and residents. The second group consisted of potential customers who were using the telecom services of Omani telecom companies. Both groups were obtained from the Telecom Regulatory Authority of Oman. To make sure the survey represented the population a non-probability sampling method was adopted.

As seen in the literature review, every interaction between the customer and the service provider leads to trust building. So I also focused on the services supplied by these Omani telecom organisations, as I anticipated that the interpersonal aspects of their services enabled relationship building (Berry, 1995). Though it is worth remembering that as well as trust building and customer interaction, telecom industries characteristically have to deal with economic risk, technical complexity and evolving rapid advancements, including social media.

Different types of service telecoms exist in Oman. First, major operators provide mobile phone and fixed line services. Second, resellers offer various services to consumers. As my study was concerned with social media managers and general customers I did not include industrial or commercial customers in the sampling method. Therefore, my sampling included different levels of managers in those types of Omani telecoms organisations, and the general customers of those services.

Questionnaires were developed through qualtrics.com and distributed through social media to reach general customers. In the case of social media managers, as I was already associated with one of the firms, I was able to reach a wide range of social media managers across the spectrum of the service providers through personal contacts.

The sample size for the first group, i.e. social media managers, was decided based on the condition that there was at least a single representation from all the existing telecom providers. The sample size for the second group was calculated based on the following formula (Hamburg, 1977):

$$x = z \times 2r \times (100 - r) \times \frac{c}{100}$$

$$n = \frac{Nx}{((N - 1) \times E^2 + x)}$$

$$E = \sqrt{\frac{(N-n)x}{n \times (N-1)}}$$

Where N is the size of the population, r is the fraction of responses interested, and c is the confidence interval.

The following is the outcome of the application of the above formula:

Quantity	Value	Remark
Margin of Error	5%	
Confidence Level	95%	
Population Size	6500000	Source: Based on 6,500,000 active subscribers to telecom services (TRA Oman, 2016)
Response Distribution	50%	Kept low to find the largest sample size required
Calculated Sample Size	385	

Table 8: Sample size estimate for this study

It is clear from the above table that to ensure a 95% confidence level with a 5% margin of error a minimum of 385 samples were required. My response rate of 455 was well above the sample size demanded by these considerations.

3.5.2 Pilot study

In order to pre-test the questionnaire and survey I conducted a mini-version of my full-scale study. This enabled me to test their feasibility. Although a pilot study does not guarantee the success of a study, it does increase the likelihood of the investigation being successful (Polit-O'Hara and Beck, 2006).

For the purposes of the present research, I anticipated the following reasons for conducting a pilot study:

- to test the adequacy of the survey;
- to test the feasibility of a full-scale study;
- to assess whether the research was realistic and workable; and
- to determine the likelihood of the survey.

3.5.3 Approaches for gaining access to respondents

One of the most important prerequisites of a successful research project is feasibility (Saunders et al., 2015). Accessing the data for a research study and the nature of access is a problematic area. According to Saunders et al. (2015) the following strategies are required in order to gain access:

- take sufficient time to access the data;
- use all existing contacts and also develop new ones;
- be aware of organisational and individual concerns in accessing data as a way of overcoming them;
- understand the possible benefits for organisations and individuals in return for granting access;
- appropriate use of language;
- facilitate easiness in replying when access is requested;
- approach data access in incremental phases; and
- promote credibility with all participators.

Most of the above considerations were possible by virtue of my previous association with a leading telecom company. Being a colleague, albeit in a different situation, enabled me to not only to gain access to potential interviewees, but also led to easy facilitation, with much credibility.

All questionnaires and interview guides were prepared with a detailed account of their purpose, confidentiality and credibility, etc. Before every interview, or questionnaire distribution, the subjects were given a clear statement of purpose which allowed them to receive further clarification in areas where they may have had any doubts.

3.5.4 Measurement of constructs

I planned to collect data from the senior and social media managers of Omani telecom companies, and from general customers who were the primary users of the telecom services supplied by these companies. To this end structured interviews *and* questionnaires were used to collect data from one manger from each of these four companies. In addition, questionnaires were also administered to customers to collect their responses about the perceived level of service they received from telecom services organisations with regards to social media usage.

A mixed method approach was most suited to the study as qualitative and quantitative data were required for the analysis. Both questionnaires (i.e. the questionnaires for the managers as well as customers) requested demography details; whilst these details included gender, age, employment status, area of living, etc., for manager's additional details about their designation and duration of employment, etc., were also requested. Appendices 1 and 2 contain the questionnaires and interview guides in full.

This mixed method strategy enabled me to gain an insight into various aspects of customers' opinions and telecom companies perspectives with reference to social media. Furthermore, as discussed under Research philosophy, an exploratory research strategy assisted an exploration of how Omani telecom companies use social media as an effective CRM tool. Added to this, an explanatory research strategy was applied in order to explain the possible relationship between social media as a CRM tool and the customers' perspective.

3.5.5 Semi-structured interviews

For group one, all Omani telecom companies registered in the Telecom Regulatory Authority of Oman were contacted to obtain at least one respondent from each firm for the survey. Amongst them, four social media managers agreed to structured interviews in addition to completing the questionnaire. The names of the organisations that took part are omitted, instead each is referred to with a label, e.g. Firm A, Firm B or Firm C, etc., to ensure the anonymity and privacy of the companies and my respondents.

Before their interviews, respondents were briefed about the research purpose and were showed a document containing important terminology, along with common definitions. This element was crucial for ensuring that the interviewees understood and responded accordingly to the subject of interest (Saunders et al., 2015). The interview guide for these semi-structured interviews was prepared based on the conceptual framework (Please see Appendix 1: Interview Guide (Social Media Managers) for semi-structured interviews).

The interview guide consisted of four sections: customer relationship management, social media usage, and current processing involving social media for customer relationships. The interview guides avoided direct questions in order to receive extensive answers. I also ensured that the interview guides were sent in advance a week prior to the interview date. This prepared the respondents and enabled them to understand the purpose of the research beforehand and facilitate an effective discussion; one without any ambiguity. For example, following a brief introduction and overview of sentiment analysis, the respondents were asked about how sentiment analysis is used in their organisations.

All interviews were recorded and transcriptions prepared from the audio clips. As a final step for added clarity, the transcripts were shown to the interviewees and they were requested to review and adjust them as and where they deemed necessary. This also minimised the risk of misinterpretation and misunderstanding, as the transcripts were validated and verified, by the interviewees, to be in line with their organisational principles and policies.

3.5.6 The questionnaire

The survey instrument (a questionnaire) was designed based on the outcome of the literature review. The questions were designed to extract the necessary information about the respondents' social media usage, in addition to their demographic details. In order to administer the survey, I planned to conduct a web-based study. As noted by many authors, including Wright (2005), an online mode of surveying bypasses many hurdles, such as cumbersome data entry and administration, thus enabling the Just-in-Time model (Wright, 2005).

For a study on social media such as this, the Internet was an appropriate channel to administer the survey. Authors such as Taylor and Maor (2000) and Yun and Trumbo (2000) have demonstrated that web-based surveys have many common advantages, such as being quicker and time-saving, irrespective of the geographical distances involved and, in addition, they can be taken at the convenience of the respondents.

In their detailed literature review, Chen and Macredie (2010) detailed the following potential advantages of online surveys:

- low cost option for data collection in comparison with traditional paper-based surveys;
- facilities for sending, reminding and consolidating them;
- reduced errors in manual data entry and recoding;
- full control of design, deletion or modification; and
- easily exportable into other formats, such as Microsoft Excel, Word or PowerPoint.

At present there are many different online survey tools available which include: SurveyMonkey, Siftdigital, Zoomerang and Qualtrics, etc. Qualtrics seems to be an effective online survey tool with potential functionalities including navigation, presentation, development and design (Isaias, 2012). In addition, Qualtrics's maintenance, distribution and reporting also seem to be exceptional and outstanding. Qualtrics, therefore, satisfies Chen and Macredie's recommendations as a potential survey tool. Interestingly, the Qualtrics Research Suite, available through the University of Stathclyde's portal, seemed to be a potential medium for administrating my survey. Thus, it was decided to use Qualtrics for administrating this survey.

Both questionnaires for customers and managers were administered through Qualitrics and hosted through Strathclyde University's department portal (https://strathsci.eu.qualtrics.com). There were five reasons for choosing Qualitrics for administrating the survey, as highlighted by Snow and Mann, 2013.

- Qualitrics provides state-of-the-art tools for both online data collection and analysis.
- The software makes it easy to administer, distribute and collect surveys.
- In-built social media sharing is a great feature that enables the easy sharing of survey links through various social media services.
- Anonymous distribution, auto-reminders and tracking help a lot to achieve good response rates.
- There are number of research papers that cite quantitative analyses performed by Qualitrics.

The questionnaire for managers contained 20 questions. The first four questions (Q1 to Q4) identified the subject's demographic details including gender and age in addition to their job title and length of service in their current role. The next six questions (Q5 to Q10) focused on the use of social media. The next five questions (Q11 to Q15) focused on the linkage between marketing strategy and social media, and the last five questions (Q16 to Q20) focused on sentiment analysis.

The customer survey questionnaire contained 18 questions. The first four questions (Q1 to Q4) established their demographic details. The rest of the questions focused on the service provider(s) these customers have chosen, their social media reach, and also the customers' acquaintances with the social media platform.

The full scale and online survey are displayed in Appendix 5. By utilising this scale the authors removed the neutral value option to create a forced choice. The second section, Social Media Use, consisted of five closed questions. The third section, SCRM Capabilities, contained five Likert Scale questions. Customers' relationship orientations were measured using a 5-point Likert Scale: with 1 representing "Strongly Disagree" and 5 representing "Strongly Agree". Similarly, social media usage, customer loyalty, retention and satisfaction were all measured using a 5-point Likert scale. Finally, the fourth section, Customer Relationship Performance, included four Likert Scale questions with regards to customer loyalty, retention, and satisfaction.

3.5.7 Number of responses for the pilot study

Out of the nine potential social media managers contacted, they all completed the survey within the time frame given. The demographic details of the respondents of the pilot study are shown below in Figure 42.

Sl. No	Gender	Age Group (years)	Job Title	Length of Experience in current position	Company's Social media usage
1	Male	30-40	Manager	5	3
2	Female	30-40	Marketing Executive (Social Media)	4	2
3	Male	40-50	Manager (Advertising)	10	3
4	Female	30-40	Asst. Manager (Advertisement and Sales)	5	3
5	Male	More than 50	Senior Manager (Social Media)	10	4
6	Male	30-40	Manager	5	2
7	Male	40-50	Manager (Advertising and Marketing)	12	4
8	Female	30-40	Manager	4	3
9	Male	More than 50	General Manager (Marketing)	15	5

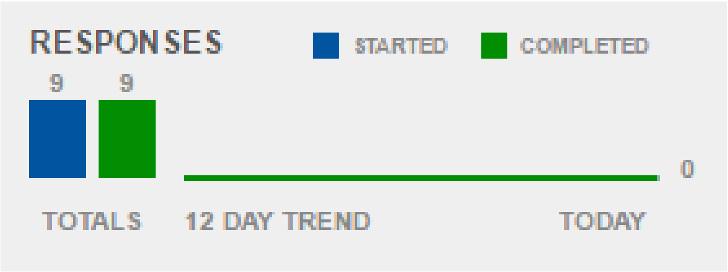

Figure 42: Pilot Study – overall response

3.5.8 Statistical Results of the pilot study

The following tables, in this section, list the statistics for each question on the survey questionnaire.

1. Is your firm active on social media?

#	Answer		Response	%
1	Yes		5	83%
2	No		0	0%
3	Don't Know/Unsure		1	17%
	Total		6	100%

Statistic	Value
Min Value	1
Max Value	3
Mean	1.33
Variance	0.67
Standard Deviation	0.82

Total Responses	6

2. Which of the following social media is actively used in your organisation? (Please select that all apply)

#	Answer		Response	%
1	Twitter		2	40%
2	Facebook		5	100%
3	Google+		0	0%
4	LinkedIn		3	60%
5	Others. Please specify:		0	0%
6	Don't Know/unsure		0	0%

Others. Please specify:

Statistic	Value
Min Value	1
Max Value	4
Total Responses	5

3. What frequency is your organisation's social profile updated?

#	Answer		Response	%
1	Weekly		3	60%
2	Bi-weekly		0	0%
3	Every day		2	40%
4	Other. Please specify:		0	0%
5	Don't Know/ Unsure		0	0%
	Total		5	100%

Other. Please specify:

Statistic	Value
Min Value	1
Max Value	3
Mean	1.80
Variance	1.20
Standard Deviation	1.10
Total Responses	5

1. What is the purpose of the corporate profile page in these social media?

#	Answer		Response	%
1	Basic details of the organisation		2	40%
2	Promotion or advertising product/service		4	80%
3	Contact customers		2	40%
4	Job recruitments		2	40%
5	measuring supporters/followers		1	20%
6	Other. Please specify:		0	0%
7	Don't Know/unsure		0	0%

Other. Please specify:

Statistic	Value
Min Value	1

Max Value	5
Total Responses	5

5. How would you rate the advantage due to the online presence of the following social networks?

#	Question	5: Significance	4: Some advantage	3: neutral	2: very few advantage	1: No advantage	Total Responses	Mean
1	Twitter	1	2	1	0	0	4	2.00
2	Facebook	1	2	2	0	0	5	2.20
3	Google+	1	1	2	0	1	5	2.80
4	LinkedIn	0	3	1	0	1	5	2.80
5	Others. Please specify:	1	1	0	0	0	2	1.50

Others. Please specify:

Statistic	Twitter	Facebook	Google+	LinkedIn	Others. Please specify:
Min Value	1	1	1	2	1
Max Value	3	3	5	5	2
Mean	2.00	2.20	2.80	2.80	1.50
Variance	0.67	0.70	2.20	1.70	0.50
Standard Deviation	0.82	0.84	1.48	1.30	0.71
Total Responses	4	5	5	5	2

1. Is there any mechanism to monitor the current topic (trend or discussion) that are relevant to the organisation?

#	Answer		Response	%
1	Yes		3	60%
2	No		0	0%
3	Don't know /unsure		2	40%
	Total		5	100%

Statistic	Value
Min Value	1
Max Value	3
Mean	1.80
Variance	1.20
Standard Deviation	1.10
Total Responses	5

7. Is there a link between marketing strategy and social media coverage?

#	Answer		Response	%
1	Yes		4	80%
2	No		0	0%
3	Don't Know/unsure		1	20%
	Total		5	100%

Statistic	Value
Min Value	1
Max Value	3

Mean	1.40
Variance	0.80
Standard Deviation	0.89
Total Responses	5

8. Do you offer any customer support online?

#	Answer		Response	%
1	Yes		3	60%
2	No		2	40%
3	Don't know /unsure		0	0%
	Total		5	100%

Statistic	Value
Min Value	1
Max Value	2
Mean	1.40
Variance	0.30
Standard Deviation	0.55
Total Responses	5

9. Could you please elaborate the link between social media coverage and marketing strategy? (Discussion through open question)

Text Response
Through media they doing marketing

Statistic	Value
Total Responses	1

10. Is there any tool in place to perform such analysis? If so please give the name.

#	Answer		Response	%
1	Yes		1	25%
2	No		2	50%
3	Name of the tool used:		1	25%
4	Don't know/unsure		0	0%
	Total		4	100%

Name of the tool used:
Books

Statistic	Value
Min Value	1
Max Value	3
Mean	2.00
Variance	0.67
Standard Deviation	0.82
Total Responses	4

11. How is the analysis conducted?

#	Answer		Response	%
1	In-house		1	25%
2	outsourced		3	75%
3	Don't know /unsure		0	0%
	Total		4	100%

Statistic	Value
Min Value	1
Max Value	2
Mean	1.75
Variance	0.25
Standard Deviation	0.50
Total Responses	4

12. Are there any problems with the current tool?

#	Answer		Response	%
1	Yes		2	50%
2	No		2	50%
3	Don't know/unsure		0	0%
	Total		4	100%

Statistic	Value
Min Value	1
Max Value	2
Mean	1.50
Variance	0.33
Standard Deviation	0.58
Total Responses	4

13. What do you think the contribution of sentiment analysis so far for the organisation? (Open ended question for discussion)

Text Response
Yes
It contributes to the products/services offering planning, and gives some predictions on the market perception of our offers.
To predict the market reaction on future offerings

Statistic	Value
Total Responses	3

14. Out of the following options what do you think sentiment analysis may achieve for your organisation?

#	Answer		Response	%
1	To know positive or negative comments about campaigns		3	75%
2	To know popularity of the organisation on social network		0	0%
3	To increase the profit		0	0%
4	Analyse and compare against competitors		1	25%
5	Others (Please specify):		0	0%
6	Don't know /unsure		0	0%
	Total		4	100%

Others (Please specify):

Statistic	Value
Min Value	1
Max Value	4
Mean	1.75
Variance	2.25
Standard Deviation	1.50
Total Responses	4

15. Are you aware of sentiment analysis/sentiment detection/opinion mining?

#	Answer		Response	%
1	Yes. If selected this option, please proceed to next question		4	67%
2	No. If selected this option Thanks for your response. You have completed the questionnaire		2	33%
	Total		6	100%

Statistic	Value
Min Value	1
Max Value	2
Mean	1.33
Variance	0.27
Standard Deviation	0.52
Total Responses	6

3.5.9 Discussion of the results of the pilot study

Examining the results of the pilot study in the above section, the following conclusions can be drawn.

- The inclusion of the "Don't know/unsure" option in many of the questions was observed to be appropriate.

- It was observed from the discussion with respondents that a few of them did not know about sentiment analysis as it was not currently being used in their organisation. Although many organisations passionately use social media campaigns, their knowledge of SA seems to be minimal; thus, a brief introduction to SA could have enabled a more effective response from them.

- Overall, the questionnaire seems to collect the data that is required for my proposed study.

- The number of questions and options seem to be suitable and aptly illustrate my case.

- Except for a very small number of respondents who doubted their knowledge about SA, all the others answered the questions correctly.

The modified version of the questionnaire is provided in Appendix 4.

3.5.10 Reliability and validity

Carmines and Zeller (1979) define reliability as the degree to which measurements are without error and provide consistent results. Therefore, any reliable experiment, test or a procedure should provide the same results during repeated trials. Saunders et al. (2015) use internal consistency to measure reliability by correlating the responses of each item with others in the survey.

Cronbach's alpha is one of the common acceptable standards for internal consistency; in which any value more than 0.60 is reliable. I obtained a Cronbach's alpha of 0.90 which illustrates a very high internal consistency.

I also used triangulation to cross validate the data from my two sources: (1) the data collected through interviews and questionnaires from the social media managers, with (2) social media data from Twitter was obtained from customers over one year. The process of such cross checking enables us to achieve better findings with greater confidence. At the same time, my selection of interviewees, as based on their designations, responsibilities and acquaintance with social media policy management in the firms also enabled us to receive valid information.

3.5.11 Empirical data

Despite commencing with a qualitative research method, we have employed the quantitative research method as well. Thus, I attempt to display my empirical data in accordance with the conceptual model developed in the literature review where the responses from social media managers and customers are classified into every dimension of the model.

As explained in Section 1.1 in the Introduction in detail, the telecoms industry in Oman has been in rapid growth mode ever since modernisation. From its advent, the telecom industry has been highly regulated, as has been seen by new market entrants from time to time.

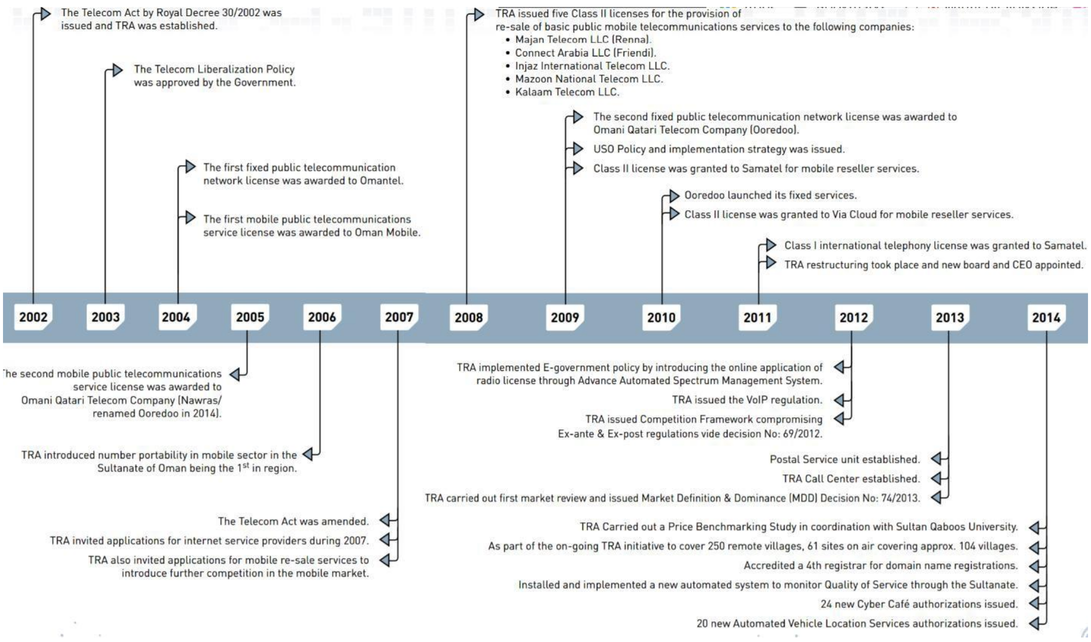

Figure 43: The Omani Telecom Industry Timeline (TRA Oman), 2016)

In particular, mobile subscription and its penetration rate has been increasing since 2011 (Figure 44), by almost 6.2 million and 155.13%, respectively over ten years.

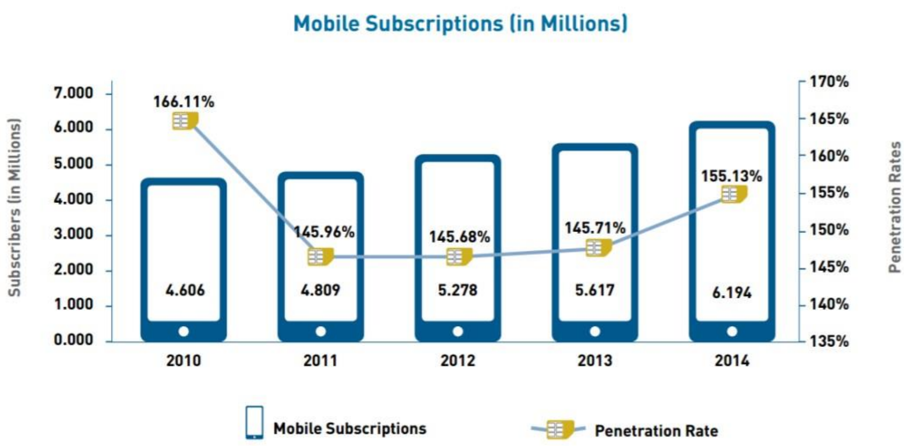

Figure 44: Mobile Subscriptions and penetrations (TRA Oman), 2016)

In order to understand the CRM scenario in Oman, we can use data made publicly available by the TRA in Oman regarding customer complaints and grievances and how they are resolved (Figure 45).

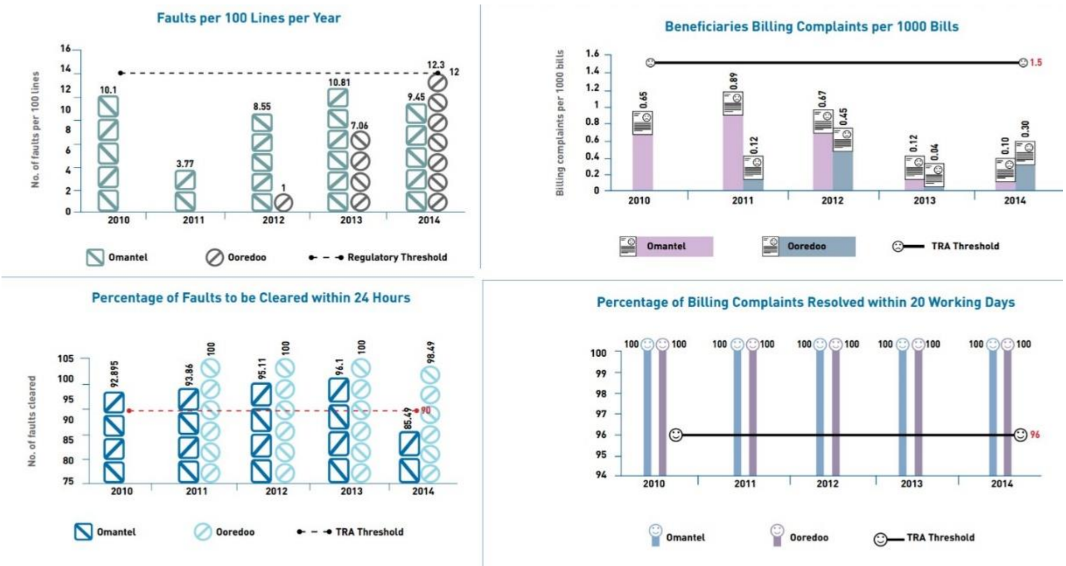

Figure 45: CRM by the Omani Telecom Industry (TRA Oman), 2016)

The increase in faults, complaints and their resolutions provides thoughtful data for my study. It is possible to triangulate discussions based on a firm's view, customers' opinions and publicly available data such as the information provided above.

3.6 Social media as a data collection tool

Social media remains a rich source of data where various inferences can be mined. Similar to the movie industry, sharing and interaction is actively taking place on social media (Kaplan and Haenlein, 2010). As users have ample opportunity to contribute and share their opinions without any physical constraints, one can identify patterns, sentiments and emotions. Poynter (2010) rightly identified the huge potential of such social interaction, and, thus, such inferences from social media provide a huge opportunity for organisations striving to enhance marketing and increase profit making to research how their practices impact their customers' opinions.

It has been demonstrated in the literature review that organisations can implement better social media strategies by understanding the conversations, shares, relationships and reputations provided in social media data by their customers (Kietzmann et al., 2011). Social media success stories demonstrate that information through social media can spread to millions just by the click of a button, unlike word of mouth.

Tweets are a popular mode of social media exchanges offering a wealth of information. A normal search available through Twitter's home page returns millions of searches and Twitter's advanced search function enables us to narrow searches based on time and topics. As a first step, all social media from the dataset was archived and tagged with a time and topic. In order to conduct sentiment analysis, the Twitter advanced search function was utilised (Figure 46) to determine the right search terms so that the data could then be collected over the different periods of time determined for the study. After several investigations of various hashtags, users and their activity, search terms involving words such as “Oman telecom”, “OmanTel”, “Omanmobile”, “OredooOman” or “TRA Oman”, etc., seemed to reveal most discussions pertaining to the Omani telecom sector.

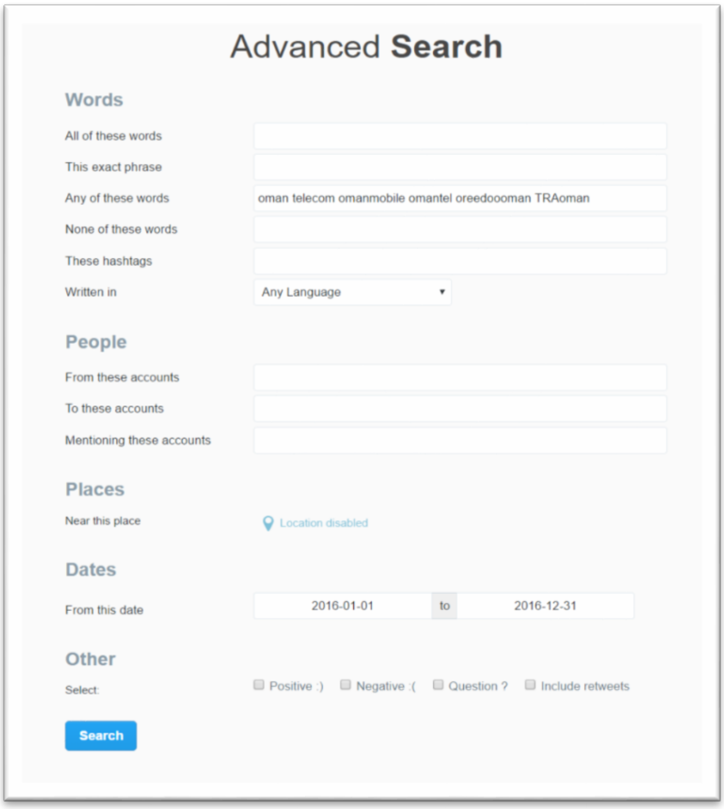

Figure 46: Twitter Advanced Search: The search terms and dates used for this study

Such advanced search functions of twitter API enabled the creation of an URL such as the following as a data source:

https://twitter.com/search?l=&q=oman%20OR%20telecom%20OR%20omanmobile%20OR%20Om a ntel%20OR%20oreedoooman%20OR%20TRAoman%20since%3A2016-01-01%20until%3A2016-12-
31&src=typd

I chose a one-year time period for data collection dating from 1st January 2016 to 31st December 2016. This enabled me to collect a sufficient number of tweets so that sentiment analysis could be carried out on a daily, weekly, monthly or annual basis.

This collection of tweets was periodically carried out over the year along with NCapture for NVivo©, a browser plug-in provided by the NVivo-11©software. This plug-in enabled me to download tweets and import them into NVivo as a data source (Fielding et al., 2008).

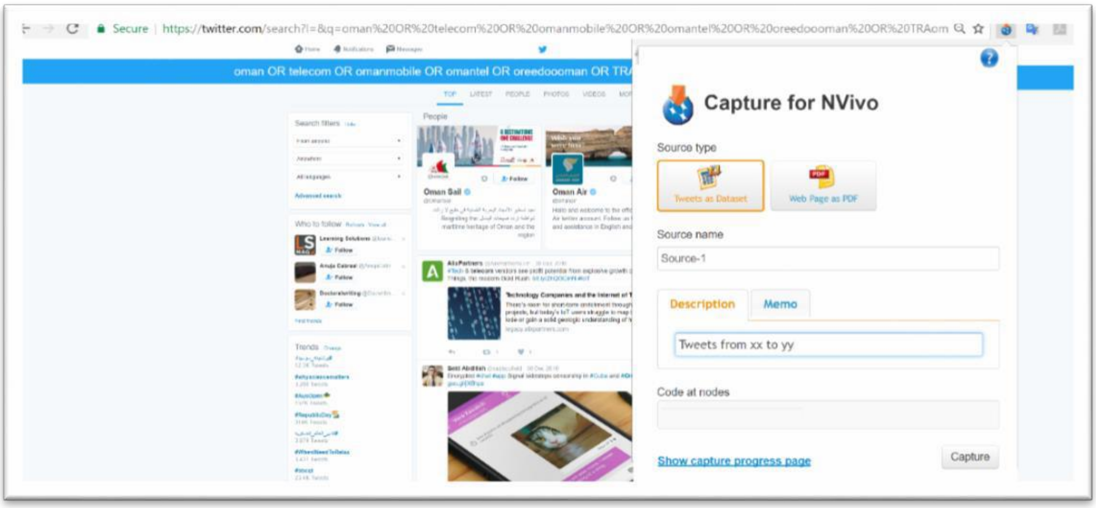

Figure 47: NCapture browser plug-in for downloading tweets

3.6.1 Basic sentiment analysis

I explained various approaches to analyse qualitative data in the literature review. Mason (2006) describes qualitative approaches as being either literal, interpretive or reflexive. These approaches help researchers to understand language or grammatical structure, and participants' narration. Many researches adopt combinations of these methods and use various software, such as NVivo. The advantage of using a reflexive approach is that it allows participants to speak for themselves rather than taking account of existing theoretical frameworks (Kelle, 2007).

The literature recommends various ways to analyse the qualitative data. Three major approaches explained by the experts are: literal, interpretive or reflexive (Mason, 2006). The first approach uses language or grammatical structure. The second makes sense of the participants' narration. And the third, the reflexive approach, takes the researcher's contribution to the data into account for analysis. Mason (2006) illustrates that often researchers use a combination of these three methods.

Most of the computer-based algorithms used for conducting qualitative data analysis built on theoretical approaches have been discussed in the previous section on Sentiment analysis. Such software makes use of what is called "memoing" tools to use theory building from the fed data. One advantage in using this approach is that these tools allow the data to speak themselves rather than taking account of existing theoretical frameworks (Kelle, 2007).

NVivo is a qualitative data analysis software tool developed by QSR International. This software can handle rich text or multimedia data for conducting deep level analyses. There are various tools available within NVivo, such as searching tools to interrogate data at a desired level. Although the validity and reliability of such analysis has various limitations, in particular, using themes, it still promises to be a better tool compared to other qualitative data analysis software currently available.

The objectives of qualitative analysis (1) draw conclusions, (2) develop theories, and, (3) test hypotheses. For example, through the following steps as proposed by Bazeley and Jackson (2013):

1. Identify similarities
2. Extract themes
3. Identify relationships
4. Highlight differences
5. Create generalisations

Coding the data involves dividing the dataset into multiple meaningful units; these codes could be data driven or theory driven. And can consist of inductive or deductive coding where deductive codes are applied before analysing the data.

NVivo helps users to manage data (creating databases of text, audio or video), to manage ideas (through annotation and attaching memos), to run queries (detect common occurring words and themes), and to model and report on these data (to illustrate relationships and report a developed model) (Bazeley and Jackson, 2013). In this way a basic sentiment analysis was carried out by using NVivo.

3.6.2 Extended sentiment analysis

The dataset that was accumulated for one year (January to December 2016) amounted to 83,981 tweets. Basic analyses were run through NVivo without any difficulties, although, overall I considered the software to be limited as finding sentiments and emotions with respect to time were challenging. For instance, there were no direct options in NVivo to find the emotions of tweets.

After trying a range of extensive software I decided to write my own codes to conduct extended sentiment analysis. Again, lots of programming platforms are available for conducting sentiment analysis or text-mining which includes Java, C++, Python and the programming language 'R'. Out of these I chose R for writing custom coding, with regards to conducting extended sentiment analysis, for the following reasons:

- R is considered as one of the most comprehensive text mining analysis tools based on statistical methods. It has built by tests and models based on managing language analysis (Meyer et al., 2008).
- As this programming language is built on computational statistical tools there is a very competent community which maintains its language development and upgrades (Torgo and Torgo, 2011).
- There are several inbuilt graphical tools that can be used to visualise analyses (Meyer et al., 2008). In fact, there are more than 4800 packages available for analysing the data.
- Above all R is an open source software, allowing anyone to use or modify it under a GNU General Public License. R has a cross-platform architecture capable of running in 32 and 64 bit processors.

I have, specifically, used the following packages (or "libraries") in my analysis coding:

1. **The tm package:** this is one of the most widely used text mining frameworks in R. Pioneered by Feinerer (2008), this library enables researchers to organise, transform and analyse textual data. Many mining methods available through this package are not yet available, even in the most popular commercial products (Eddelbuettel, 2016).

   All these processes were followed through our codes and the outputs obtained are explained in the following sections.

2. **WordCloud package:** This package enables the creation of a WordCloud from the text processed through the tem-package. The following is the syntax of the function implemented in my code (Fellows, 2014):

```
wordCloud(words,freq,scale=c(4,.5),min.freq=3,max.words=Inf, random.order=
TRUE, random.color=FALSE,rot.per=.1, colors="bla ck",ordered.colors=FALSE,u
se.r.layout=FALSE, fixed.asp=TRUE,...)
```

   By using the above functions, I was able to obtain various WordClouds, WordCorpus and emotions necessary for the extended analyses.

3. **Syuzhet package:** This library calculated the sentiment analysis of the data pre-

processed through the tm package. Based on NRC Word Emotion Association, unlike many commercial softwares, it does not just return sentiments but also calculates emotions (Jockers, 2016). I implemented this library in my code through:

```
get_sent_values(char_v, method = "syuzhet")
```

Where char_v involves string and the methods indicate the sentiment dictionary used.

4. **Additional packages used:** In the coding, in addition to the above packages, I also used the following functions.
   a. **Lubridate** for effective handling of the date and time format of tweets.
   b. **ggplot2** for producing various plots obtained through the codes. (The outputs of this are given in the following section.)
   c. **Dplyr** for data manipulation, such as identifying verbs, sentences and patterns in the tweets.

3.6.3 The need for a new visualising methodology beyond sentiment

I found a gap in available tools to visualize emotions from social media data. Therefore, I created a new visualising methodology, the first, to the best of my knowledge, to visualise the emotions of tweets. Motivated by one of the theories of emotions widely used by practicing psychologists, my visualising methodology assists us to 'see' emotions in the data; Plutchik (1980) proposed the popular "psycho-evolutionary theory" to classify emotional responses (see Figure 48).

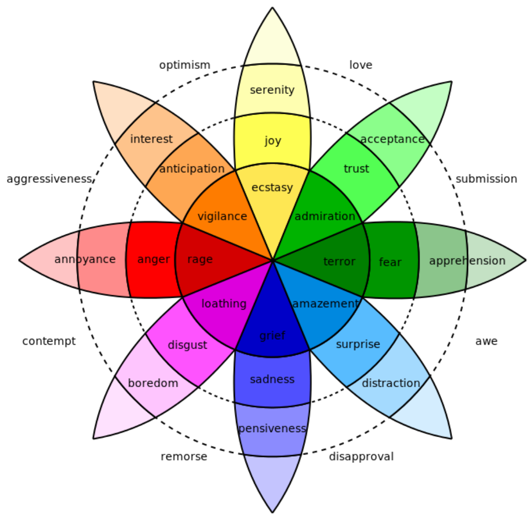

Figure 48: The Wheel of Emotions (Plutchik, 1980)

Our extended analysis, using custom built codes in R, enabled me to extract more than just sentiments from the tweets. I call this extended analysis the "choreography of tweets" the term incorporates a dancing display of tweets and emotions through the graphical display obtained through my analysis.

3.7 Challenges and solutions

There were three major difficulties encountered during data collection: the first was that the majority of the tweets returned results in Arabic; the second issue was due to the data collection period spanning one year; and the third issue related to identifying an appropriate sentiment analysis tool to analyse and visualise the sentiments and emotions arising from the study.

3.7.1 Handling the Arabic language

Unlike other languages, Arabic has differences not only in linguistics but also in its format (right to left). Most sentiment algorithms have been developed in English, however, there are some that have been developed in other languages, such as Chinese, German and French. With regards to our study in Oman, most of the tweets were in the Arabic language. At the time of writing, the chosen sentiment analysis software, NVivo-11, did not support the Arabic language for sentiment analysis. There was no effective algorithm or dictionaries available for the Arabic language regarding sentiment classification and, unsurprisingly, this was the first major issue encountered during the data collection phase.

Thus, in order to translate the downloaded tweets, I utilised the Google Spreadsheet function and Google Translate (Bahdanau et al., 2014). This function is of the following form:

```
=GoogleTranslate("text", "source language","target language")
```

I used the above Google spreadsheet function to translate all Arabic text into English. Then exported the data source as comma separated values (CSV) and imported them into a Google Spreadsheet (Figure 49). The following formula was used to translate Arabic to English:

```
=GoogleTranslate("tweet", "ar","n")
```

In the above formula “tweet” referred to a column where tweets were stored, and the cell which contained the above formula was translated. One of the advantages of the above formula was, if the tweets were already in English it did not modify them but translated the Arabic tweets.

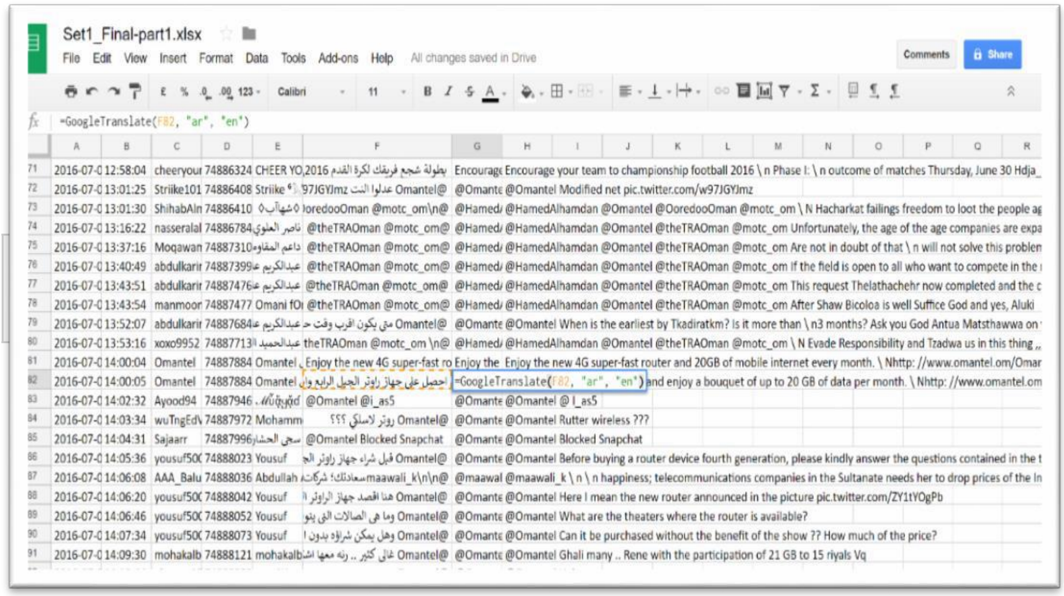

Figure 49: Using A Google Translate Spreadsheet Formula

Initially the process was intermittently slow and experienced periodic crashing when I attempted to use the entire dataset; however, by splitting the dataset into several parts the entire collection was successfully translated.

I manually verified a sample of the translations from the original Arabic tweets to make sure that the software translated the correct word from Arabic to English, i.e. with the same meaning; it was confirmed that the translations reflected the originally posted information. The following table (Table 9) shows a list of Arabic texts and their translations obtained through the Google Translate function. As mentioned above, translated tweets were saved in a CSV format. The data was then imported back into NVivo and sentiment analysis was conducted; the same CSV file was also used for extended sentiment analysis involving emotion detection.

Arabic Text	**Translations by the googleTranslate function**
مبادره جميلة، لكنها خاطئة لأنها تشجع الناس المستهترة إنها ترمي فضلاتها.	Beautiful initiative, but it is wrong because it encourages irresponsible people it aimed droppings.
رجعوا العرض مال ياخي	Snape returned money Stales
زامنا مع #يوم_البيئة_العماني ؛ #عمانتل تنتج فيلما توعويا بأسلوب مبتكر، شاهد حتى النهاية لتصلك الرسالة https://t.co/7SSZ… :	Coinciding with #Aom_albaih_alamana; #OmanTel produced an awareness film an innovative manner, watch until the end to receive the message https://t.co/7SSZ...

Table 9: Sample sentences in Arabic and their translations in English

With the first row highlighted to show respective words.

3.7.2 Collecting tweets over one year

A Twitter search provided numerous historical search results, yet downloading the data so that sentiment analysis could be conducted was a critical issue. Although NCapture obtains Twitter authentication to access its data, NCapture is only able to download datasets with a maximum of 2000 tweets each time (Nvivo, 2017). This limitation became a major issue when collecting data as the datasets were larger than 2000 tweets. Consequently, I got around this by conducting search processes periodically throughout the year, and collected tweets at least once a week.

One of the excellent features of NCapture is its facility to remove duplicates. Each time Twitter data was captured, a new NCapture file was created; while importing and merging these files together NVivo merges them as a single data source and removes any duplicate contents (Nvivo, 2017). This made the data collection process somewhat easier as it allowed me to make sure tweets were not duplicated which would have influenced the sentiment analysis at a later stage.

3.7.3 Identifying an appropriate sentiment analysis tool

Although NVivo was useful for conducting basic sentiment analysis, as described, it was unable to handle the 83,981 tweets collected to produce a timeline chart. The software also experienced frequent crashes, and, despite the assistance of NVivo's customer support team, there were found several limitations in conducting extended sentiment analysis using the software. However, to overcome this obstacle I developed codes in R to resolve this issue (as described in Section 3.12). This coding enabled me to handle 83,981 tweets without any further problems. I was also able to generate all sorts of outputs including WordCloud and daily, monthly and annual sentiment totals. This code also enabled me to obtain a timeline view of emotions which greatly helped to visualise the data in greater detail. After this I was able to run an extended sentiment analysis, as per my plan.

3.8 Chapter three summary

In order to realise the research objectives of this study a combination of epistemology, ontology and axiology techniques was employed via the onion research methodology (Saunders et al., 2015). Thus, the methods chapter has been organised following the onion research method by philosophies, approaches, strategies, choices, time horizons and, lastly, techniques and procedures of the data collection, with separate sections for social media as a data collection tool and the challenges of the study.

The term philosophy may mean different things in different disciplines. According to Saunders et al. (2015), any epistemology is expected to draw out acceptable knowledge in the field of study. This philosophical approach highlights the importance of differentiating between conducting research among people and other objects. Though the research is affecting the reality that is being investigated, my research is not measuring the "reality" of CRM in telecom sector; yet it is providing a snapshot of some customers and workers experiences that are useful to help firms attract and retain customers by meeting their needs. As the research in sentiment analysis is still developing, it is difficult to try to quantify and measure these improvements. As such, epistemology provides a good indication of what acceptable knowledge in the area of sentiment analysis can be applied to the data.

A Marketing 3.0 perspective of firms is one that considers customers as multidimensional entities, and necessitates firms to use all possible forms of technology to visualise customers' opinions. As customers are unique and highly interactive, comprehending their needs becomes important to maintain a company-customer relationship. Social media is rich in data about customer opinions holding important information that firms need.

Considering different research approaches, while surveys and interviews are useful to capture data from customers and managers respectively, social media posts have to be analysed using suitable methods. Existing sentiment analysis techniques help organisations to understanding positive or negative sentiments, but firms need more than these binary dimensions to fully understand customers and serve them better.

The part of the chapter regarding research strategy focused on information science, computer mediated communication, sentiment analysis, human structure interaction and social interaction. The review of information science enabled us to understand what information is and how it is transmitted from the source to the receiver. As the objective of this study is to extract certain specific and useful information from social media, as per Zins's (2007) description of information science, my task was to identify how another knowledge domain of information science, such as those capable of handling multiple domains, can be applied more accurately.

Understanding information use behaviour will enable us to find information that is unintentional, passive or even purposeful (Case, 2007). According to Spink et al. (2006), more than the information itself, information use behaviour will enable us to enrich our knowledge base. The information process therefore has to coordinate a cognitive state, a level of knowledge and an individual understanding that results in a coherent series of activities (Kuhlthau, 1993). Although various theories of information science exist, human information coordinating behaviour seems to be the one that is most suitable for my study as this encompasses information finding, as well as organising and using information for further analysis.

The main data source for this study was derived from a digital medium. Therefore, reviewing the literature on computer mediated communication (CMC) has illustrated the dynamics of digital communication. Another notable point from the definitions of Fragoso et al. (2008) is that the flow of information can be to oneself, another person, a group, or even to some imaginary audience. With this in mind, whilst looking for the data it is important to have a note on the openness of the receivers of the information flow, i.e. to make sure who the receivers are, and to accordingly send proper data which can be read and processed by the receiver. The mechanism that is finally employed for the research process should be able to tap into real time information (synchronous), time-delayed (asynchronous) or even super synchronous (with multiple users at a time). The constraints and affordances explained by Clark (1996), Clark and Wilke-Gibbs (1986) and Clark and Brennan (1991) should be taken into consideration when analysing CMC. In addition, the social media usage needs to be analysed using both the online interaction and technology adoption dimensions of CMC.

The review of sentiment analysis from historical and technological perspectives has enabled me to justify the use of this tool for the present study. Whether it is with huge data or during a real-time analysis, the algorithms of sentiment analysis (SA) are capable of extracting useful information from the data which is otherwise humanely impossible. As discussed by Mostafa (2013), the contribution of sentiment analysis for brand tracking is plausible and robust, and although there are challenges to using sentiment analysis, the tools of natural language processing (NLP) offer promising solutions to overcome the constraints we may face while extracting useful information from social media data. Recall that Tsytsarau and Palpanas (2010) provided a seven step approach to explain the technicalities of sentiment analysis which is, indeed, applicable for my study.

Therefore, for its data collection methods this study gathered data from Omani telecom customers (through questionnaires and social media data via tweets) and from the social media managers of Oman telecom firms (through questionnaires and semi-structured interviews). The social media data and interview texts were then subjected to sentiment analysis, and the customer survey responses were analysed using quantitative and qualitative statistical analyses. As discussed, sentiment analysis was conducted in two parts. Firstly, basic sentiment analysis where sentiment scores and their polarity was observed with respect to time. Secondly, as the needs of customer service providers evolve, in addition to the polarity of sentiments emotional scores were also calculated for the data. Variation of emotions were also observed throughout the event window; thus, using the Wheel of Emotions, emotion scores were obtained in real-time for the data to attain possible correlations.

This study is both descriptive and explorative with reference to the parameters and factors affecting service quality, customer satisfaction and retention. Research Question 1 has been addressed through the literature review on marketing and management to explore and understand the function of customer behaviour in the given business context. In order to answer Research Question 2, I gathered social media data and extracted further data from it about key service attributes in line with findings from the literature review. This was in addition to the surveys and interviews I conducted. The collected data was then analysed using various statistical procedures, including regression and structural equation modelling.

Based on the variables and constructs tested in the pilot study, a conceptual model was established that can help organisations to improve their CRM initiatives (Research Question 3).

The following flow chart illustrates the whole process of the research that has been carried out.

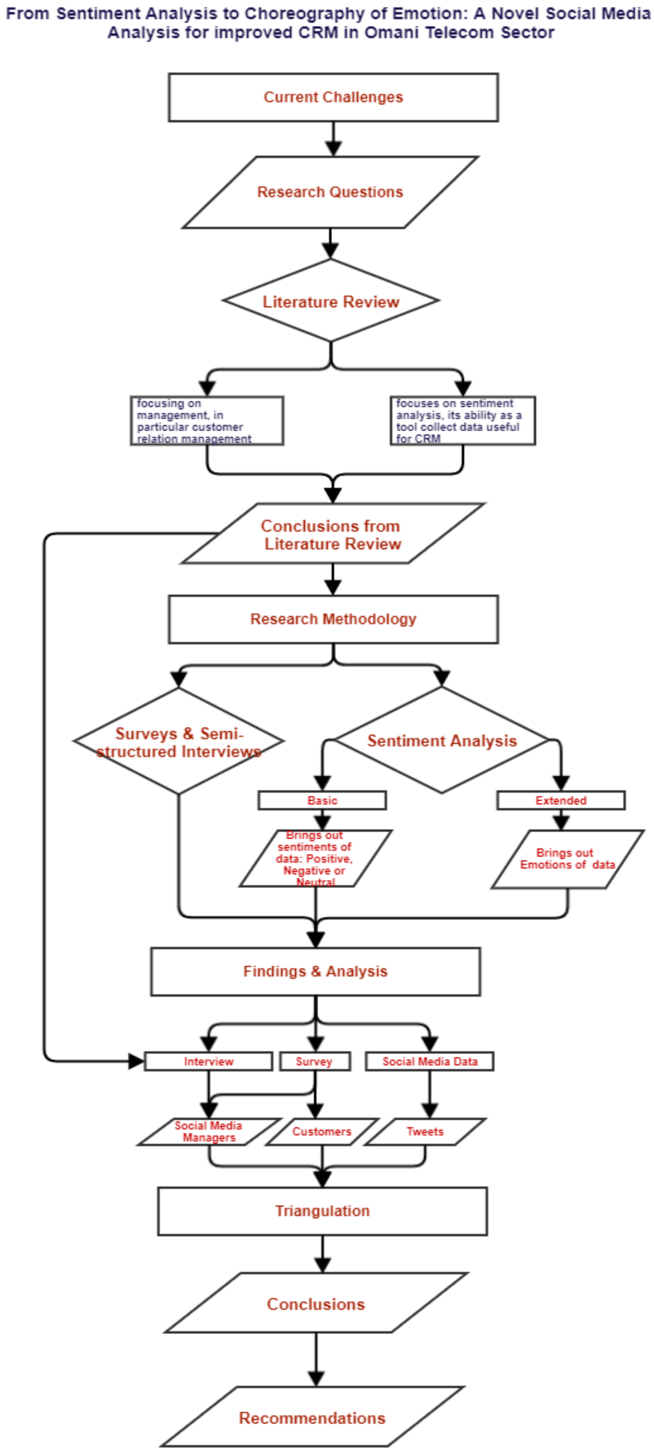

Figure 50: The flow chart of our research study

4 Findings and Analysis

4.1 Survey and interview results

My data collection methodology included collecting quantitative and qualitative data from social media managers and customers. In addition to this I also conducted semi- structured interviews with social media managers, as explained in the methodology chapter. The first section of this findings and analysis chapter (Section 4.1), provides the results from the data obtained from these managers (Sections 4.1.1 and 4.1.2), followed by the results of the data collected from customers (Section 4.1.3).

4.1.1 Data collected from social media managers

A survey consisting of 20 questions was administered through Qualtrics to collect data about the social media usage patterns and demographic details of social media managers (see Appendix 3: Transcripts of Interview with Omani Telecom Managers). The results of this survey are presented here.

4.1.1.1 Survey results

Responses were received from all sixteen managers who were requested to complete a questionnaire. The responses were recorded in Qualtrics from 21st May 2016, 8:18 pm through to 31st May 2016, 9:04 am.

4.1.1.1.1 Demographic details

The first question, aimed at identifying respondents' job titles, illustrated that many telecom firms in Oman do not have a specific Social Media Manager position. Instead, the responsibilities of this role were handled by various people with designations such as marketing managers, brand managers, event managers and customer care officers, etc.

When asked how long they had been in their current position more than 50% of respondents had been employed in their current position for at least 15 years or more; 40% for the last 1 to 5 years; and 10% for the last 10 to 15 years. This data is presented in the following chart (Figure 51).

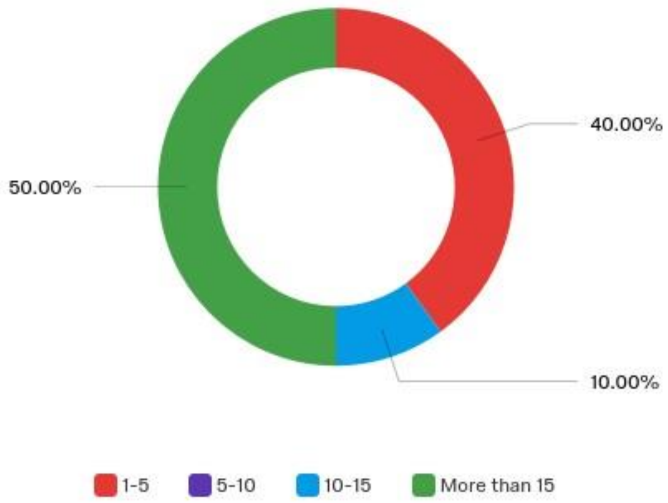

Figure 51: Number of years in current position for social media managers (n=16).

As the next question related to gender illustrated, all 16 respondents were male showing it is a role handled by men in all the Omani telecom firms that participated in the survey. Therefore, a further exploration of gender difference was not carried out.

The question related to age group revealed that the majority of managers (80%) were 30 to 50 years old. The percentage of respondents between 20 and 30 years old and 50 and above, equated to 10% each. The following chart shows this distribution graphically (Figure 52).

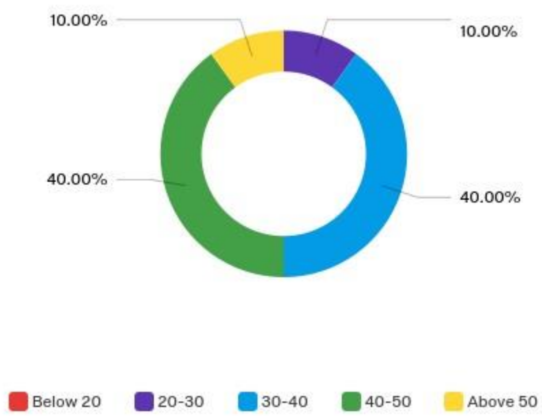

Figure 52: Age groups of the participating managers (n=16)

4.1.1.1.2 Social media usage patterns

When we asked about the respondents' active participation with social media, 80% of managers agreed that their firm is very active on social media. Only 20%

of respondents said that they did not use social media at all. Figure 53 shows this scenario graphically.

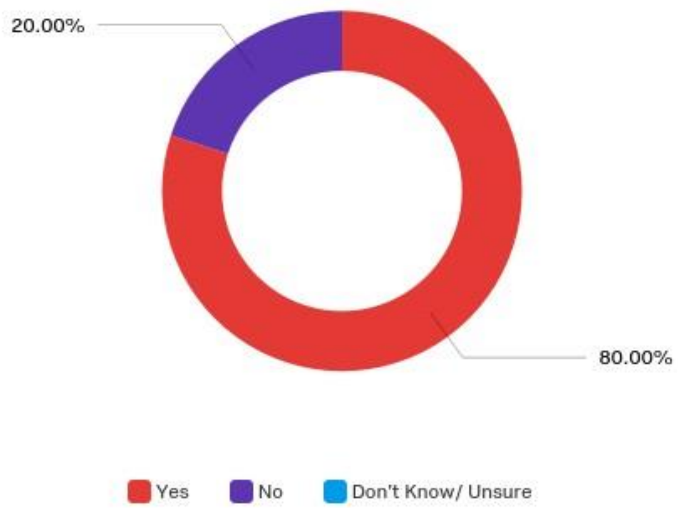

Figure 53: Social media usage (n=16).

Further to this, from the question on social media activity it was revealed that Twitter is the most sought-after social media platform with 30% of managers endorsing it. This was followed by Facebook, LinkedIn and Google+. Figure 54 illustrates this scenario.

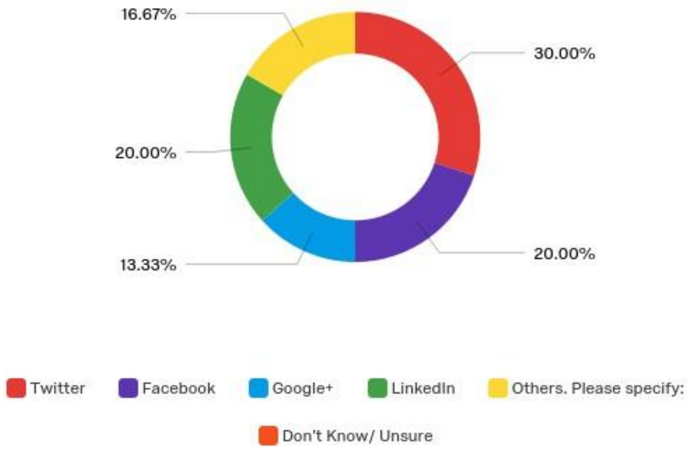

Figure 54: Social media platforms in use (n=16)

Four respondents (16.67%) also opted for Instagram which was observed as an active platform used less than LinkedIn but more than Google+.

When asked about the frequency of updating social media content, 40% of respondents said their organisation's social media profile is updated every day. 10% of respondents said that their firm's social media profile is updated at least bi-weekly. Amongst the others, 10% responded that their organisation's profile is updated monthly, or only when there is a product launch, promotion or special offer. This information is provided in the following pie chart (Figure 55)

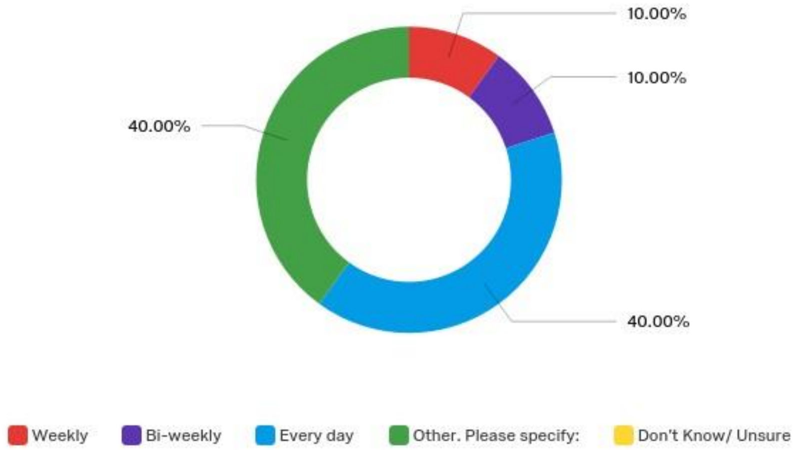

Figure 55: Frequency of profile update (n=16)

In order to understand this further, I asked about the purpose of each firm's profile page on social media. Approximately 29% of managers mentioned that a firm's profile is maintained merely to provide the basic details of the organisation. Twenty-five percent said that social media is used to advertise a promotion, product or service and another 25% opined that their profile page is used as a way of contacting customers. Job recruitment and "supporter", or "follower", measures were observed by another 10%, respectively. The following figure illustrates these details graphically.

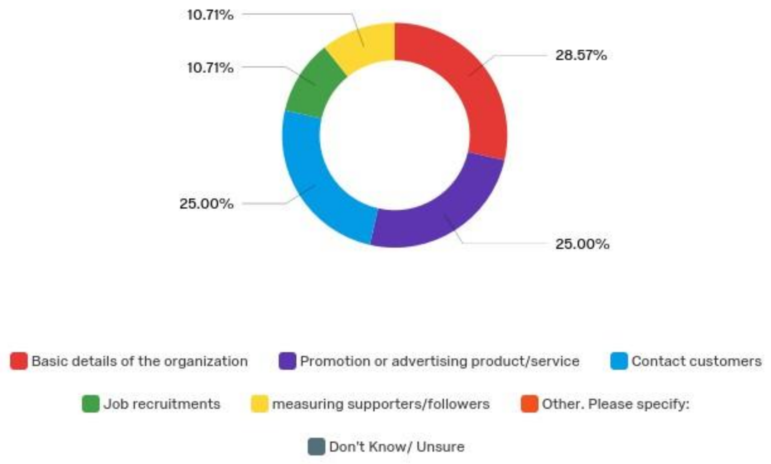

Figure 56: Purpose of a firm's social media profile page (n=16)

The next question, asked users to rate each social network platform as being either "Significant", "Some advantages", "Neutral", "Very few advantages" and "No advantages" on a 5-point Likert scale. The chart and its data are presented in Table 10 and Figure 57 below. The following table shows the raw data collected for each platform in terms of percentage of social media managers.

Platform	Significance	Some advantage	Neutral	Very few advantage	No advantage
Twitter	70%	30%	0%	0%	0%
Instagram	67%	0%	33%	0%	0%
Facebook	44%	44%	11%	0%	0%
LinkedIn	22%	67%	11%	0%	0%
Google+	0%	44%	11%	33%	11%

Table 10: Significance of social media platforms

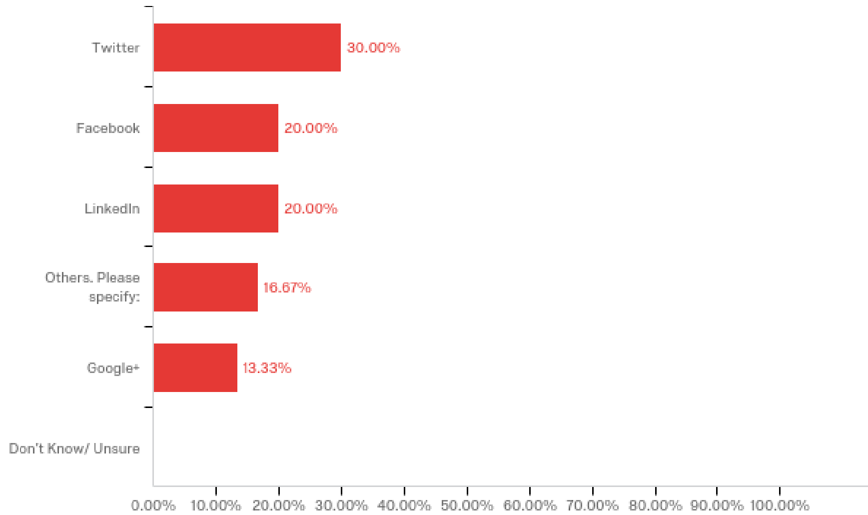

Figure 57: Managers' ratings of social media platforms (n=16)

The above charts illustrate the following facts:

- Twitter is considered to be the most significant social media platform by 30% of managers, followed by Facebook and LinkedIn with 20% (Figure 57).
- Twitter is considered to be the most significant social media platform by 70% of managers, followed by Instagram with 67% and Facebook with 44% (Table 10).
- The least significant platform was found to be Google+.
- Around 67% of managers stated that LinkedIn brings some advantages to their firms, followed by Google+ with 40% and Facebook with 40%.
- 11% of managers opined that Google+ brings no advantage to their firms.

4.1.1.1.3 Marketing strategy

The next part of the questionnaire focused on marketing strategy. Firstly, I asked whether there is a link between marketing strategy and social media coverage. Ninety percent of managers agreed that there is a clear link between marketing strategy and social media coverage (Figure 58).

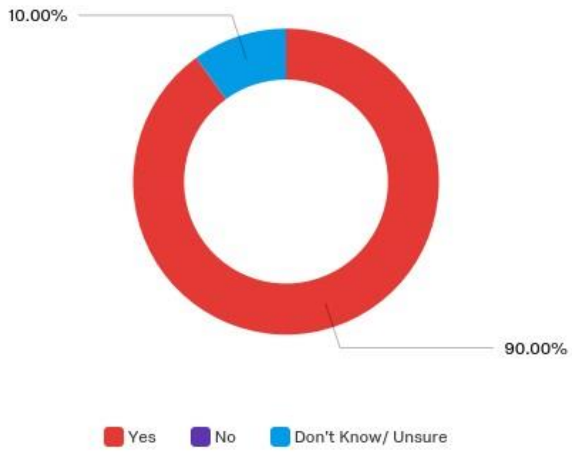

Figure 58: Link between marketing strategy and social media coverage (n=16)

As indicated in the above figure, Omani telecom firms make deliberate attempts to link their marketing strategy with their social media coverage. Conversely, approximately 10% of managers were not aware of any such linkage. Thus, I asked open-ended questions in an attempt to obtain further clarification on this issue. I received further input from the second manager, in particular, who described this connection as being innovative. He went on further to state that: "*The link is in stimulating some innovative ideas from the audience, as well as getting some good insight into how the customer(s) perceive the company*". This shows that firms are open to their customers, and are keen to understand what their customers think of the firm and its services.

Another manager enunciated, *"Social media is becoming the most important channel for approaching clients and customers and understanding their behaviours and needs; these types of information are very critical in establishing and implementing the organisation's [marketing] strategy".* This is in accordance with what the studies of Xu and Walton (2005) concluded as being the best customer relationship strategies for an organisation to follow, which are:

- improved customer satisfaction;
- retaining a customer base;
- obtaining strategic information; and
- enhancing the value of the customer lifetime.

Another manager also supported this view by confirming that such alignment opens up two-way channels of communication, and he cited the lower costs and wider customer reach obtained by a company by doing so. Therefore, it is commonly agreed amongst managers thatsocial media is a powerful vehicle for transferring strong messages to a targeted audience. They also agreed that social media is suitable platform to obtain immediate customer feedback on promotions and offers.

4.1.1.1.4 Customer support

The next part of the survey focused on customer support. Nguyen et al. (2007) specified that the most important objectives of CRM are:

- increasing customer loyalty (obtaining and making information about customers available across the organisation);
- superior data collection and sharing (maintaining an updated history of customers and their interactions);
- knowing customers and providing a superior service (using all information about customers' habits and interactions with an organisation to provide information about products and/or services tailored to the needs of each customer).

Providing high-quality customer support is an extremely vital step towards achieving better CRM practices. Therefore, my first question in this section was aimed at finding out whether Omani telecom firms provide online customer support. The results revealed that 80% of the managers confirmed that their firms provide online customer support, 10% said that their firms do not provide online customer support with the remaining 10% of managers being unsure (as shown in Figure 59).

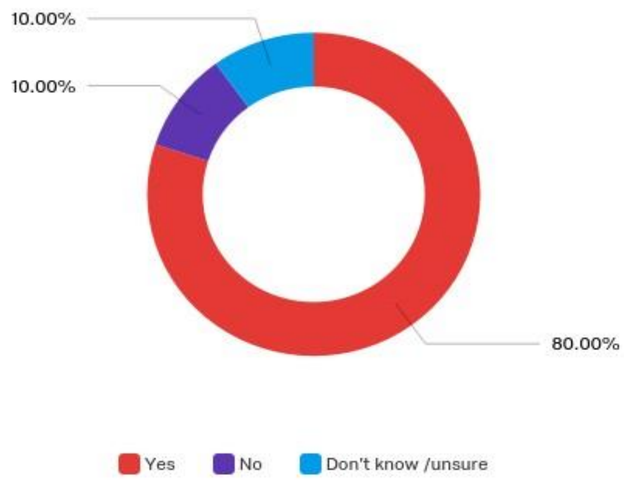

Figure 59: Online Customer Support by Omani telecom firms (n=16)

Keeping in touch with customers is essentially a continuous, analytical and strategic approach, that is necessary to identify potential customers, and should be built-in and proactively integrated within the processes of the business. It is important that businesses are in touch with customers in real-time and that feedback on every service, or offers, are obtained from time to time.

Therefore, I asked whether there was any mechanism available for managers to monitor current topics, trends or discussions, pertaining to the organisation. For this question, 70% of managers agreed that their firms do follow trends and discussions to get a feel for what messages have been reaching their customers; 10% said they do not have any such mechanism in place; and another 20% were not aware of such process in their organisation (Figure 60).

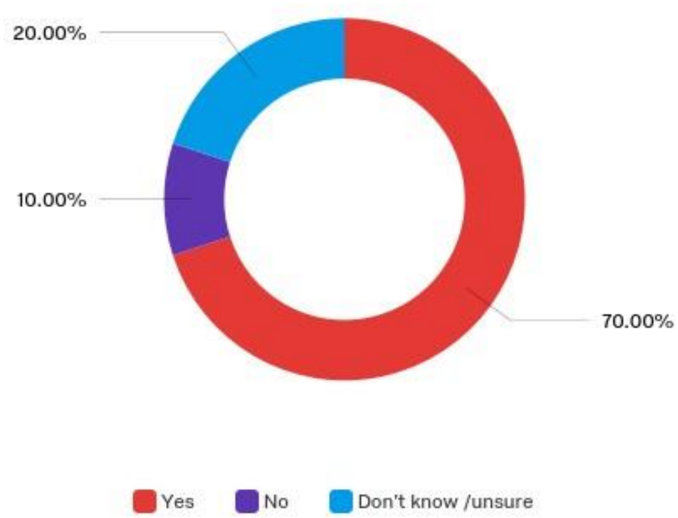

Figure 60: Monitoring current topics in Omani telecom firms (n=16)

Monitoring trends and discussions is vital; it provides a vast amount of rich information which enables firms to cater for different segments that should, in theory, result in increased profitability (Leventhal and Zineldin, 2006). This type of analysis provides current and in depth information which can be of great benefit to the organisation. For example, it can be used to draft effective marketing strategies, provide insight and knowledge of the learning limitations of competitors, and capitalise on these limitations to lure new customers. Leventhal and Zineldin (2006) pointed out that the main use of CRM is to engage in defensive marketing which enables firms to understand why their customers leave and thereby initiate a suitable

customer retention program. They suggest that the implementation of such a retention program not only improves customer retention but also increases customer satisfaction, and hence profitability.

4.1.1.1.5 The application of sentiment analysis tools

Using the discussions taking place on social media it is possible to put sentiment analysis into practice, and obtain an opinion about how healthy the images of the brands are. Therefore, I asked the social media managers whether they were aware of any such tools in their firms. I included all sorts of alternative tools such as opinion mining, text mining or sentiment detection. And while 71% percent of the managers informed me that they are aware of sentiment analysis, about 29% said they did not know of the existence of any such tools (Figure 61).

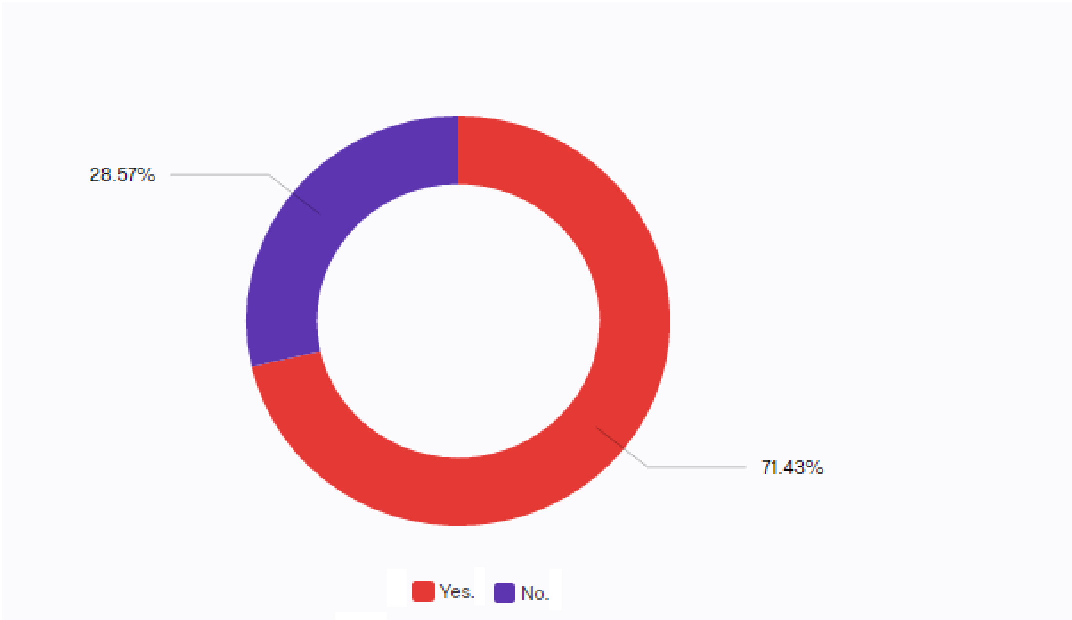

Figure 61: Awareness of sentiment analysis amongst managers (n=16)

Further to this, those mangers who knew about sentiment analysis were further asked about the presence of any such tools in their firms. Thirty-eight percent of the managers said that they saw such tools in use in their firms, and about 25% said they had not. Out of those mangers who were aware of the existence of sentiment analysis, 25% did not know or were unsure about the use of such tools in their organisation. About 12.5% of the mangers knew the names of the tools used in their organisation (Figure 62).

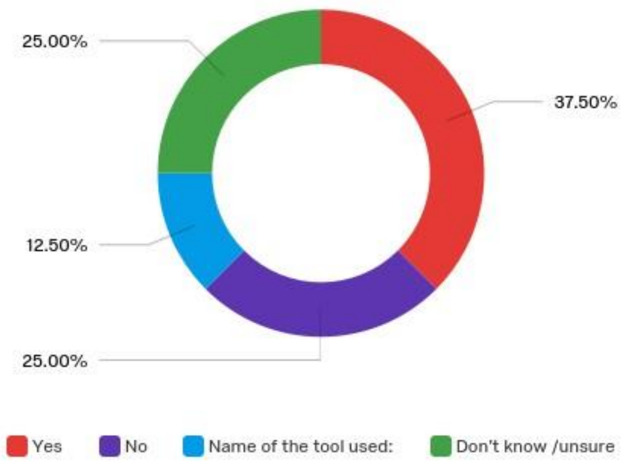

Figure 62: Use of sentiment analysis in social managers' firms (n=16)

I further established how sentiment analysis tools were built, i.e. in-house or outsourced. About 63% of the managers said that their organisation outsources both the developing and managing of sentiment analysis tools, whereas 25% of the managers informed us that they are built in-house. About 12% of the managers were not sure how such tools are implemented in their organisation (Figure 63).

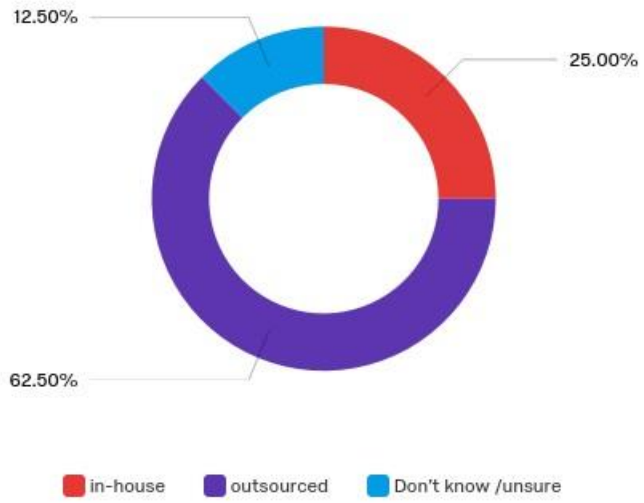

Figure 63: Implementation of sentiment analysis tools (n=16)

When asked if they were aware of any issues with the present tools, 62.5% of the managers were not sure, 25% informed us that there are no issues with the present tools,

and only 12.5% of the respondents said that there is a problem with the existing tools.

The next question asked about the level of contribution sentiment analysis provides to the organisation; this was an open-ended question that revealed many details. One respondent reflected, *"… it helps the organisation to assess the existing strategy, bridge the gaps and rectify the challenges". Another* said, *"… it is very important as it gives insight to the voice of customer"*. Another respondent, aptly, said that sentiment analysis tools are useful to analyse "*… consumer concern and behaviour"* whilst another agreed that these tools are *"… very effective and getting instant feedback and proactive resolution for any unhappy customers"*. Overall managers accepted that sentiment analysis tools are *"… a very useful tool for high-level management to make decisions".*

As a final question, I provided a list of the following options to ask managers how sentiment analysis was or would be useful in their organisations in the future, as follows:

- to receive both positive and negative comments about campaigns;
- to establish the popularity of the organisation on social networks;
- to increase profit;
- to analyse and compare themselves against competitors;
- all of the above;
- any other reason (please specify).

The responses provided are shown in the following chart (Figure 64). It is interesting to note that the respondents chose reasons such as increasing profit or measuring the popularity of the organisation. The most important reason identified for using sentiment analysis tools is to ascertain what positive and negative comments are being made about the organisation.

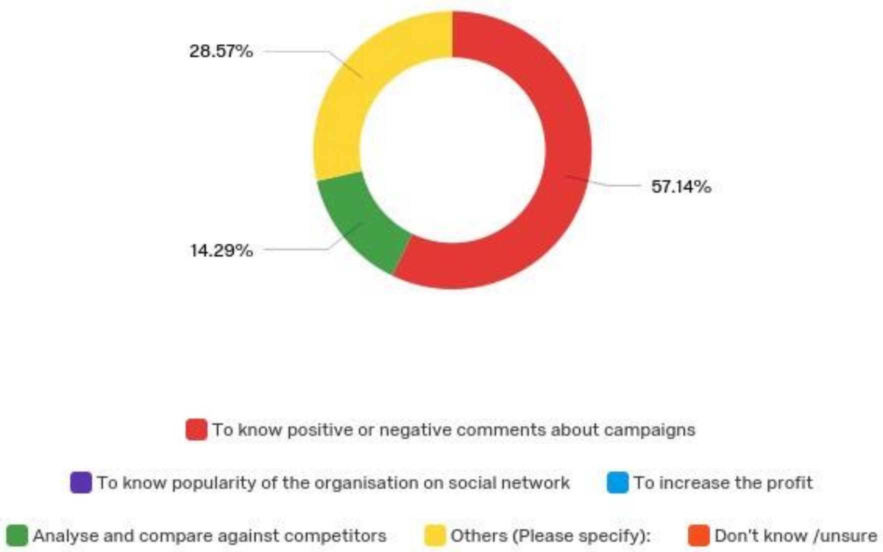

Figure 64: Best use of sentiment analysis (n=16)

Respondents that chose "others" specified in their comments that they saw more than one option being applicable (such as "To know positive or negative comments about campaigns" and "To know the popularity of the organisation on social networks"). This again reinforces our assumptions about the important contributions sentiment analysis can bring to market research.

4.1.2 Interview results

Semi-structured interviews were conducted using a custom-developed user guide (Appendix 1: Interview Guide (Social Media Managers) for semi-structured interviews). This user guide consisted of four themes, namely: Customer Relationship Orientation, Social Media Usage, Social CRM capabilities and Customer Relationship Performance. The data obtained and their results are presented here.

As the semi-structured interviews were designed to bring out qualitative information, I also conducted sentiment analysis on this data using NVivo (as described in the Methodology section).

4.1.2.1 Outcomes of the discussion

The interviews were structured in such a way that I collected all information pertaining to the interviewee, such as their background, the current sentiment analysis practices in his or her organisation and their familiarity with sentiment analysis tools. I also gathered qualitative information about the problems they faced in using such tools. I then tried to correlate how those practices would affect profitability and share price. Finally, I asked the interviewees about the relevance of sentiment analysis as a promising and appropriate customer service or marketing tool.

The excerpts from each interviewee are provided here for analysis and interpretation. For anonymity the interviewees were referred to in my dataset as SM1, SM2, SM3 and SM4 and their Omani telecom providers were referred to as A, B, C and D.

4.1.2.1.1. The interviewees backgrounds

The first interview was conducted with the general manager of projects for one of the utility providers for telecom services (Telecom B). This interviewee previously worked for one of the biggest telecom operators in Oman as a manager in the access network planning and design department. In his present company he recently moved from the planning department into the project department to take up a new role.

The second interviewee was a senior manager for Telecom A. The company operates a customer management system responsible for a leading telecom provider's interfacing system which is used by customers. Services offered include mobile apps, online chatting or online services, websites, CRM applications, billing platforms, analytical tools, big data and so on. He has been with the organisation for more than eighteen years in the same telecom domain.

The third interviewee was a social media manager at Telecom C. His role is basically to oversee and manage the firm's presence on different social media platforms like Facebook, Twitter, YouTube, LinkedIn, Snapchat and Soundcloud, etc.. His role also includes two main aspects: content and customer service.

The last interview was conducted with an employee at Telecom D who had worked there for ten years. He is currently employed as the Director of Corporate Affairs and Government Relations.

4.1.2.1.2. Social media presence

The interviewees were asked about the sentiment analysis processes that currently exist in the organisation in order to gain a deeper understanding of the scenario in the Omani telecom sector. The first manager explained in detail where, how and why he considers the growth and presence of social media to be important. He stated:

> "Social media has been a really powerful tool and it has made a complete change in the way the company communicates and interacts with their customers. So far I can see that most of the telecom operators in our country have really made quite a substantial use of social media and it has really strengthened the way they have positioned their brands, the way they advertise their products and services, as well as the way they manage their approach to customer service and customer relations. Social media has also been a powerful tool for communicating any incidents, cable cuts and service interruptions proactively".

Few Omani telecom organisations have included social media as a part of their customer care process. For example, the second manager illustrated that his organisation has a dedicated group, headed by a manager, who are specifically responsible for looking into social media activities. He said, *"…we have specific tools which also monitor the responses, the social media trends and customer feedback, etc., in real time"*. This trend is clearly felt across all the Omani telecom firms focused on social media. The third manager provided additional details, such as how active they are on social media on a daily basis–normally more than once per day. Firms tend to use social media at different times based on when their users are most active, so that they can post their content at that time on the different platforms. In addition, they also implement different updating intervals, i.e. frequency changes or variations between different channels. For example, posts on Facebook are less frequent, but Twitter is a fast-moving channel so posts are more frequent.

The forth manager, from a leading Omani telecom company, enunciates how his firm has evolved into using the social media platforms. He commented:

> "We started with Facebook as, at the time, this was the main platform that people were using. Soon after we very quickly launched our Twitter account. We were the leading social media users at that time, and probably still are to a certain extent. We use social media as a customer service tool rather than a tool just to broadcast information. We use it as a two-way communication platform and consider it be the pulse for our customers. We know very quickly when there is a problem with the social media platforms, for example, if there is a technical problem in a certain area. We know this before anyone calls us".

Information relating to the evolution of social media is very useful as it enables us to gain a better understanding of how important social media is perceived by telecoms organisations in Oman. In addition, I can conclude that my observations of this transformation towards the accelerated usage of social media are in line with findings in the literature review. Kumar and Reinartz (2005) provided a timeline of CRM to show how a shift from transactional marketing to relational marketing raises the economic value of a customer for a firm. They reiterate the use of customer value which emphasises the benefit of long-term customer relationships instead of short-term sales goals.

Therefore, I can conclude that the scenario in the Omani telecoms industry is well into its third generation, where customer service is approached as an integrated service.

4.1.2.1.3. Familiarity with SA tools

After understanding the state of CRM and observing its growth, I focused my discussion with respondents on their familiary, or their firms', familiarity with sentiment analysis. All four managers shared their experiences in their respective organisations, and this provides us with more insight and a deeper level of understanding about the current situation in the Oman telecom sector.

The first manger enunciated how sentiment analysis is utilized by stating:

> "Yes we do monitor all the social media firms and the chats. Therefore, if someone says something good about our organisation, for example, then we capture that. Also, if someone is upset and is not happy, we take that, analyse it and then we establish a connection with the customer to try to understand the specific problem and see how we can resolve it; we always will resolve it. We also give a lot of statistics to our management team to show them the latest social media trends. The feedback that we are getting is either positive or negative to our brand and we get all these kinds of statistics from the tools".

This response clearly shows that both he and his firm are aware of the procedures required to capture social media data, and have a system in place to feedback metrics to the relevant, designated members of the organisation for further processing. Furthermore, as discussed in the literature review, the use of sentiment analysis to track the image of the corporate brand and how this is perceived by customers is vital. Via discussions taking place in social media, it is therefore possible to put sentiment analysis into practice and obtain information about how healthy the images of the brands are.

The second manager opined that monitoring the behaviour of the organisation's followers and the general public enables an organisation to monitor current trends. He also illustrated that they go to the extent of monitoring their competitors to be aware of any trends which are being shared and actively discussed. Thus, as confirmed in the literature review, to know and understand both their customers and their competitors will help an organisation in many ways.

Firstly, knowing about customers is a process that is essentially continuous, analytical and strategic; thus, the process of identifying potential customers should be built-in and proactively integrated within the processes of the business. Secondly, the information received from customers, as well as competitors, will enable firms to cater for different segments and this will ultimately result in increased profitability. Thirdly, trending discussions can provide organisations with the most pertinent and up-to-date information which can be used to draft targeted marketing strategies as well as learning about the limitations of their competitors and capitalising on them to attract new customers.

All of the steps outlined above, are being consciously instigated by companies for them to better understand why customers are leaving, and this also forms the basis and structure of their customer retention programme. The implementation of such retention programmes not only improves the rate of customer retention but also increases the level of customer satisfaction and profitability.

From the responses received it is clear that the telecom companies involved in this study are aware of the potential benefits associated with using social media to keep abreast of their customers and competitors. The answers given by social media managers confirm that there is a deliberate attempt by managers to capitalise on the use of sentiment analysis in their respective organisations.

4.1.2.1.4. Problems with using SA tools

The managers' answers to the question on this topic highlighted the issues relating to language and images. The first manger gave the following statement when asked about the challenges he encountered while using sentiment tools:
"It is difficult when people write in Arabic when using Roman numerals as there is a lot of conversation that happens online that is not [written] in Arabic. Well, they are in Arabic, but they are in this English, you know, type, with the letter "A", you know. So how is that captured? Is it there? Where is it?, you know, and so on. Then you have, at least if I remember correctly, the challenge to aggregate and get rich sentiments and information across platforms. So maybe now, I think, some tools can go across platforms but in the past there was a big problem. How can I look at my online sort of personality across platforms? Do people

on Facebook like me more? Or on Twitter more? Or is there a sort of cross between them? Am I able to get an overall online picture without looking at Facebook and Twitter specifically? Am I able to look at the scenario? So this will continue to be a challenge I think - the cross-platform analysis of data".

This response portrays the fear of relying on the information obtained from a single platform; as a user may show a different face on a different platform. Obtaining a perspective of such "colours" across the platform remains critical.

The second manager explained that obtaining sentiments from discussions and trending topics indeed assists organisations to devise their strategy and customer segmentation. At the same time, he felt that if we could extract more than just positive and negative sentiments it would be very useful.

It is interesting to note that my version of the "Wheel of Emotion" will most certainly address this issue and by using such a tool, organisations can obtain a spectrum of sentiments, or, rather, a spectrum of emotions on each and every issue that is trending and/or being followed on social media.

4.1.2.2 Sentiment analysis of the interview transcripts

I prepared transcripts of each of the interviews, and subjected these interview texts to sentiment analysis. This section illustrates the outcome of the analysis and explains how this helped me to establish further conclusions from the semi-structured interviews conducted with the managers of the Omani telecom firms.

4.1.2.2.1 A WordCloud of important terms

The following WordCloud shows the important terms and dialogue that was used by the managers during their interviews. In order to see the important terms appearing in discussion with social media managers I created a WordCloud, a Tree Map and a cluster analysis to observe what words arose most often in our discussions.

Figure 65: WordCloud illustrating the terminology used in interviews with social media manager's

As you can see, Figure 65 highlights that words such as "social" and "media" were the two most prominent words being discussed during the interviews. Further to this, WordCloud Tree Maps also help us to understand how these discussions proceeded.

4.1.2.2.2 A Tree Map of the most frequent words

The following Tree Map (Figure 66) shows how the most frequent words, such as "social" and "media", branch out further in the interview discussions. Words such as "tool", "yes" and "know" advance on this tree and move onto a discussion of social media managers' brands, customers, markets, etc. Inspection of the following Tree Map offers further insights into the path of discussion.

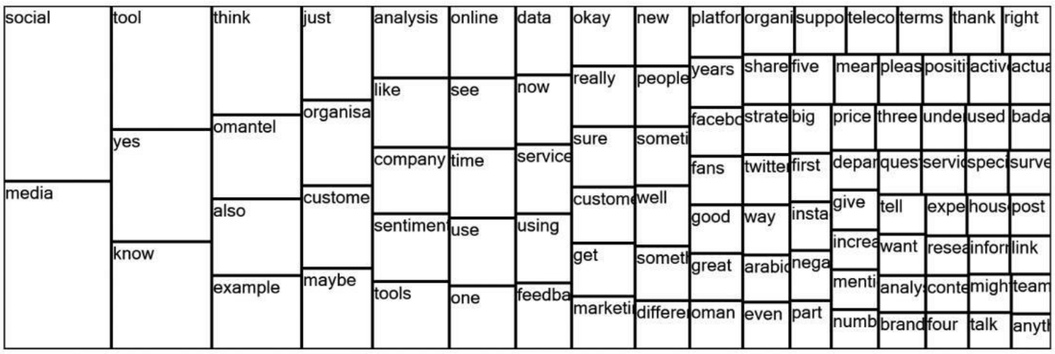

Figure 66: Tree Map of interview speeches

During the next stage of my analysis I ran a cluster analysis. The following section shows how the WordClouds gave rise to Tree Maps, and my further exploration of cluster analysis.

4.1.2.2.3 Hierarchy chart and comparison diagram

The following hierarchy chart is arranged based on the topics of the semi-structured interviews. The chart offers further insights into the interview discussion in terms of the "weight" of the entire text (with weight referring to how often each topic was discussed in comparison with the others). As you can see from Figure 67, almost all topics were discussed equally with additional sentiment analysis-related topics arising from the discussion.

Figure 67: Hierarchy Chart

A comparison diagram, offers additional insights on the discussions between the interviewer and the interviewees (Figure 68).

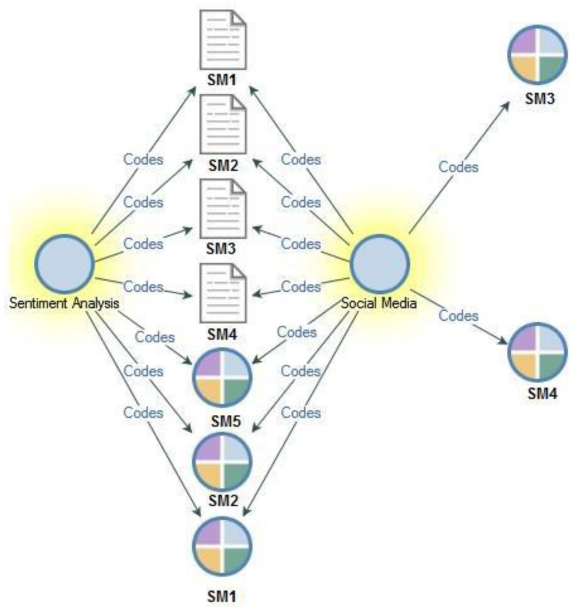

Figure 68: Comparison Diagram

The comparison diagram enables us to see the relationship between sentiment analysis and social media. NVivo generates comparison diagrams that include various items like sources, nodes or cases. These help us see differences and similarities within the data. In Figure 68 there is a clear linkage in the discussions with the managers. Most of these SM's envisage stronger connections between social media and sentiment analysis in the future. Although the codes for SM3 and SM4 do not involve this connection, further nodes related to their discussion texts points to a rigid connection between sentiment analysis and social media.

The analysis of the discussion seems to connect sentiment analysis with social media. The codes and nodes chosen for the analysis directs us to conclude that all the interviewees are equally contributing to the process of building relationships between topics. The structure of the nodes was designed to coincide with the structure of the interview in a variety of areas, such as background, SA practices, familiarity with SA, problems, profitability and the possibility of better customer service.

Table 11 shows the structure of the nodes and their level and order. The node structure presented here is in line with the structure developed for the semi- structured interviews, as explained in the methodology chapter. The table consists of 5 columns, including names of the nodes and their location (directory path) in the NVivo project. The list level shows the number of any existing child nodes; all the nodes presented here are the first level child nodes. The list order indicates the order of precedence of nodes that is being discussed in the analysis.

Name	Node Type	Folder Location	List Level	List Order
Background	Node	Nodes/Interview Questions	1	1
Current SA practices	Node	Nodes/Interview Questions	1	8
Familiarity with SA tool	Node	Nodes/Interview Questions	1	6
Problems in using SA tools	Node	Nodes/Interview Questions	1	7
SA and profitability	Node	Nodes/Interview Questions	1	3
SA and share price	Node	Nodes/Interview Questions	1	4
SA as a customer service tool	Node	Nodes/Interview Questions	1	5
SA as a promising marketing tool	Node	Nodes/Interview Questions	1	2
Sentiment Analysis	Node	Nodes	1	1
Sentiment Analysis	Results Node	Results	1	2
Social Media	Node	Nodes	1	2
Social Media	Results Node	Results	1	1

Table 11: Node structure

4.1.2.2.4 Sentiment scores

The content of the managers' dialogue and terminology used during their interviews were subjected to detailed sentiment analysis to obtain sentiment scores. NVivo categorised the sentiment scores into four broad categories which are "very negative", "moderately negative", "moderately positive" and "very positive". The outcome of this analysis is presented in the following table. The rows refer to each SM and the columns depict the sentiment score category. The highlighted boxes refer to the maximum score obtained for each of the categories.

Cases	A Very negative	B Moderately negative	C Moderately positive	D Very positive
1. Internals//SM1	1	1	15	7
2. Internals//SM2	1	3	10	10
3. Internals//SM3	1	6	8	1
4. Internals//SM4	3	6	9	3

Table 12: Managers' sentiment scores based on interview dialogue

As we can see, the maximum "moderately positive" scores were obtained by SM1 and the highest "very negative" score (of 3) was given by SM4. Fifteen was the highest score obtained for "moderately positive". And the lowest score – 1 – was scattered across "very negative", "moderately negative" and "very positive". We can observe that most of their speech swayed towards positive. In particular, the whole discussion is clustered around "moderately positive" and "very positive" (as shown in Table 12).

We can obtain further insights on the above scores by considering the following 3D chart (Figure 69) which shows sentiment scores plotted with respect to classification.

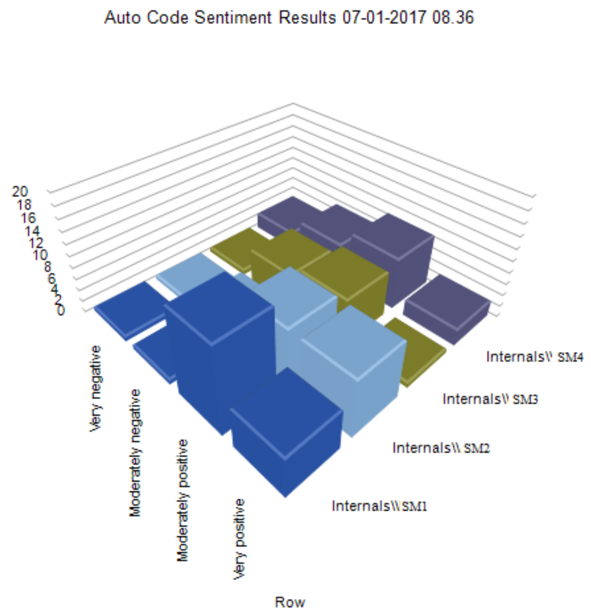

Figure 69: Sentiment results

On exploring the nodes, developed based on the themes of the semi-structured interviews (as explained in the methodology), the following node diagram shows quantitative information gathered for the sentiment scores of each topic that was discussed in the interview.

Figure 70: Node diagram

The diagram shows that when the discussion revolves around sentiment analysis as a marketing tool the outcome is mixed, rather than completely positive or negative; so, although there are positive and neutral scores the mixed sentiment is influential on this topic. When the discussion moves towards the problems of using sentiment analysis tools the outcome indicates mixed *and* positive sentiment scores. There are no negative sentiment scores, and almost no discussions which displayed negative scores as a majority; which illustrates that these discussions are taking shape in a positive atmosphere. Thus, I was able to build a diagram (Figure 71) to show the evolving themes of discussion arranged hierarchically based on each term, and by utilising the previous Tree Maps.

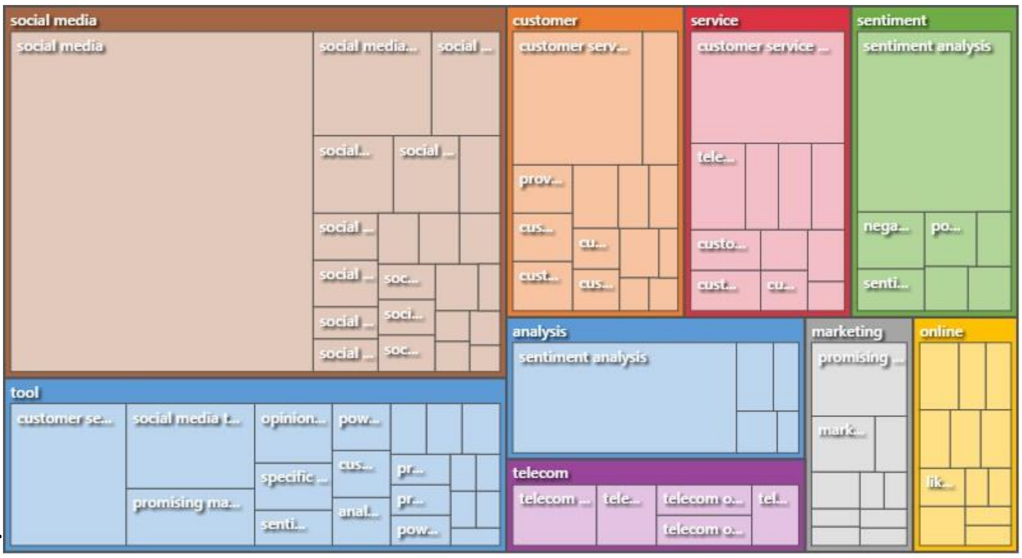

Figure 71: Evolving themes in the interview discussions

The major theme "social media" was the most influential theme discussed and is followed by "customer", "service", "sentiment" and "marketing".

The top 50 list of words that appear in the interview script also illustrate similar trends (Table 13):

Rank	Word	Count	Weighted Percentage (%)	Rank	Word3	Count	Weighted Percentage (%)
1	Social	120	2.52	26	service	25	0.53
2	media	115	2.42	27	Using	25	0.53
3	Tool	79	1.66	28	feedback	24	0.5
4	Yes	71	1.49	29	Okay	24	0.5
5	Know	68	1.43	30	Really	24	0.5
6	Think	62	1.3	31	Sure	24	0.5
7	OmanTel	48	1.01	32	customers	22	0.46
8	Also	43	0.9	33	Get	21	0.44
9	example	42	0.88	34	marketing	21	0.44
10	Just	42	0.88	35	New	21	0.44
11	organisation	38	0.8	36	people	21	0.44
12	customer	37	0.78	37	sometimes	21	0.44
13	maybe	36	0.76	38	Well	21	0.44
14	analysis	35	0.74	39	something	19	0.4
15	Like	34	0.71	40	different	17	0.36
16	company	33	0.69	41	platforms	17	0.36
17	sentiment	33	0.69	42	Years	17	0.36
18	Tools	33	0.69	43	Facebook	16	0.34
19	online	30	0.63	44	Fans	16	0.34
20	See	29	0.61	45	Good	16	0.34
21	Time	29	0.61	46	Great	16	0.34
22	Use	28	0.59	47	Oman	16	0.34
23	One	26	0.55	48	organisations	16	0.34
24	Data	25	0.53	49	support	16	0.34
25	Now	25	0.53	50	telecom	16	0.34

Table 13: List of the top 50 words

The next section shows the results from the customer survey.

4.1.3 Survey results collected from customers

In order to obtain information pertaining to customers' thoughts I used a different survey for customers (Appendix 4: Questionnaire for customers). This survey contained 24 questions that were designed to collect quantitative and qualitative data: the demographic details of respondents, their usage pattern of telecom services, their providers, as well as their acquaintance with social media.

4.1.3.1 Qualitative analysis

The customer survey (Appendix 4: Questionnaire for customers) brought out various features pertaining to the study. The questionnaire was bilingual as the majority of the customers' first language was Arabic. I present the collected information under each category: demographic information, details of the service providers and their services, and social media usage patterns.

4.1.3.2 Demography

The first question on gender brought out the fact that 72.2% of the customers were male and 26% were female; the remaining 1.7% did not want to disclose their gender (see Figure 72). It is important to note that this information was collected from a total of 455 respondents.

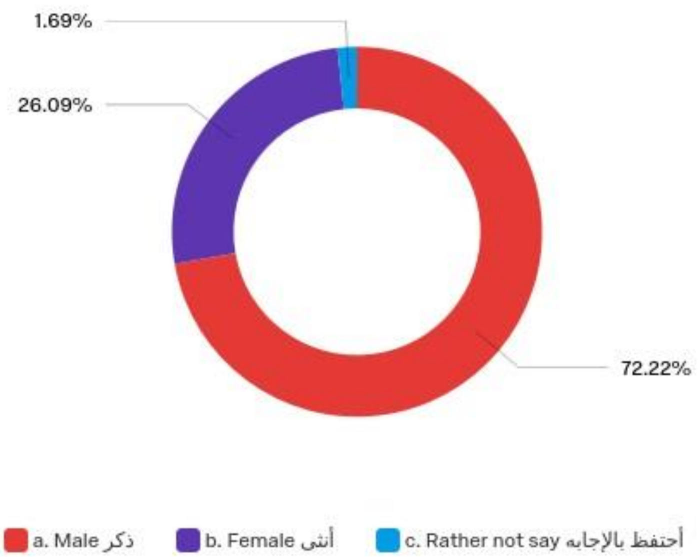

Figure 72: Gender distribution of respondents in the customer survey (n=455)

The next question showed that 49% of the customers were 30-40 years of age, 25.3% were 40-50, 21.2% were 20-30, and 2.41% were less than 19. Only 1.9% of the respondents were above 50 years. It is interesting to note here; the distribution is close to ideal normal distribution where a bell-shaped curve indicates a good sample of the population (Figure 73).

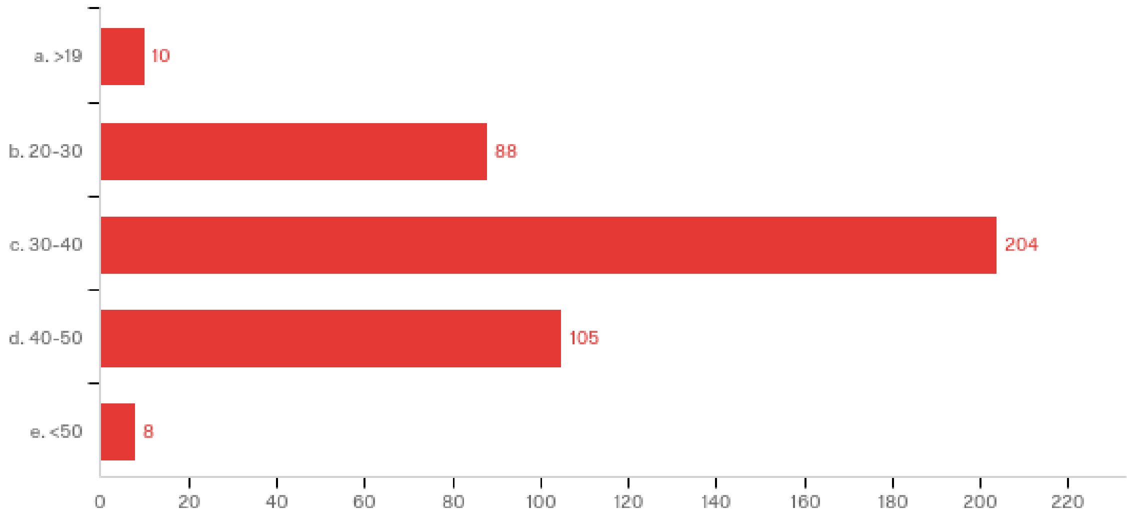

Figure 73: Age distribution of the respondents – bell-shaped normal distribution (n=455, $\bar{x}$ = 35.6 ± 9)

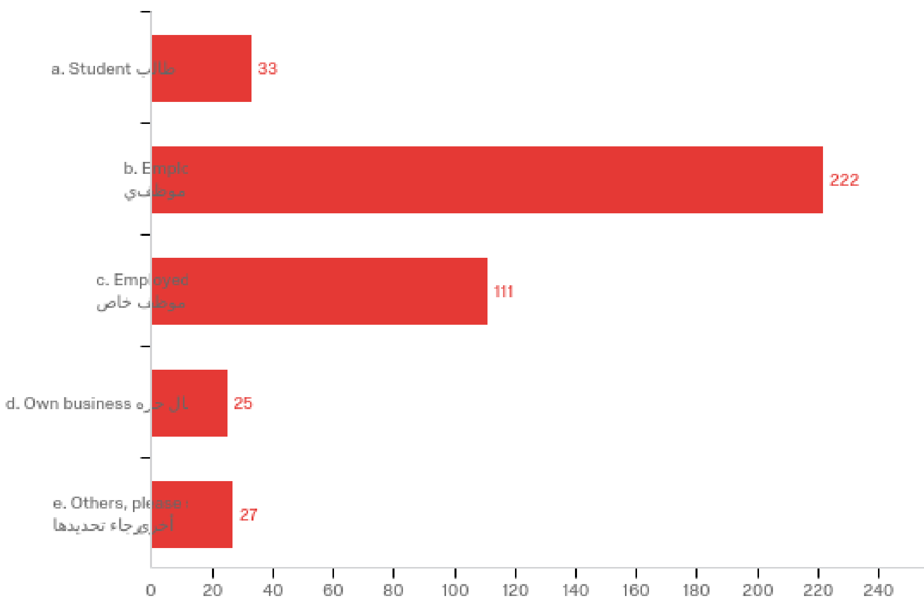

Figure 74: Employment status of the respondents (n=455)

The next question on the customer survey was related to the employment status of the customers. The majority of customers were working in the government sector (53%) followed by those employed in the private sector (26.6%). Amongst the customers, 7.9% were students and 6% owned their own business. There were about

6.5% others mainly comprised of pensioners and job seekers, etc. The data is graphically presented in Figure 74.

In order to identify the customer's ways of living, the fourth question in the customer survey focused on the region where they live. The majority of the customers (50%) were from the Muscat region which is the capital of the country. Next to this the Al Batinah North region is represented by 31.4% of the respondents. The other regions were represented by less than 7% (See Figure 75).

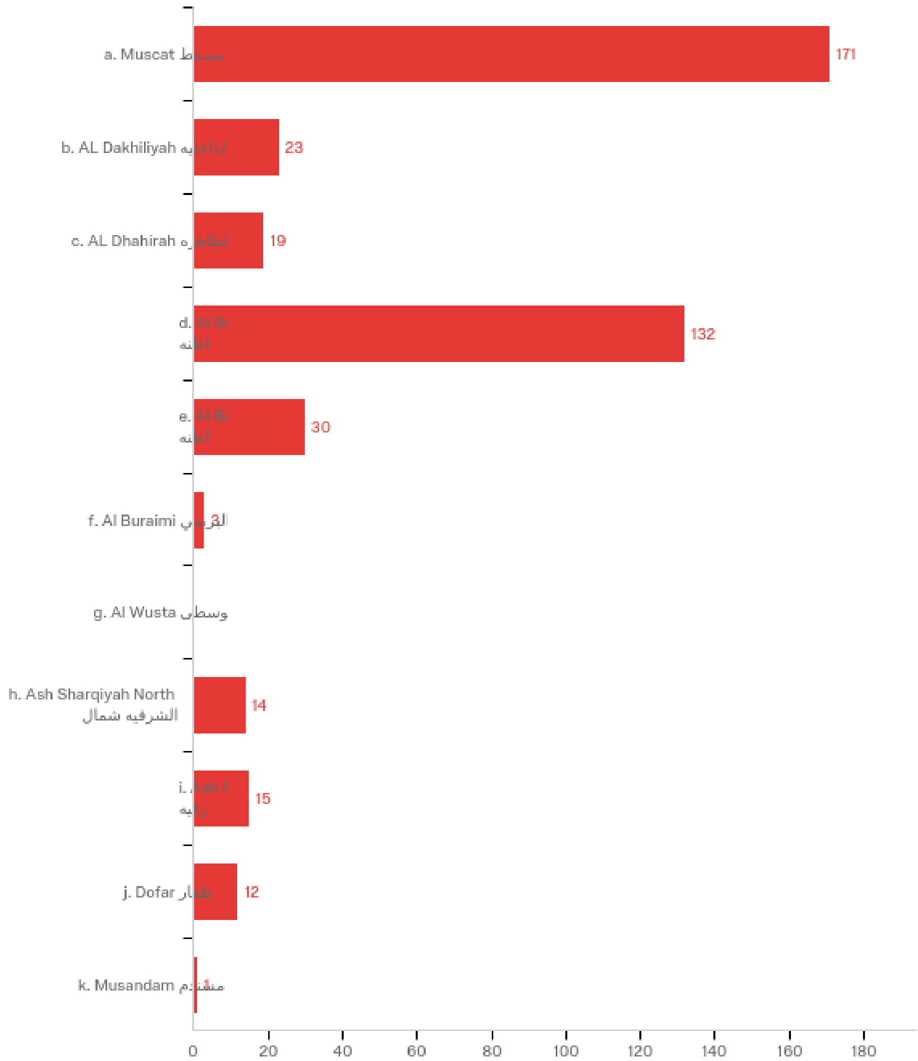

Figure 75: Region of living (n=455)

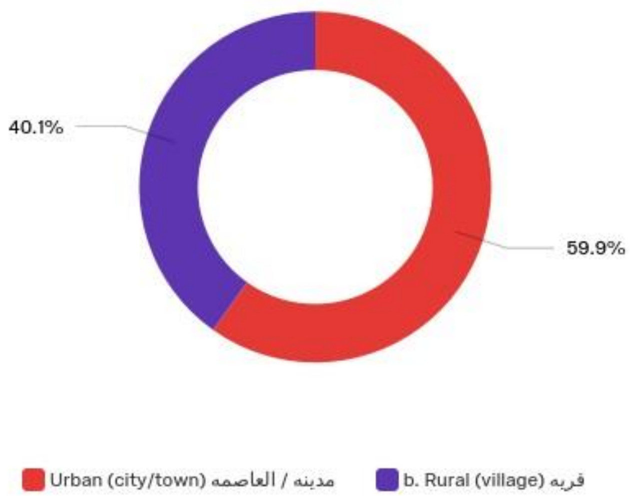

Figure 76: Type of area of living (n=455)

In order to determine whether the customers' region of residence is either urban or rural the fifth question confirmed the fact that about 60% of the respondents were from urban areas and the rest were from rural areas (Figure 76). This distribution typically reflects the Omani population and hence has representation from both types of areas. The next section brings out the data related to the service providers of the Omani telecom sector.

4.1.3.3 Details of the service providers and their services

Questions 6 to 9 focused on obtaining details about service providers and the services they provided to their customers. 64.8% of the respondents found OmanTel to be a major service provider; this was followed by Oredoo who provided services to 34% of the customers. Resellers, like Renna and Friendi, provided services to less than 1% of the respondents (Figure 77).

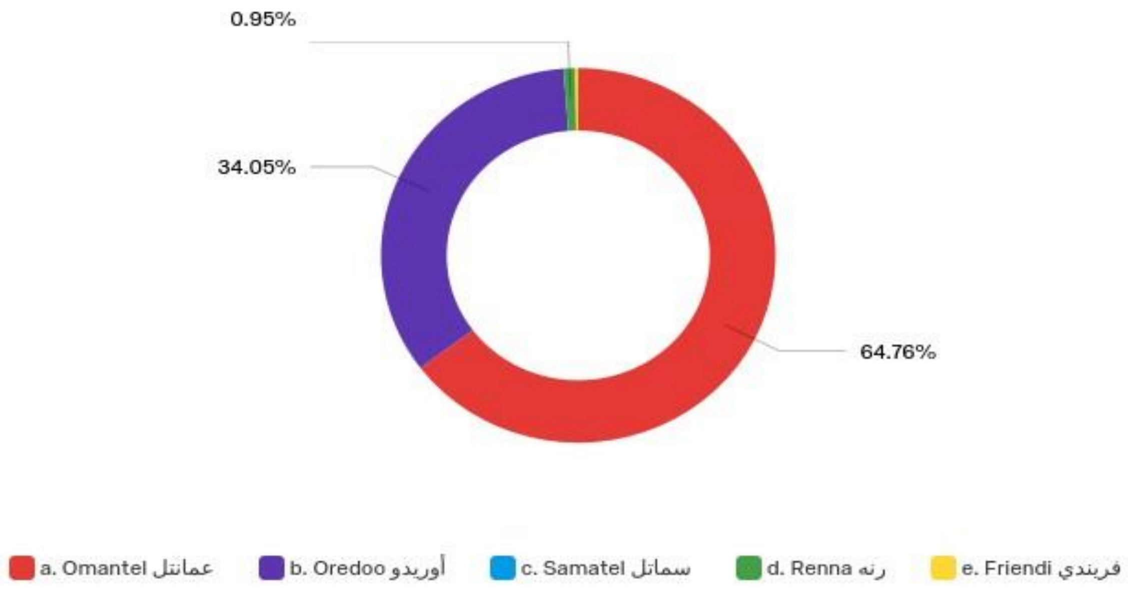

Figure 77: Service providers of the respondents (n=455)

I identified through the literature review that the most important reason for CRM use is to provide firms with an ongoing relationship that can provide a sense of trust, control and security. The literature reviews also brought out the fact that the primary reason for organisations to implement CRM are as follows:

- to improve customer satisfaction;
- to retain their customer base;
- to obtain strategic information; and
- to enhance the value of the customer lifetime.

CRM should enable corporations to build relationships and reach and maintain a prosperous market share. Its other benefits can be divided into the following two categories:

- Retentions: knowledge about customers, such as their names, habits, likes, dislikes and expectations, information which will facilitate customer retention.
- Intimacy and profits: information technology can help firms to create intimacy with their customers. This can also increase the degree of mutual trust between the customer and the organisation and ultimately lead to an increase in profits.

Considering these facts, my next question focused on identifying how highly service providers prioritised customer retention. This question was modelled on a 1-5 Likert scale with answers ranging from" Strongly Disagree" to "Strongly Agree".

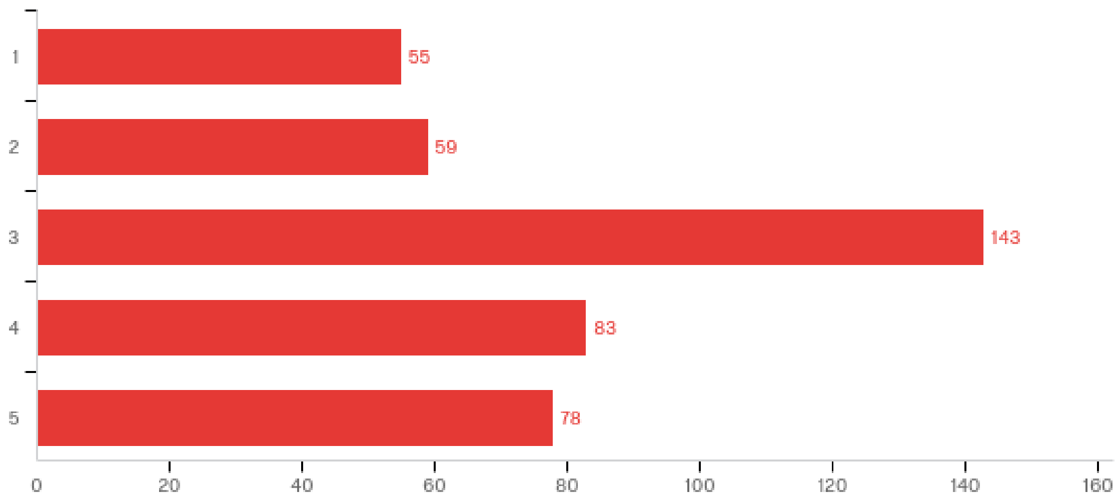

Figure 78: Priority on retaining customers (1-strongly disagree and 5-strongly agree) (n=455, median=3, mode=3)

It is clear that the majority percentage (34.2%) of the respondents were taking a neutral stand: neither strongly disagreeing nor strongly agreeing. However, the average score of all the respondents was 3.2 which represents "Agree" on the Likert scale (Figure 79).

Figure 79: Average customer retention rating

I further dissected customer responses to include gender, age, region of residence, type of place and service provider. This exercise can help us to further understand how retention is experienced amongst different groups.

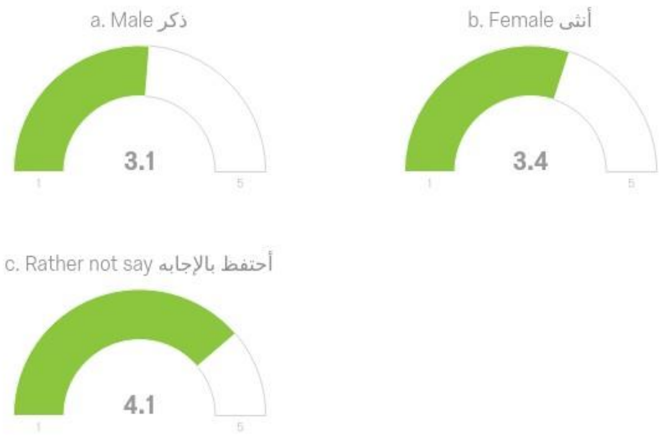

Figure 80: Gender and perceived customer retention

In Figure 80, it is interesting to note that females were more satisfied with a score of 3.4 which is more than the overall average score. The males also surpassed the median score of 2.5 and gave a score of 3.1 which was closer to the overall average. At the same time, those people who did not want to divulge their gender were actually more satisfied than the rest of the group; yet, they represented just 7 people which equalled 1.69% of the entire number of respondents.

Figure 81: Age group and customer retention

A similar trend was also observed when we compared the scores of the different age groups. Respondents in the age group of >50 years and between 30-40 years gave a higher than average score of 3.3. The younger age groups, i.e. <19 years and between 20-30 years old gave a score of 3 which is less than the overall average score. There are various possible reasons for this result, which can be attributed to respondents giving lower scores including the expectations of the younger-aged respondents being unfulfilled. Usage patterns, expected services and perceived quality can very well vary within this younger group of customers. Therefore, the lower scores for this group are a point of concern for the organisations involved.

When the scores are compared region-wise, it can be seen that customer opinions differ in different regions. Regions like Muscat, Al Dhahirah, Al Batinah North, Al Buraimi, Ash Shaqriya South, Dofar surpassed the median score. The remaining regions gave a score of less than 3 (see Figure 82). The gauge charts are coloured in such a way that all values of less than 3 are coloured in blue whilst values greater than 3 are coloured in green.

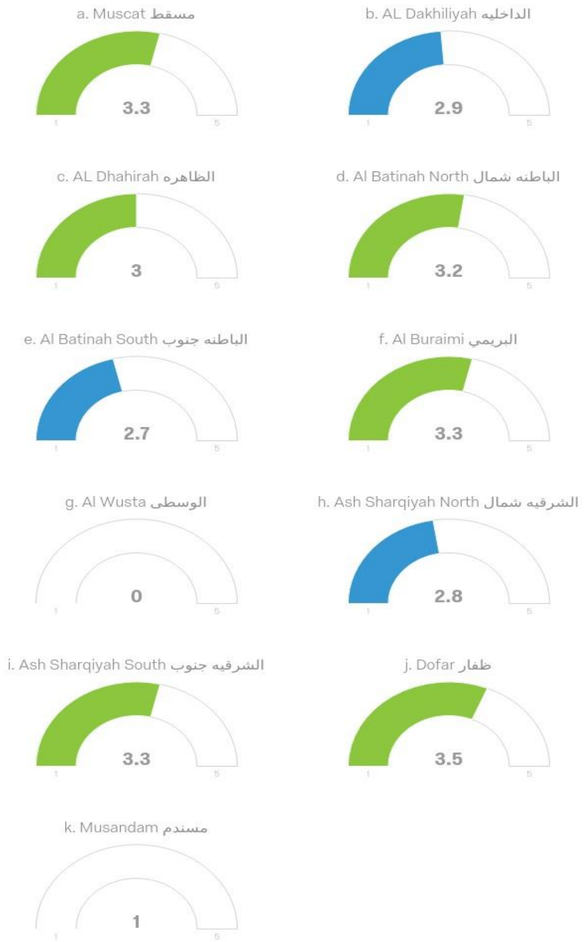

Figure 82: The different regions of the respondents and their perception on retention

When we focus on employment status there is not much difference as they all surpass the median value of 3 (Figure 83).

Figure 83: Employment status and retention

It is the privately employed customers who, in the category of "others", gave the high score of 3.3. The lowest score of 3.1 was given by the students and government employed customers. When I tried to classify how their perceptions changed it was observed that urban customers who reside in cities or towns gave a score of 3.3 whereas rural customers were a bit less satisfied, giving a score of 3 (Figure 84).

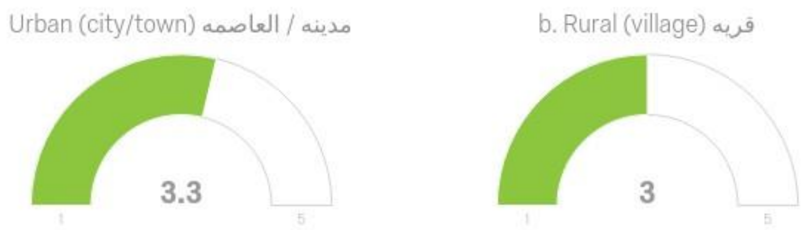

Figure 84: Retention and area of residence

As a next analysis, I tried to see how this perception varied with various service providers. OmanTel's customers showed a maximum score of 3.2 followed by Oredoo with a score of 3.1 (Figure 85).

Figure 85: Perception of customer retention from various service providers

The next question focused on how service providers treat their customers, specifically whether they treat them as a valuable asset. On a Likert scale the majority of customers (32.5%) gave a score of 3. The result of the histogram distribution is similar to that for the customers' answers about whether the service provider placed a high priority on customer retention (Figure 86, Appendix 4).

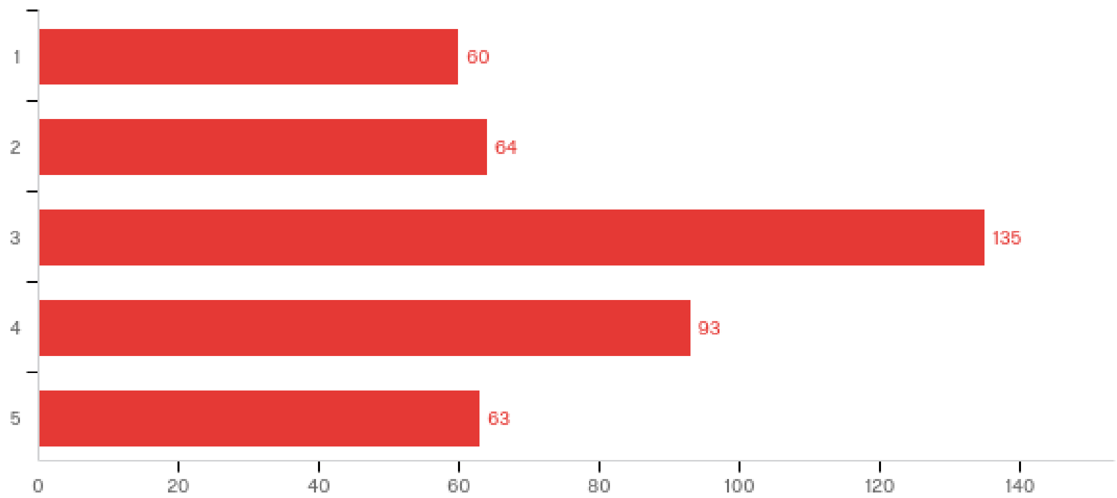

Figure 86: Customers as a valuable assets in a scale of 1-5 (n=455, median =3)

This distribution gave an average score of 3.1 which is halfway through the Likert scale. The gauge chart given below shows the average score in terms of a customer being a valuable asset (Figure 87).

Figure 87: Customer as an asset average perception

It is important to note that the value 3.1 is the average score from 415 respondents with a maximum of 5 and standard deviation of 1.2.

On further classifying the response of the customers, on the grounds of gender, age group, region, place of stay and service providers, we obtain further insight about the perception of the customer as an asset.

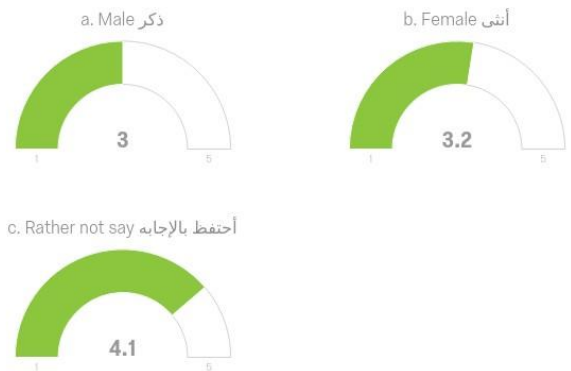

Figure 88: Gender distribution on the customer as an asset perception

Again, in this case females were very positive with a score of 3.2 whereas males gave an average score of 3 (Figure 88). The classification of the age groups did not provide any significant difference as all female respondents scored close to the average score of 3 (Figure 89).

Figure 89: Age group and customer as an asset perception

Similar to the previous perception, private sector employees gave a higher score than the others. Those employed in the government sector gave a score of 3 which is less than average (Figure 90).

Figure 90: The classification of employment status and the perception of the customer as an asset

Further classification on the grounds of service provider illustrates OmanTel is rated highly with a score of 3.1, followed by Oredoo with a score of 3 (Figure 91).

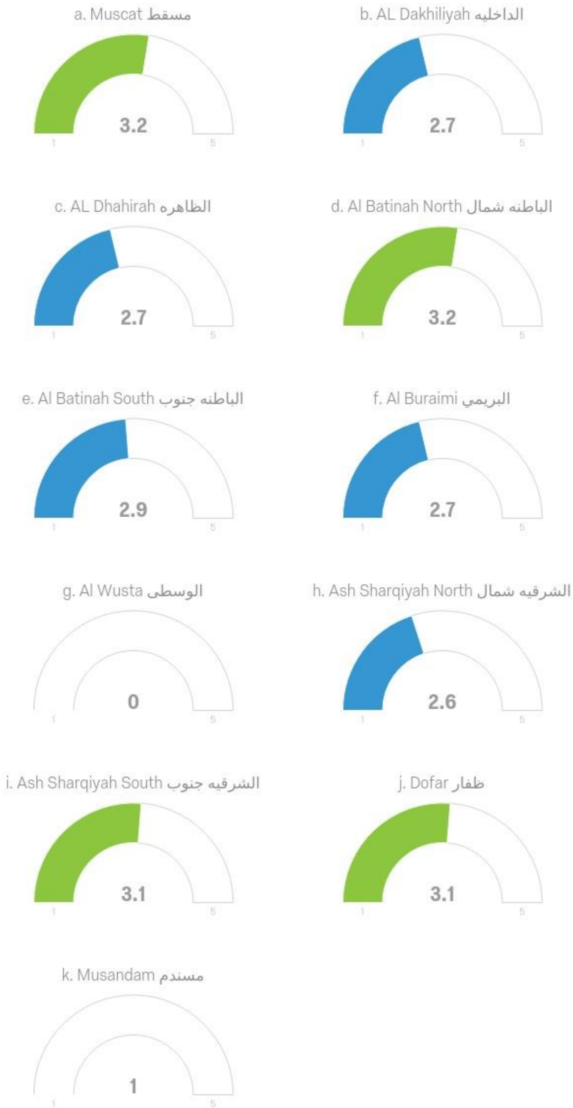

Figure 91: Regions and perception of customer as an asset

Again, as seen in the previous case, respondents from urban areas have gave a slightly higher score of 3.1, whereas respondents from rural areas gave a score of 3 (Figure 92). And when we compare the score of regions to the perception of customers as an asset, respondents from Muscat, Al Batinah North, AlSharqiya south and Dofar gave a higher score than the rest of the region (Figure 93).

Figure 92: Urban/Rural and perception

Figure 93: Service provider versus customer as an asset perception

4.1.3.4 Social media usage pattern

In order to understand social media usage, the next question collected information related to social media usage patterns. When respondents were asked which social media platform was actively used by them, WhatsApp was considered to be the main medium with 90% of respondents supporting it, followed by Instagram and Twitter. Facebook has been used by only 24% of the respondents and, at this lower end, most of the other respondents (4.2%) mentioned Snapchat as their preferred social media tool. The following bar chart explains this scenario (Figure 94).

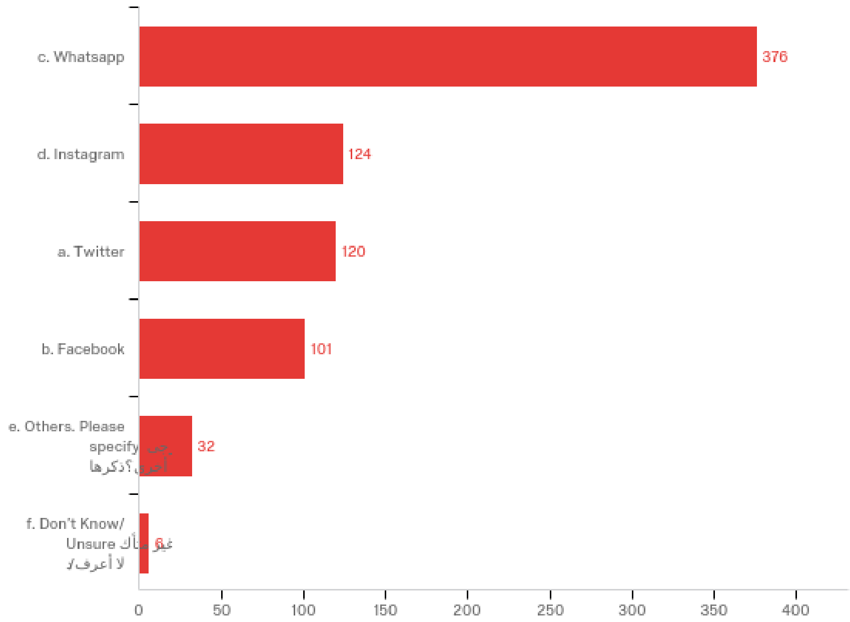

Figure 94: Favourite social media platform (n=455)

In order to understand this information further I grouped the respondents based on gender and found that the trend differed across genders (Figure 95).

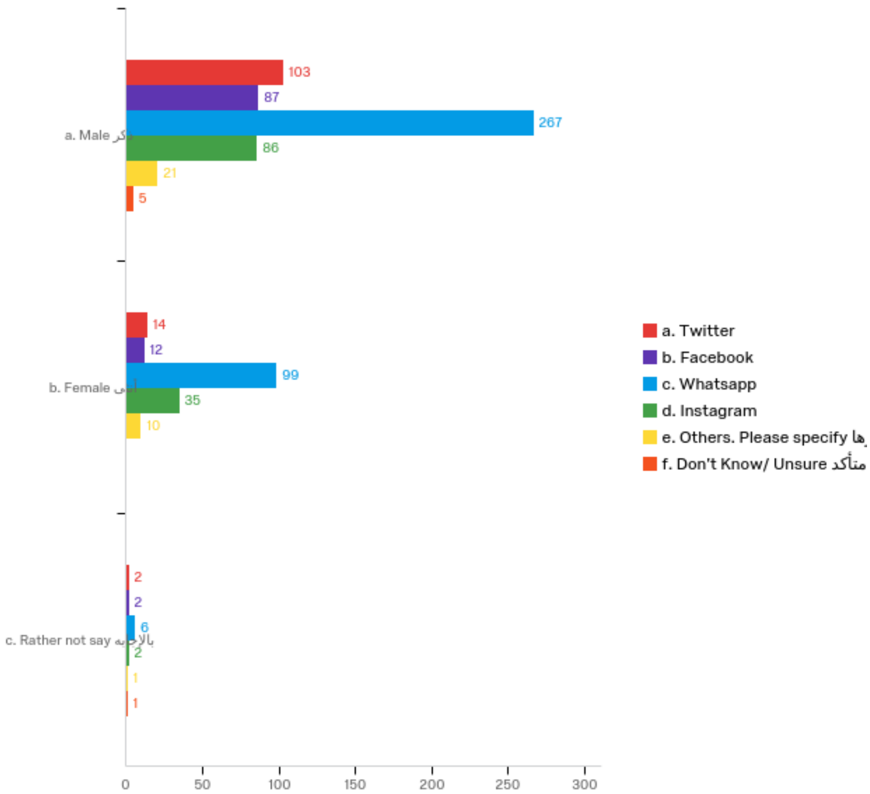

Figure 95: Social media usage and gender (n=455)

When we focus on service providers and social media usage we find that both the OmanTel and Oredoo users were active on WhatsApp (Figure 96).

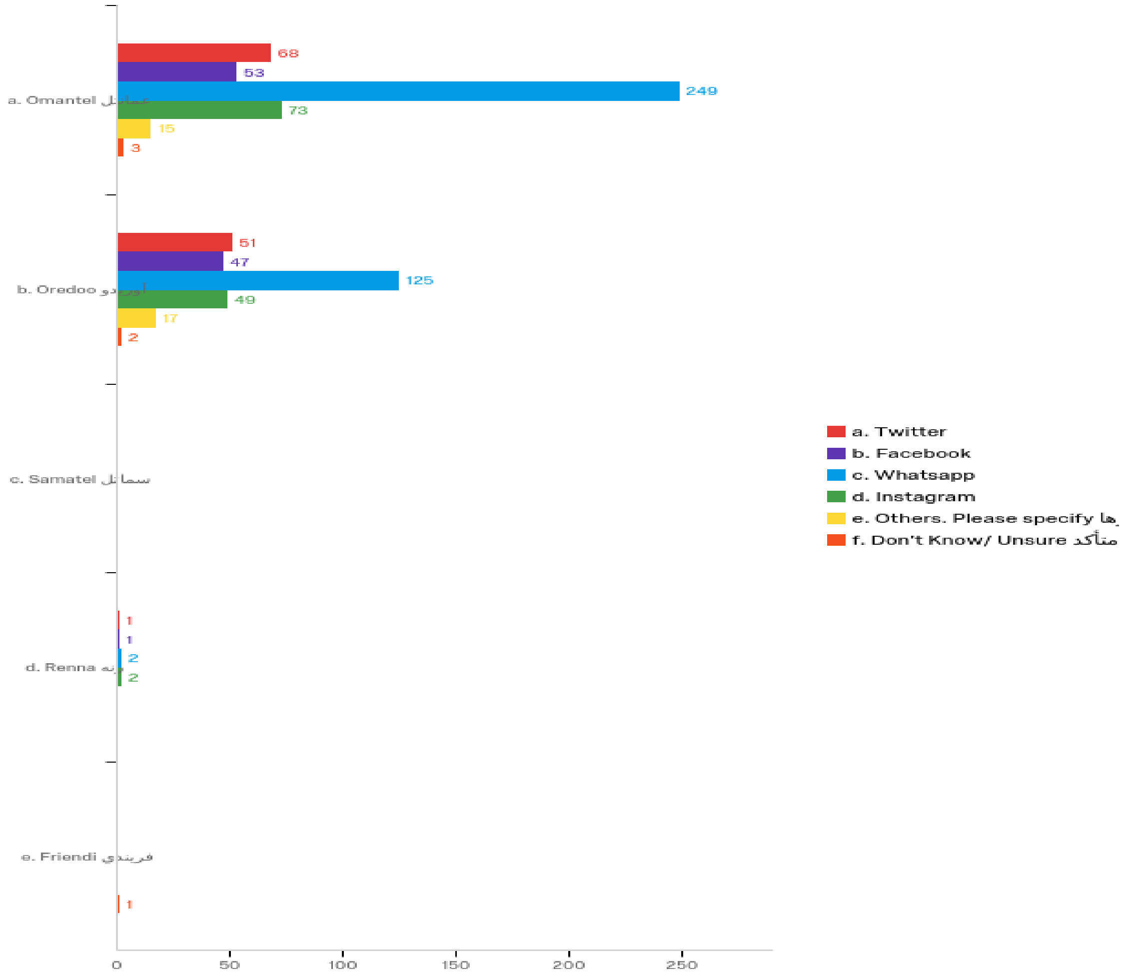

Figure 96: Service providers and social media usage (n=455)

The next question was aimed at finding out exactly what social media platforms were actively used by service providers. Overall the respondents felt that Twitter was actively used by their service providers (Figure 97).

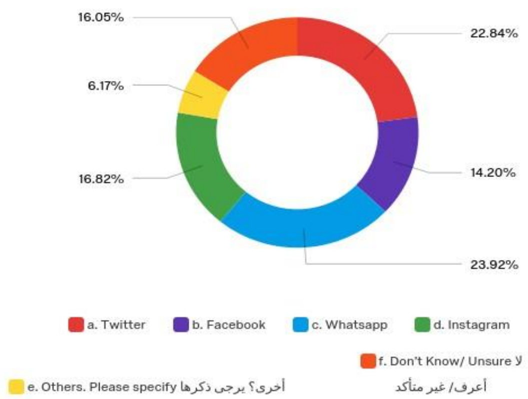

Figure 97: Social Media usage of the service providers

In order to cross validate this outcome, I grouped respondents' responses to the above answer based on which service provider they were using. The responses also confirmed that OmanTel and Oredoo were using Twitter very actively (Figure 98).

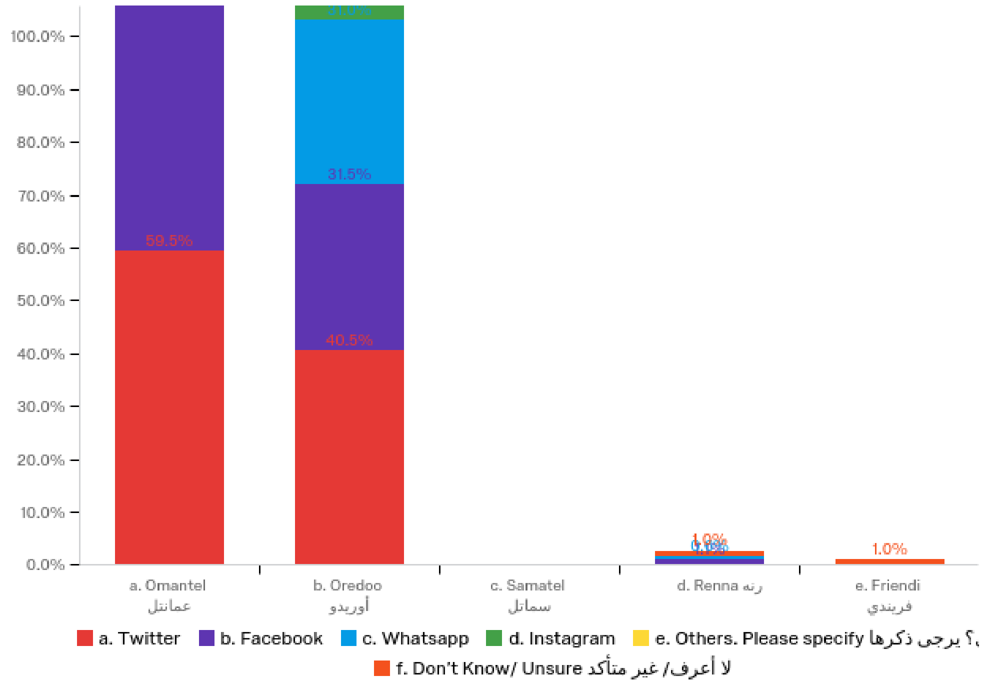

Figure 98: Service Providers' social media usage as perceived by the respondents

For the next question, whether respondents followed their service provider on social media, 57% of the respondents said that they did not follow their service providers on social media, while 43% said that they did follow their service providers on social media (Figure 99).

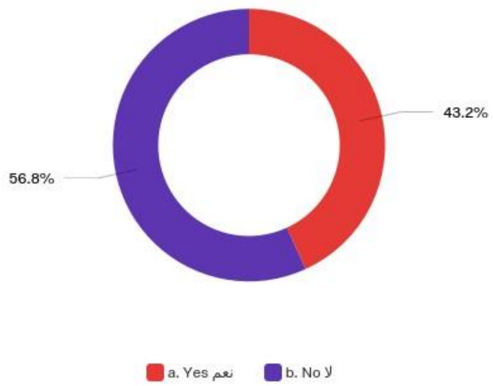

Figure 99: Respondents following their service provider on social media

This information did not alter when the answers, to this question, were grouped based on service providers, thus indicating similar trends across the sector (Figure 100).

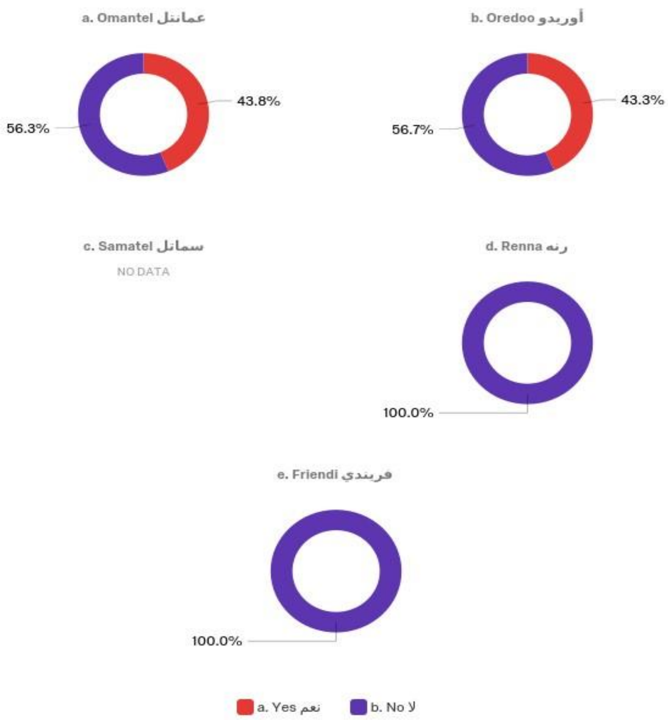

Figure 100: Social media followers of service providers

Amongst those who followed their service providers on social media, Twitter is an active platform where many customers *will* follow service provider feeds (Figure 101). For instance, it is interesting to note that the leading providers, OmanTel and Oredoo, both have a similar percentage of followers on social media.

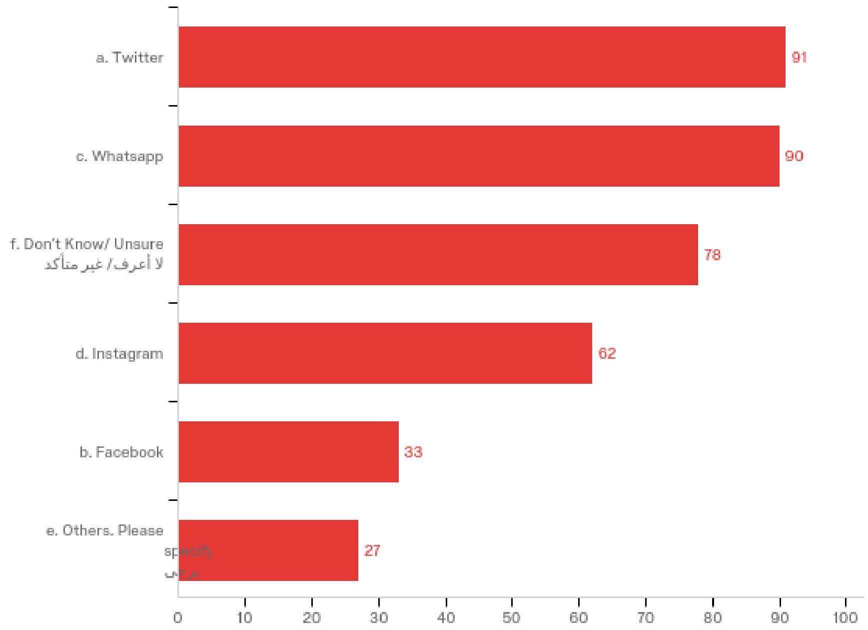

Figure 101: Platform used to follow service providers (n=455)

When I asked respondents if they had ever used social media to share any information 62% said they had never used social media for information sharing (Figure 102).

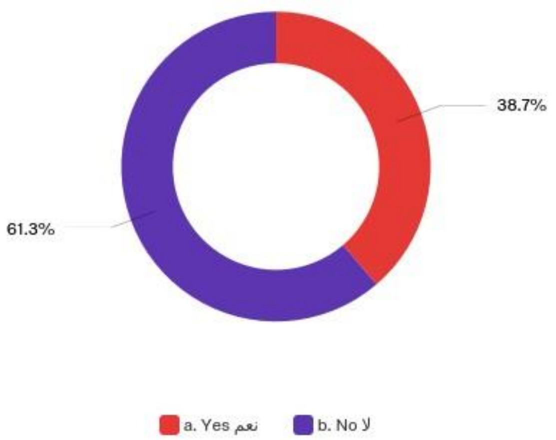

Figure 102: Sharing information on social media with service providers

I then asked the respondents who confirmed that they shared information to provide details of the types of information they shared; 21% said that they shared news or live feeds and 15% said that they shared information regarding social networking. The remainder said that they shared photos and videos, etc. (Figure 103). When the respondents were asked "What is the most important function of social media?" they said:

- news or live feeds (57.34%);
- social networking (39.61%);

- micro-blogging/Twitter (37.67%);
- sharing photos (31.30%); and
- sharing videos (27.15%)

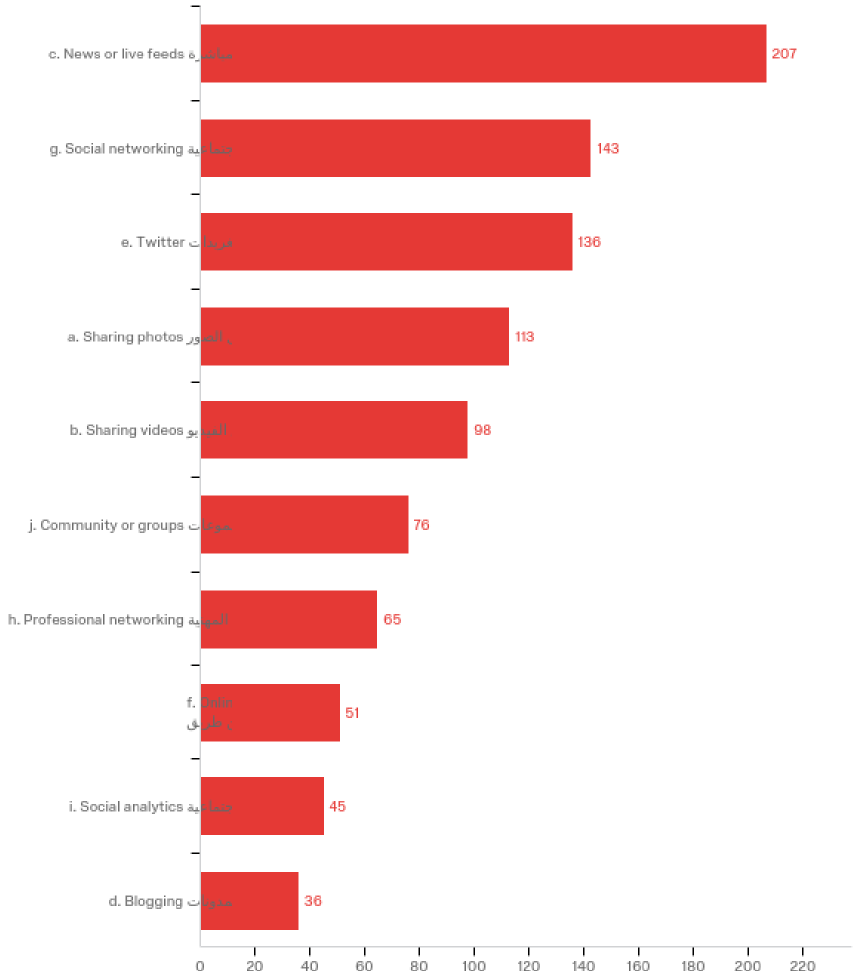

Figure 103: Main functions of social media (n=455)

The next question focused on whether service providers ever conducted any market research. These results were recorded using a Likert scale as customers may have felt that

their service providers tried to get information to them through various methods. The majority of respondents (36.3%) agreed that their providers did conduct market research (Figure 104).

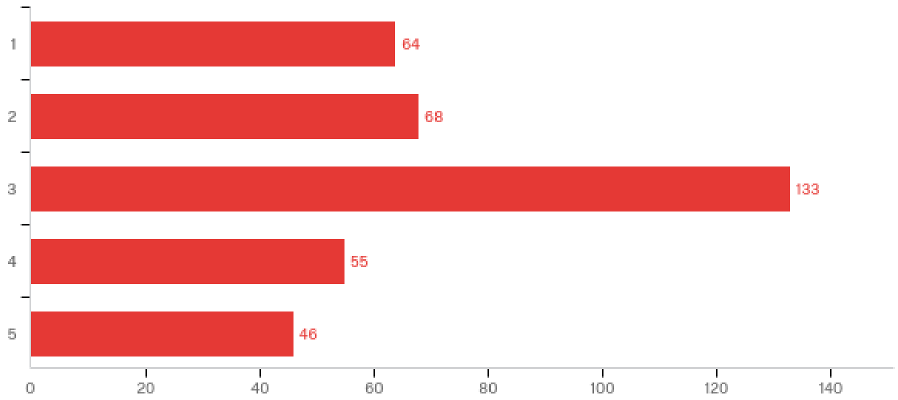

Figure 104: Market research of service providers (n=455, median=3)

This amounted to an average score of 2.9 which is just below the half-way mark (Figure 105).

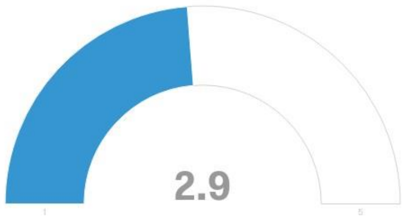

Figure 105: Market research average score

Grouping the above responses with respect to service providers did not result in any further interpretations, as the trend remained the same across the major service providers (Figure 106).

Figure 106: Average score across the service providers

I asked respondents if their service providers requested their preferences through social media: 121 respondents (33.2%) neither strongly disagreed nor strongly agreed with the question, indicating that either their service provider collected such data or the respondents did not know the answer (Figure 107).

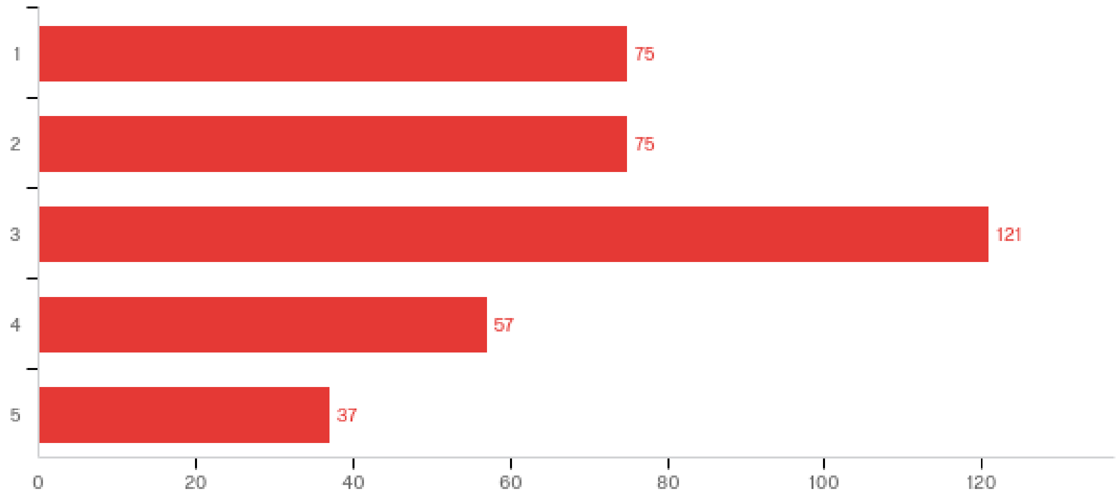

Figure 107: Collection of customer preferences through social media (n=455, median= 3)

I also added a question to establish whether respondents felt that their service providers identified the current trends being discussed on social media. This resulted in a similar pattern to the one obtained in the previous question (see Figure 108).

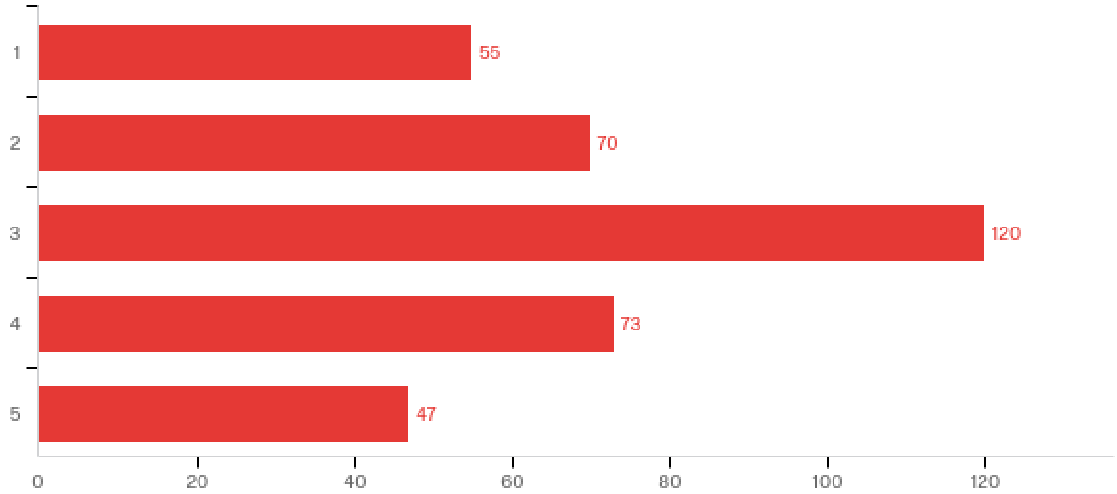

Figure 108: Perception of whether service providers follow current trends on social media (n=455, median = 3)

This Likert scale gave an average score of 3 (as shown in Figure 109) which represents the halfway mark exactly for whether service providers followed current trends on social media.

Figure 109: Average score on the current trends followed by service providers

The next question asked the respondents about whether service providers resolved problems and complaints through social media (Figure 110). In this case too, we can observe a score of 3 which represents the majority at 26.8%.

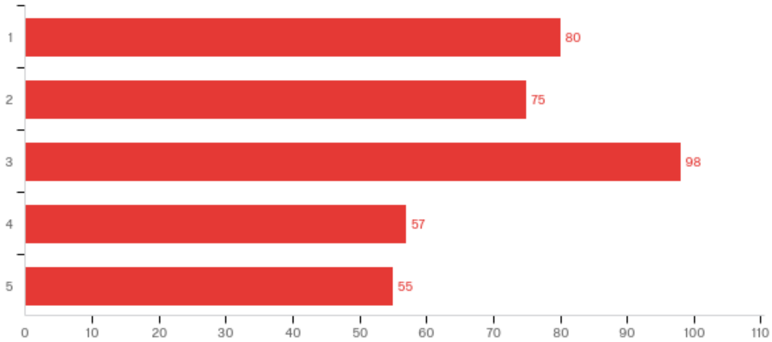

Figure 110: Usage of social media for complaint resolution (n=455, median = 3)

The Likert scale produced an average of 2.8 showing slightly below the halfway mark (Figure 111).

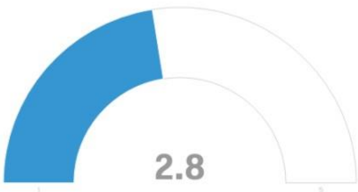

Figure 111: Average score for resolving complaints through social media

This did not change when the responses were split across providers, but showed a similar trend (Figure 112). The major providers OmanTel and Oredoo obtained similar scores of 2.8 with Renna having a slightly higher score of 3 (Figure 112).

Figure 112: Average scores of complaints resolved by providers through social media

The responses to the next question, “Do you think social media is a good tool for conducting research, collecting customer preferences, identifying industry trends and resolving complaints?” were very interesting. The majority of people strongly agreed with this question (Figure 113).

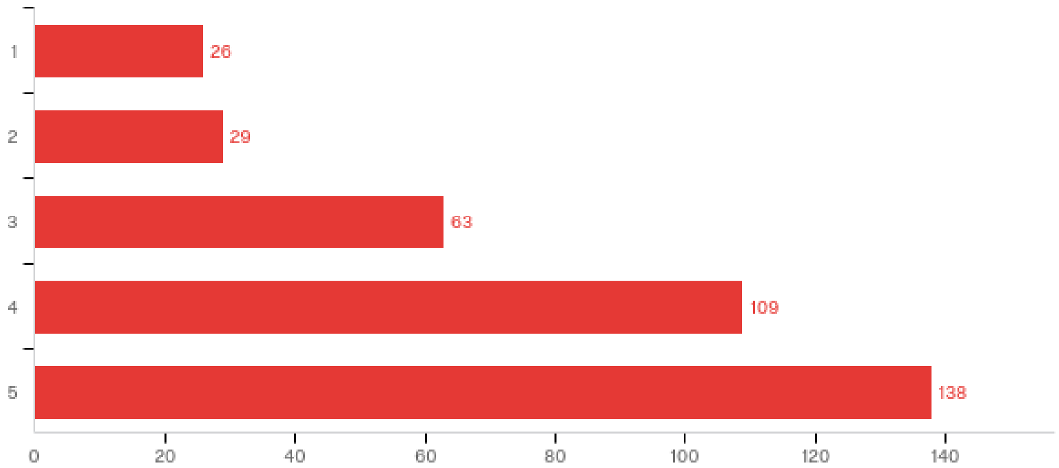

Figure 113: Aptness of social media for collecting customer preference (n=455, median =4, mode=5)

The responses produced a very high-value average score of 3.8 (Figure 114) indicating that customers definitely prefered that their service providers conduct research through social media.

Figure 114: Average score on the aptness of social media for customer preference

The next section will discuss the outcomes of the customer survey in relation to retention and loyalty.

4.1.3.5 Retention, loyalty and satisfaction

It has been established in the literature review that the main objective of CRM is to provide an ongoing relationship with customers which is built on trust, control and security. This is the primary reason for organisations to implement CRM, as previously mentioned.

CRM should enable corporations to build strong relationships with their customers in order to achieve and maintain a prosperous market share through customer retention. Furthermore, knowing detailed information about customers, such as their names, habits, likes, dislikes

and expectations, will also enable organisations to increase their rate of customer retention.

Customer loyalty is another attribute that an effective CRM strategy should take note of. Customer loyalty as an intended behavior–triggered by the level of service received and, thus, operationalised loyalty–could result in re-purchase intention and a willingness to provide positive word-of-mouth recommendations. Therefore, firms should focus heavily on loyalty as this generates increased revenues, lowers costs and attracts new customers–all of which ultimately lead to increased profitability.

When we asked customers the likelihood of them remaining with their present service providers 27.5% gave a score of 3 and, interestingly, the next highest score was 5 which was selected by 26.4% of the respondents.

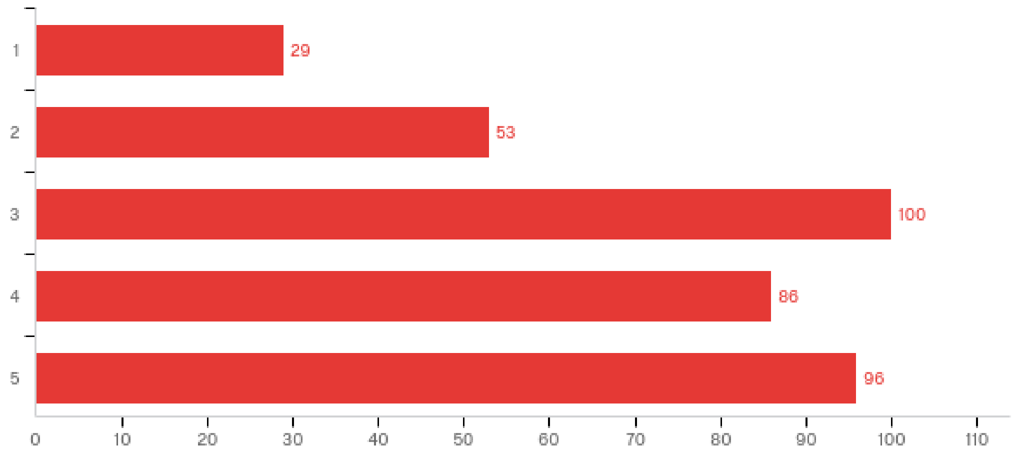

Figure 115: Staying with the present service provider (n=455, median = 3.5, mode =3))

These Likert scale responses produced an average score of 3.5, as shown in Figure 116

Figure 116: Expected to stay for longer period

When these scores were segregated in terms of gender, we see that the females agree to stay longer, with a score of 3.7, than the male respondents, who gave a score of 3.4 (see Figure 117).

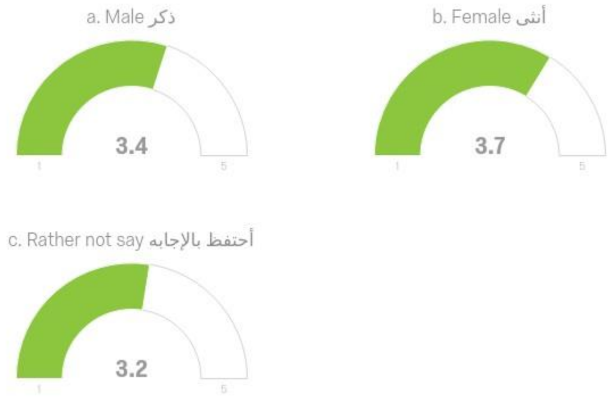

Figure 117: Retention and gender

The highest retention score was observed in the 50+ age group, who gave a score of 4, indicating their intention to stay with their providers for a long period of time. The 20-30 age group gave the lowest score of 3.2, although this score is still higher than the halfway mark (Figure 118).

Figure 118: Retention and age group

In the private sector, employees have presented higher retention scores than other respondents with different employment statuses, while students and business owners gave a lower score of 3.3 (Figure 119).

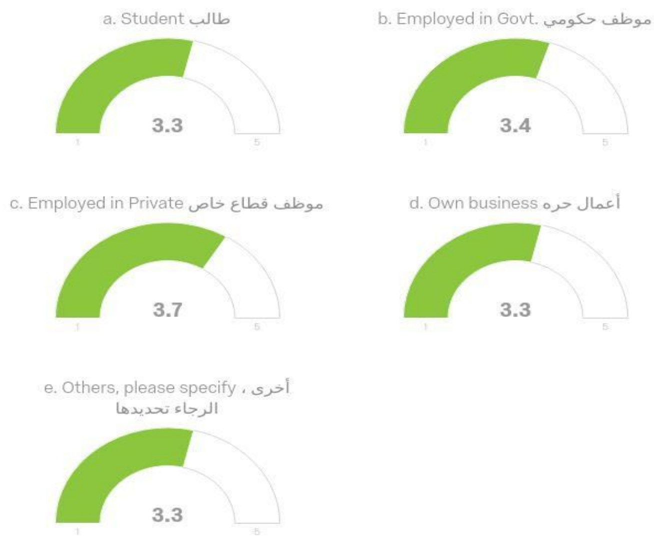

Figure 119: Employment status and retention

When the results were segregated based on region, I found that respondents from the Muscat region gave the highest score of 3.7, and the respondents from the Alsharqiya North region gave the lowest score of 2.4 (Figure 120).

Figure 120: Customer retention and region

I observed that the respondents living in urban areas had higher retention expectations to those living in rural areas with scores of 3.6 and 3.2, respectively (see Figure 121).

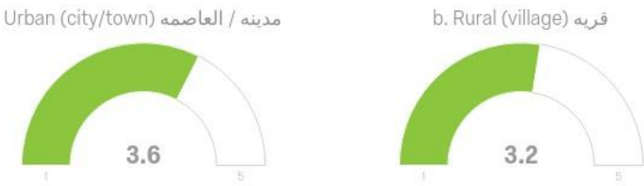

Figure 121: Retention rates of respondents from urban and rural areas

Respondents using different service providers gave similar scores, whilst respondents using OmanTel gave a slightly higher score of 3.5. Ooredoo gave a score of 3.4 (Figure 122).

Figure 122: Retention and service providers

The next question, on loyalty, was again measured through the 1-5 Likert scale. Unlike earlier cases respondents' responses were mixed: with 26.3% of respondents giving a score of 3 and 21.2% of the respondents giving a score of 5 (Figure 123).

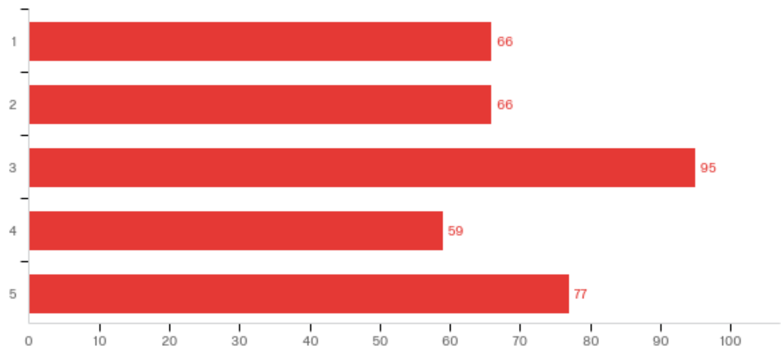

Figure 123: Customer loyalty to their present provider (n=455, median =3)

This produced an overall average score of 3 which is exactly halfway through (Figure 124).

Figure 124: Average score on loyalty to the present provider

I grouped the average scores based on gender, age group, employment status, region, type of place and service provider. This analysis provided the following outcomes:

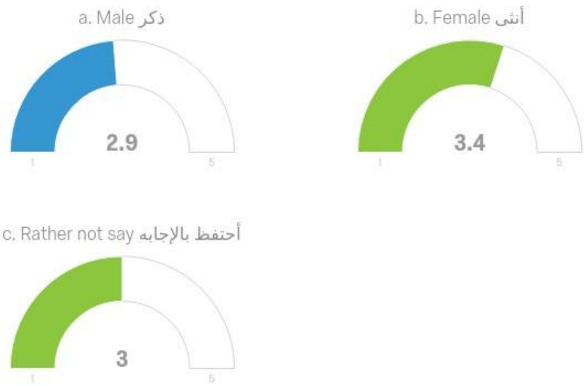

Figure 125: Loyalty and gender

Females were shown to be more loyal than males with a score of 3.4 and 2.9, respectively (Figure 125). Age group segregation reflected that respondents aged <19 years old and between 30-40 years old scored higher than halfway with scores of 3.4 and 3.2, respectively (see Figure 126).

Figure 126: Age group and loyalty

The respondents from urban areas exhibited more loyalty than those from rural areas with a score of 3.2 and 2.8, respectively (Figure 127).

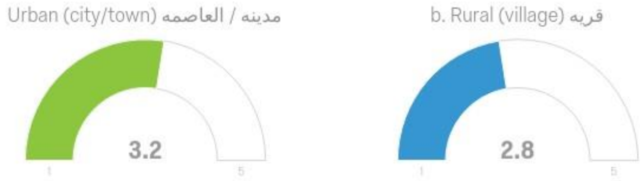

Figure 127: Loyalty and type of living place

Respondents from Muscat and Al Buraimi gave high loyalty scores of 3.3 and 3, respectively (Figure 128).

Figure 128: Loyalty and region of domicile

Privately employed respondents produced higher loyalty scores of 3.3, compared with government employed respondents and those running their own business who gave a score of 2.9 (Figure 130).

Figure 129: Loyalty and employment status

Grouping the loyalty scores in respect of service provider shows that OmanTel customers had a higher loyalty score than Oreedoo's customers.

Figure 130: Loyalty and service providers

Customer satisfaction is a very important factor in maintaining effective CRM. The last question asked customers how satisfied they were with the services they had received from their providers. They again answered using a 5-point Likert scale and the results of this question are shown below. The majority of respondents gave a score of 3 which sits halfway between strongly disagree and strongly agree (Figure 131).

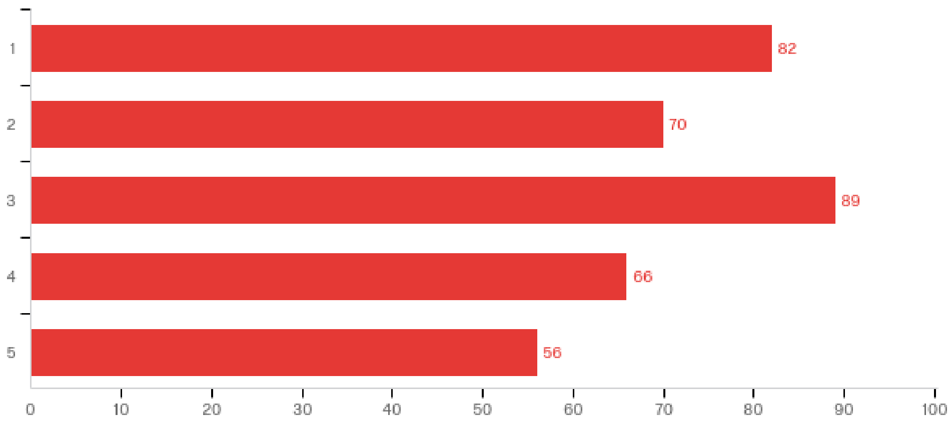

Figure 131: Respondents' satisfaction scores (n=455, median=3, mode=3)

This Likert-scale response produced an average score of 2.8 which is just below the halfway mark and indicates as leaning towards the negative side (Figure 132).

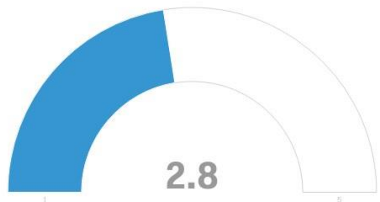

Figure 132: Average score on satisfaction

The female respondents gave higher satisfaction scores than the males: scoring 3 and 2.8, respectively (Figure 133).

Figure 133: Gender and satisfaction

A breakdown of age groups highlighted the fact that responds aged between 30-40 years and above 50 years were more satisfied than other age groups (Figure 134).

Figure 134: Age group and satisfaction

The last segregation of the service providers illustrated that both OmanTel and Oredoo have obtained a satisfaction score of 2.9 and 2.7 respectively, both scoring below the halfway mark (Figure 135).

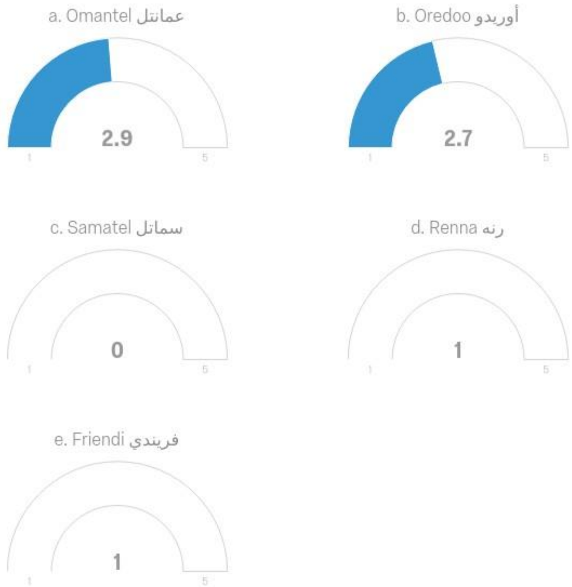

Figure 135: Satisfaction and service providers

These measurements of retention, loyalty and satisfaction enabled me to match these parameters with the customers' perspectives. These results are summarised and triangulated in the following Discussion Chapter.

4.2 Summary of the survey and interview findings

This section analyses the collected data through the use of questionnaires, social media and semi-structured interviews. My data collection methodology included data that was collected from social media managers and customers; thus, I collected quantitative and qualitative data from both customers and managers. In addition, I also conducted semi-structured interviews with the managers, as explained in the Methodology Chapter. Their analysis and their results are detailed in this section.

4.2.1 Conclusions from data collected from social media managers in Omani telecom firms

A survey was administered through Qualtrics which consisted of 20 questions designed to collect data about the demographic details and the social media usage patterns of social media managers (Appendix 2: Modified Questionnaire (Social Media Managers)).All sixteen managers who were requested to participate responded to the survey. Their responses were recorded in Qualitrics from 8:18 pm on 21st May 2016 through to 09:04 am on 31st May 2016.

My above analyses of the survey results determined that:

- Twitter is considered to be the most significant social media platform by 70% of managers, followed by Instagram with 67% and Facebook with 44%;
- the least significant platform was found to be Google+;
- around 67% of managers thought LinkedIn brought some advantages to the firm, followed by Google+ with 40% and Facebook with 40%; and
- 11% of managers opined that Google + brought no advantage to their firms.

The next part of the questionnaire focused on marketing strategy. The first question asked whether there is a link between marketing strategy and social media coverage. Ninety percent of the managers agreed that there is a clear link between the two (as shown in Figure 58). This clearly indicates that Omani telecom firms make deliberate attempts to link their marketing strategy with their social media coverage. Conversely, 10% of the managers were not aware of any such linkage.

I followed this by asking an open-ended question about marketing strategy and social media to obtain a more in depth response. The second manager illustrated that it is very innovative and went on to say: “The link is in stimulating some innovative ideas from the crowd, as well as getting some good insight of how the customers perceive the company”. This shows that firms are open to their customers, and are keen to understand what their customers think of the firm and its services.

The next part of the survey focused on customer support. Nguyen et al. (2007) specify some of the most important objectives of CRM, as listed below:

- to increase customer loyalty (obtaining and making information about customers' available across the whole organisation);
- superior data collection and sharing (updated history of customers and their interactions);
- knowing one's customers and providing a superior service (using all available information about customers' habits and interactions with the organisation to providing information about products and services which are tailored to the needs of each customer).

Therefore, providing customer support is a vital step towards achieving better CRM practices. My question in this regard was aimed at finding out whether Omani telecom firms provide online customer support: 80% of the managers informed me that their firms provide online customer support; 10% said their organisations do not provide online customer support, and the remaining 10% either did not know or were unsure (Figure 59: Online Customer Support (n=16)).

Keeping in touch with customers should, essentially, be continuous and analytical. Furthermore, specific targeted strategies to identify potential customers should be built- in and proactively integrated within the processes of the business. It is important that customers are in touch with a company in real-time, and their feedback on every service or offer is obtained from time to time.

I investigated this point further by asking whether there were any mechanisms in place designed to monitor current topics (trends or discussions) pertaining to an organisation. For this question, 70% of managers agreed that their firm followed trends and discussions to get a feel for what information reaches customers; 10% said they did not have any such mechanism in place, and another 20% were not aware of such a process in their organisation (Figure 60).

Monitoring trends and discussions is vital and such rich information enables firms to cater for different segments, which ultimately results in increased profitability. Customer trends can also be useful for drafting targeted marketing strategies, understanding the limitations of competitors, and capitalising on these limitations or gathered customer knowledge to lure new customers. As previously pointed out, the main use of CRM is to engage in defensive marketing. This could involve firms’ understanding why customers are leaving to initiate a suitable customer retention programme. The implementation of such retention programmes not only improves customer retention rates but also increases customer satisfaction and ultimately increases profitability.

I have reviewed the importance of sentiment analysis for obtaining information from a huge amount of text. And I have explained that sentiment analysis will be very handy for firms that need to collect information using a robust process. Product reviews affect the decision-making processes of the common man, so it is very important for firms to devise their marketing strategy to address potential problem areas. This is another area where sentiment analysis helps corporations to track the image of their brands. Thus, by using the discussions taking place in social media, it is possible to put sentiment analysis into practice and gain information about how healthy the image of a brand actually is.

Therefore, I asked the social media managers whether they were aware of the use of sentiment analysis tools in their firms, such as opinion mining, text mining and sentiment detection. Seventy-one percentage of the managers informed were aware of sentiment analysis, and about 29% said they did not know of the existence of any such tools (see Figure 61).

Further to this, mangers who knew about sentiment analysis were asked about the presence of any such tools in their firms. Thirty-eight percentage of the managers agreed that they had seen such tools in their firms in use, and about 25% said they had not seen any tools in their firms. Out of those mangers who were aware of sentiment analysis, 25% were either not aware or were unsure about the use of such tools in their organisations. About 12.5% of the managers were aware of the name of the tools used in their organisations (see Figure 62).

I probed deeper to establish how sentiment analysis tools are built, i.e. in-house or outsourced. About 63% of the managers said they outsourced the development and management of sentiment analysis tools, and 25% of the managers informed us that they were built in-house. About 12% of the managers were not sure how sentiment analysis was implemented in their organisations (see Figure 63). In addition, when asked if they knew of any issues with the existing tools, 62.5% of the managers were not sure and 25% of the managers informed us that there were no issues with the existing tools. Only 12.5% of the respondents said that there was a problem with the existing tools.

The next question, about the contribution that sentiment analysis makes to an organisation, was an open-ended question that revealed many details. One respondent reflected that: *"… it helps the organisation to assess the existing strategy, bridge the gaps and rectify the challenges";* while another said: *"… it is very important as it gives insight to the voice of customer"*.

Another respondent aptly said that sentiment analysis tools are useful "… *to analyse consumer concern and behaviour"*. The next manager agreed that these tools are *"… very effective in getting instant feedback and proactively resolving issues with unhappy customers"*. Overall, they have accepted that sentiment analysis tools are *"… very useful tools for high level management to use when making decisions".*

This evolution is very useful for us in understanding how vital telecom organisations in Oman consider social media to be. We can observe that this transformation towards the accelerated usage of social media is in line with my findings in the literature review. The results reiterate the need to value the customer and focus on long-term customer relationships instead of short-term sales goals. It is, therefore, obvious to conclude that the scenario in the Omani telecoms industry is very well into its third generation where customer service is approached as an integrated service.

4.2.2 Analysis of the data collected from customers

The data collected from telecom service customers brought out a variety of interesting facts. In order to understand the thoughts of these customers a survey was conducted (Appendix 4: Questionnaire for customer). This survey contained twenty-four questions that were designed to collect quantitative and qualitative data, such as demographic details, the usage pattern of telecoms services, their providers and their acquaintance with social media. As a result, the customer survey brought out various features pertaining to this study. My questionnaire was bilingual as the first language of the majority of the customers' is Arabic.

Our first question on gender brought out the fact that the majority of the customers (72.2%) were males and 26% were female; the remaining (1.7%) did not want to disclose their gender (see Figure 72). It is important to note that this info was collected from a total of 455 respondents. The next question on age group showed that 49% of the customers were in the age group of 30-40 years. This was followed by the 40-50-year age group representing 25.3% and the 20-30-year age group represented 21.2%. Those aged 19 years and under represented 2.41% with only 1.9% of the respondents being aged above 50 years. It is interesting to note here that the distribution is close to an ideally normal distribution where a bell-shaped curve perfectly shows the good sampling of the population (Figure 73).

Our next question on the customer survey was related to the employment status of the customers. The majority of the customers were working in the government sector (53%) followed by 26% of customers who were employed in the private sector. Amongst the customers the students represented 7.9% and 6% owned their own business. The remaining 6.5% mainly comprised pensioners and job seekers etc. The data is graphically presented in Figure 74.

In order to identity the customers' way of life the fourth question in the customer survey focused on the region where they live. The majority of the customers (50%) were from the Muscat region which is the capital of the country. Next to that the Al Batinah North region is represented by 31.4% of respondents. The rest of the regions were represented by less than 7% (Figure 75).

In order to find out whether the place they live is urban or rural, our fifth question established that about 60% of the respondents were from urban areas and the rest were from rural areas (see Figure 76). This distribution typically reflects the Omani population and hence has a representation from both types of areas. The next section brings out the data relating to the service providers in the Omani telecoms sector.

Questions 6 to 9 in the survey focused on obtaining details about the service providers and their customer service. OmanTel is found to be a major service provider amongst the respondents with a percentage of 64.8%. Next to that Oredoo was the service provider for 34% of the customers. The resellers like Renna and Friendi represented less than 1% of the respondents.

Considering these facts, our next question focused on identifying how highly the service providers prioritise retaining their customers. This question was modelled on a 1-5 Likert scale from 'Strongly Disagree' to 'Strongly Agree'. It is clear that the majority (34.2%) of the respondents were taking a neutral stand of neither strongly disagreeing nor strongly agreeing. However, the Likert average score of entire respondents was 3.2 leaning towards the point of agreeing (Figure 79).

On further breaking down this response by gender, age, region of residence, type of place and service providers, this exercise helped us to understand further how the retention is experienced amongst different groups. It is interesting to note that females were more satisfied, with a score of 3.4 which is higher than the overall average score. Males also

surpassed the median score of 2.5 with a score of 3.1 which is close to the overall average. At the same time, those people who did not want to say their gender were actually more satisfied than the rest of the group, however, they consisted just 7 people, a mere total of
1.69% of the entire number of respondents.

When comparing the scores by region we can see that the respondents from the different regions differ in their opinions. The regions like Muscat, Al Dhahirah, Al Batinah, Al Buraimi, Ash Shaqriya South and Dofar surpassed the median score. The remaining regions gave a score of less than 3 (see Figure 82). The gauge charts are coloured in such a way all values less than 3 are coloured with blue whilst values greater than 3 are coloured in green.

When we focus on the employment status there is not much difference in the scores as they all surpass the median value of 3. It is the privately employed customers and those categorised as ‘others’ who gave the highest score of 3.3. The lowest score was given by the students and government employed customers with a score of 3.1. When we tried to classify how the perception changes it was observed that it was the urban (city/town) customers who gave the highest score of 3.3 whereas the rural customers were bit less satisfied with a score of 3 (Figure 84)

In our next analysis we tried to see how this perception varies by comparing the various service providers. OmanTel’s customers have scored the maximum at 3.2 followed by Oredoo’s customers with a score of 3.1 (see Figure 85). Our next question focused on if and how the service providers treat the customers as a valuable asset. As this question used a Likert scale we saw that the majority (32.5%) of customers gave a score of 3. The distribution of scores relating to customers being considered valuable assets is too close to the previous question on retention (Figure 86). This distribution gives an average score of 3.1 which is halfway through.

The gauge chart given shows the average score for this question (Figure 87). It is important to note that the value 3.1 is the average score from 415 respondents with a maximum of 5
On further classifying the responses of the customers in relation to gender, age group, region, place of stay and service providers, we got further insight on the perception of customers being considered an asset.

Again, in this case the females were very positive with a score of 3.2 whereas the males gavean average score of 3 (Figure 88). The classification of age group has not provided any significant difference as all age groups gave similar scores and were close to the average score of 3 (Figure 89). Similar to the previous perception, the private sector employees gave higher scores the other respondents. The employees in the government sector gave a score of 3 which is less than average (Figure 90).

The further classification on the grounds of service provider illustrates that OmanTel gave the higher score of 3.1 followed by Oredoo with a score of 3 (Figure 93). Again, as seen in the previous case, the respondents from the urban areas gave a slightly higher score of 3.1 whereas the respondents from rural areas gave a score of 3 (Figure 92). When we compared the scores by region, the respondents from Muscat, Al Batinah North, AlSharqiya South and Dofar gave a higher score than the rest of the regions (Figure 91).

Customer satisfaction is a very important factor in maintaining effective CRM. Our last question with customers asked about how satisfied they are with the services they receive from their providers. They answered again using a 5-point Likert scale. We have presented the outcome of this question here.

The majority of the respondents gave a score of 3 which is the halfway mark between strongly disagree and strongly agree (Figure 131). This Likert-scale response produced an average score of 2.8 which is less than halfway illustrating that the score is skewed towards negative side (Figure 132). The age group breakdown showed that the responses from the 30-40-year age group age and the above 50 age group were more satisfied than the other age groups (Figure 134).

The last segregation on service providers illustrated that both OmanTel and Oredoo have obtained a satisfaction score of 2.9 and 2.7 respectively, both being less than the halfway mark (Figure 135). The measurement of retention, loyalty and satisfaction has enabled us to obtain these parameters from the perspective of the customers. These results are summarised and triangulated in the following Discussion Chapter.

4.3 Analysis of social media: descriptive and sentiment analyses

Basic and extended sentiment analysis has been conducted using proprietary NVivo code and custom developed R scripts, as explained in the methodology section. The outcomes of such analyses are presented in this section organized by descriptive, sentiment and extended sentiment analysis, and, lastly, the Wheel of Emotion.

4.3.1 Descriptive analyses

This section will present a descriptive analysis of tweet counts and detail each users', monthly, daily, and hourly statistics with the aim of identifying tweeting patterns during the monitoring period.

4.3.1.1 Tweet counts

I captured a total of 83,981 tweets during the period 01-01-2016 to 31-12-2016, a total of 366 days. I recorded an average of 229 tweets (per day) ranging from a minimum of 46 tweets collected on 06-05-2016 to a maximum of 1816 tweets collected on 2-10-2016. The median number of tweets (per day) totaled 180, and the more frequent count of tweets (mode) during this period was 85. The complete descriptive statistical analysis of tweet counts is shown below in Table 14.

The descriptive analysis contains the following statistical terms, for which I provide their definitions and formulae as used for the calculations.

1. **Mean**: This is the sum of all the data divided by the number of values (n) calculated as:

$$\overline{x} = \frac{\sum_{1}^{n} x_i}{n}$$

2. **Standard Error:** This is calculated by dividing the standard deviation by the square root of n. The formula used was:

$$\frac{s}{\sqrt{n}} = \sqrt{\frac{\sum_{1}^{n}(x_i - \overline{x})^2}{n(n-1)}}$$

3. **Median:** The middle value if data are arranged in order.
4. **Mode:** The most frequently occurring value.
5. **Standard deviation:** A measure of how each value is dispersed from the average value. This is calculated as:

$$s = \sqrt{\frac{\sum(x_i - \overline{x})^2}{n-1}}$$

6. **Sample variance:** is the square [root] of the standard deviation.
7. **Kurtosis:** measures the peaks and flatness of a distribution.
8. **Skewness:** measures the degree of asymmetry of a distribution.
9. **Range:** is the difference between the maximum and minimum value.
10. **Maximum:** is the maximum value in the given dataset.
11. **Minimum**: is the minimum value in the given dataset.

12. **Sum:** is the total of the entire data.

13. **Count**: is the total number of values in the dataset.

Parameter	Value	Remark
Mean	229	This indicates on an average there were 229 tweets everyday
Standard Error	9	
Median	180	
Mode	85	Many of the days, the number of tweets were limited to 85
Standard Deviation	180	
Sample Variance	32,348	
Kurtosis	20	Shows good variation
Skewness	3	
Range	1770	
Minimum	46	It was on 06-05-2016, there were only 46 tweets were recorded
Maximum	1816	On 06-05-2016, a record number of 1816 tweets were recorded
Sum	83,981	Total number of tweets in our archive
Count	366	The number of days (01-01-2016 and 31-12-2016)

Table 14: Descriptive statistics of tweets

4.3.1.2 The top 10 Twitter users

There were 17,331 unique user tweets recorded during the search in this period. On an average day, every user was tweeting at least 5 times during this one-year period. The top 10 active users and their number of tweets are shown in the following chart.

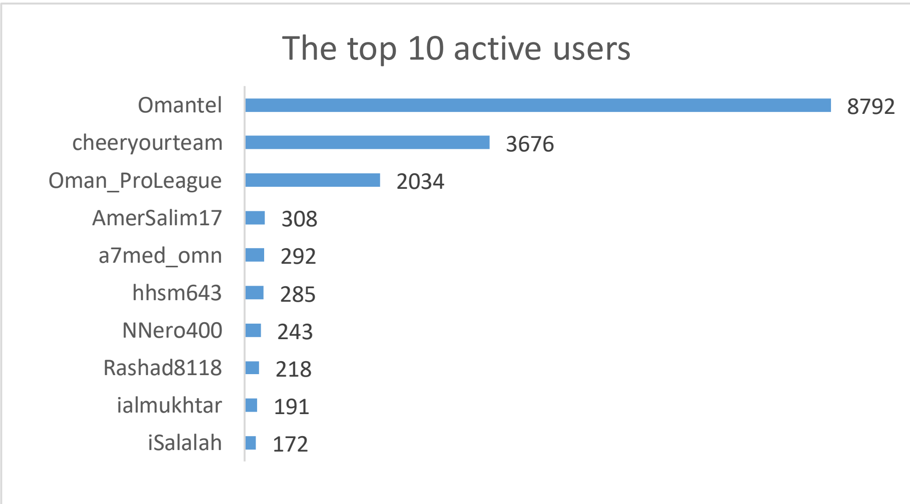

Figure 136: The top 10 active Twitter users during the monitoring period

The top user “OmanTel” tweeted a total of 8,792 times which is around 10% of the total number of tweets recorded. The next highest users were “cheeryourteam” and “Oman_ProLeague” who tweeted a total of 3,676 (4%) and 2,034 (2%), respectively. The remaining users’ tweets equated to less than 1% of the total number of counts recorded during the monitoring period.

4.3.1.3 Temporal analysis of tweets

In order to understand the tweeting patterns, we have investigated the hourly, daily and monthly tweeting activities.

4.3.1.3.1 Monthly variation

The following chart (Figure 137) illustrates the difference in tweet counts over different months during the monitoring period.

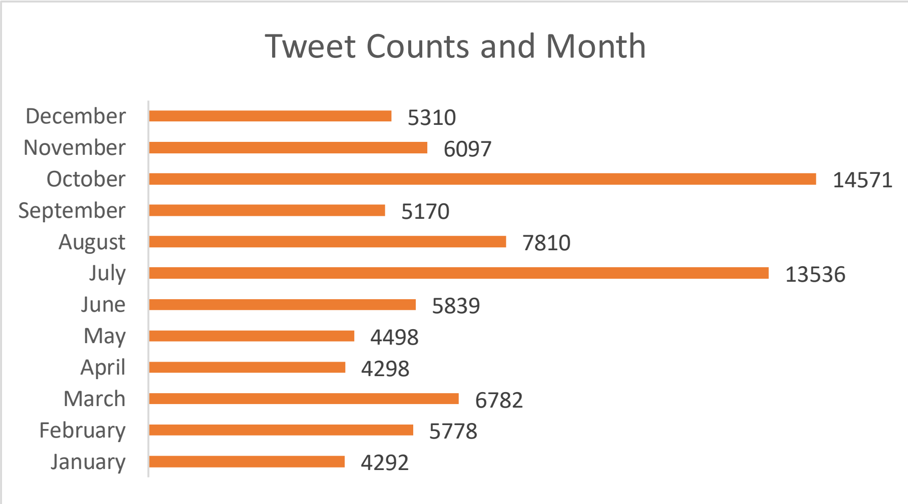

Figure 137: Monthly distribution of tweets.

This illustrates that the highest number of tweets were recording during October and totaled 14,571 which represents 17% of the total number of tweets. It is interesting to note that there were various incidents which occurred during October which could explain this significant rise. In particular, October 2016 was the month when Omani telecom firms were officially and publicly boycotted by the citizens and residents of Oman as they protested against high prices and bad services. The boycott lasted for the whole month of October from 4 - 6 pm each day.

The second highest number of tweets were recorded in July with a total of 13,536 which represents 16% of the total recorded number of tweets. The remaining counts equated to less than 10% of the total number of tweets recorded during the monitoring period. January saw the least number of recorded tweets and represents approximately 5% of the overall total. Again, it was in during the month of July that one of the biggest telecom service providers began to implement new and additional plans incorporating unlimited data. This correlation is further analysed in the following sections.

4.3.1.3.2 Variation in tweet counts on different dates

The number of tweets varied strongly during the different dates during the period of monitoring. Figure 138 shows the variation of the tweet counts on randomly selected dates.

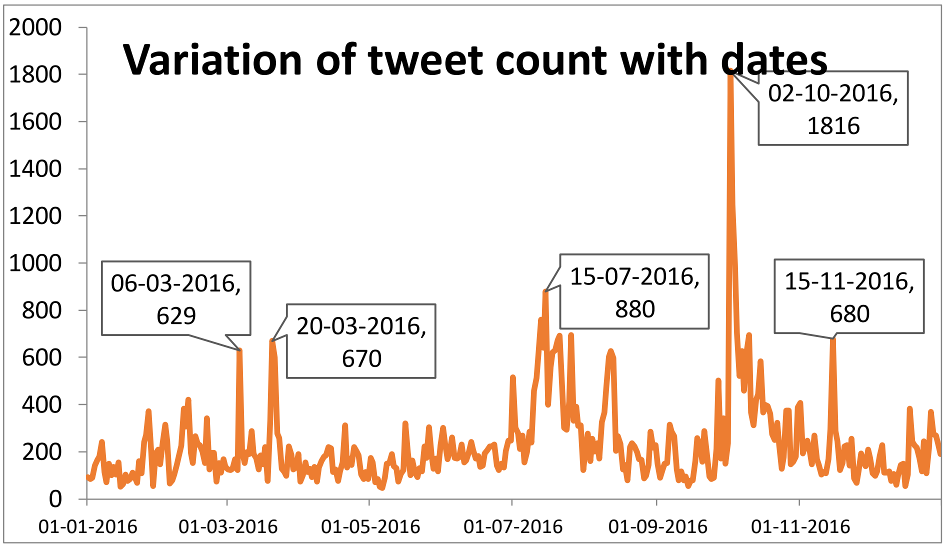

Figure 138: Tweet counts and dates

On 2nd October tweeting activity is observed to be at its highest with 1,816 tweets being recorded. July 15th shows the second highest recorded number of tweets at 880, which is significantly lower than the number of tweets recorded on 2nd October. Similar peaks were observed on the 6th March, 20th March and 15th November.

4.3.1.3.3 Weekday variation

The number of tweets recorded during the days of the week remained almost constant with an average of about 12,000 tweets each day. The most tweets occurred on Tuesday, and Friday saw the least number of tweets. The following chart shows how the tweet count varies with respect to the day of a week (Figure 139: Tweet count and day of the week).

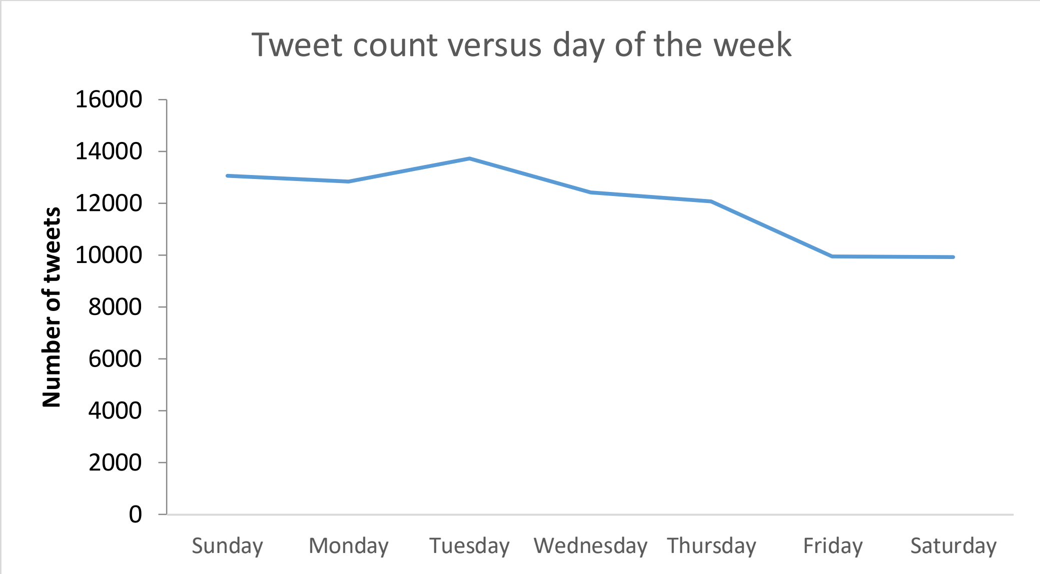

Figure 139: Tweet count and day of the week.

4.3.1.3.4 Time of the day

The number of tweets peaked at specific times of the day. For example, the maximum number of tweets were made at 10:00 am and the next significant peak in the number of tweets occurred at 6 pm (Figure 140).

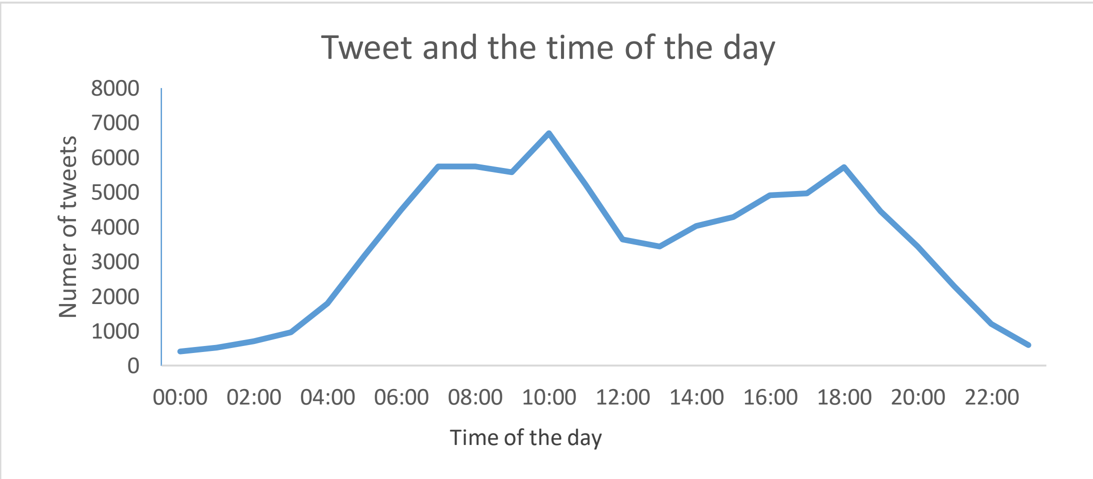

Figure 140: Tweeting pattern with respect to time of the day.

4.3.1.4 Conclusions arising from the descriptive analysis

The descriptive analysis of the historical data highlights the various characteristics of the tweeting patterns. The following conclusions were obtained from the analysis conducted with the data obtained during the monitoring period:

1. On average, a total number of 229 tweets relating to a particular topic were tweeted every day.
2. Weekly and monthly average tweet counts were 1,615 and 7,000, respectively.

3. The maximum number of tweets 14,571 (17% of overall total of recorded tweets) were recorded during the month of October.
4. On 2nd October tweeting activity was observed to be the highest with 1,816 tweets; this figure is approximately 800% higher than the daily average.
5. The highest number of tweets were recorded on Tuesdays, followed by Sundays.
6. The peak times for the highest recorded tweeting activity were observed to be at 10 am followed by 6 pm.
7. There were 17,331 unique users actively tweeting during the monitoring period on my chosen topic.

4.3.2 Sentiment analysis of tweets

I used various features of NVivo to extract sentiments from the tweets. The "autocode" feature of the software enabled me to classify themes, structure, and obtain sentiments from the source data. Additonal features like "word frequency", "matrix coding" and "text search query", etc., enabled me to gain further insights of the data. Whilst the word frequency feature helped to build word clouds, matrix coding enabled me to observe sentiment variation (positive, negative or neutral) with respect to the data. The following sections illustrate the various data visualisation techniques that will help us to understand the theme, structure and sentiments of the datasets.

4.3.2.1 Word clouds

Word Clouds, also known as Text Clouds or Tag Clouds are visualisation techniques which are used to display specific words as they appear in textual data, such as tweets or interview transcripts. Bigger and bolder words refer to the more frequently used text. Many authors including Flamary et al. (2011) mention the following as being the most important applications of word clouds:

1. help to establish any difficulties experienced by the customer;
2. enable organisations to understand their employees; and
3. highlight the keywords which have the potential to be used for marketing purposes and search engine optimisations.

The following diagram presents the outcome of the word cloud images for our data.

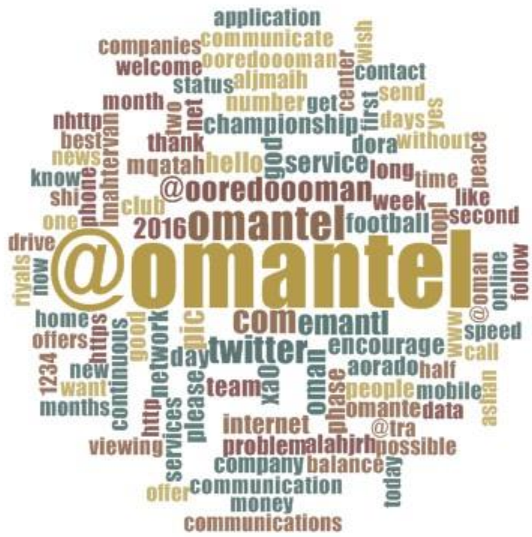

Figure 141: WordCloud visualisation of captured data

Words like @OmanTel and OmanTel represent about 7% of the total number of words which appeared in the dataset. Words like oredoooman represent 1% of the number of words in the word lists. More additional word clouds are given in Section 4.3.3.

4.3.2.2 Tree maps

As most of communication information is hierarchically structured, Tree Maps are often used in order to understand this hierarchical information (Johnson, 1992). Moreover, as the human mind can read pictures faster than reading text, such visualisations aid us in grasping the content of captured data (Figure 142).

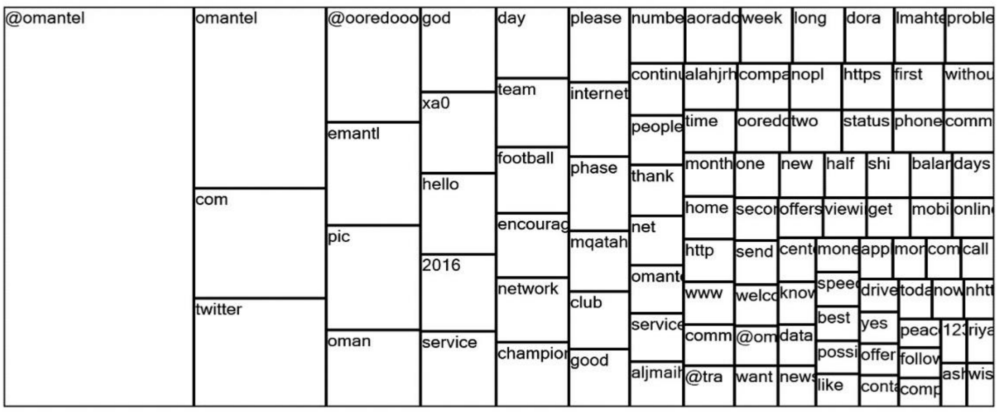

Figure 142: Tree Map of the captured data

4.3.2.3 Sentiments

The overall sentiment scores were projected by the "autocode" function and used the matrix query method of NVivo.

4.3.2.3.1 Overall sentiment

The hierarchy chart (Figure 143) was built using NVivo's sentiment "autocode" wizard that, in turn, produced a sentiment distribution consisting of neutral, negative, positive and mixed results.

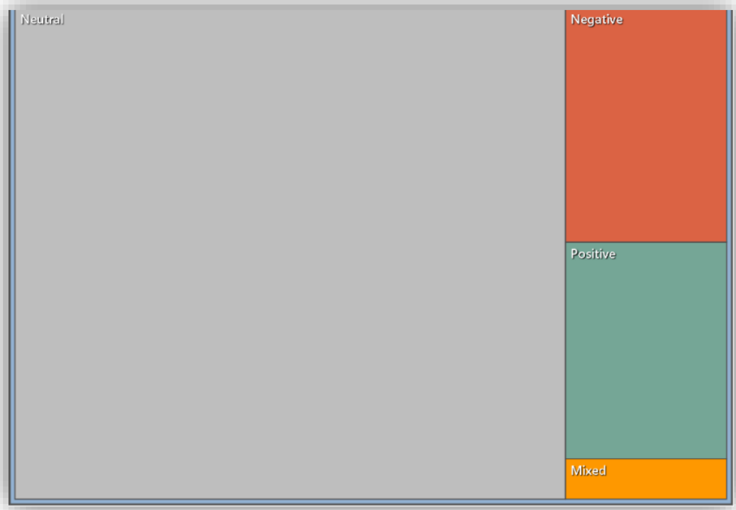

Figure 143: Hierarchy chart of entire captured data

Further examination of this illustrates that almost 77% of the captured data contained neutral sentiments, with negative sentiments representing 11% of the data. Positive sentiment was observed in 10% of the tweets. And there were about 2% of texts that contained mixed sentiments.

4.3.2.3.2 Variation of sentiment with date

Sentiment scores varied depending on the date. The following descriptive statistical analysis of positive and negative sentiment scores offer various insights.

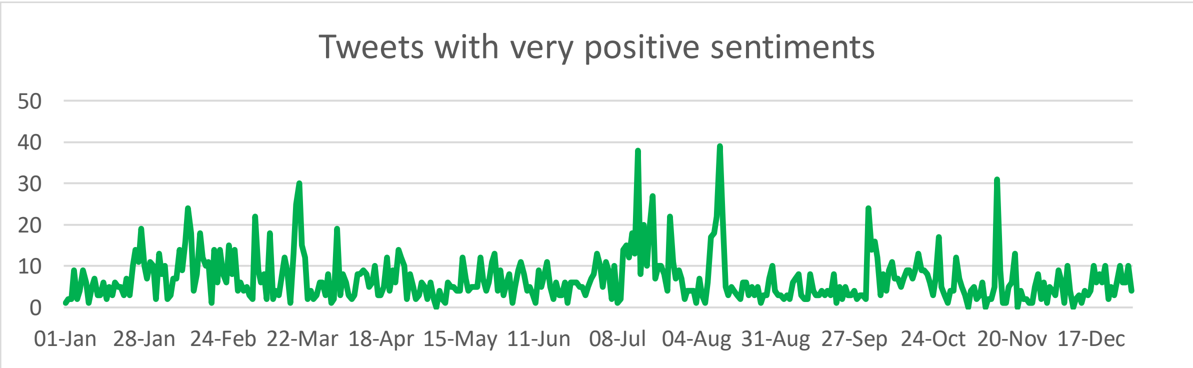

Figure 144: Variation of number of tweets with very positive sentiments by date

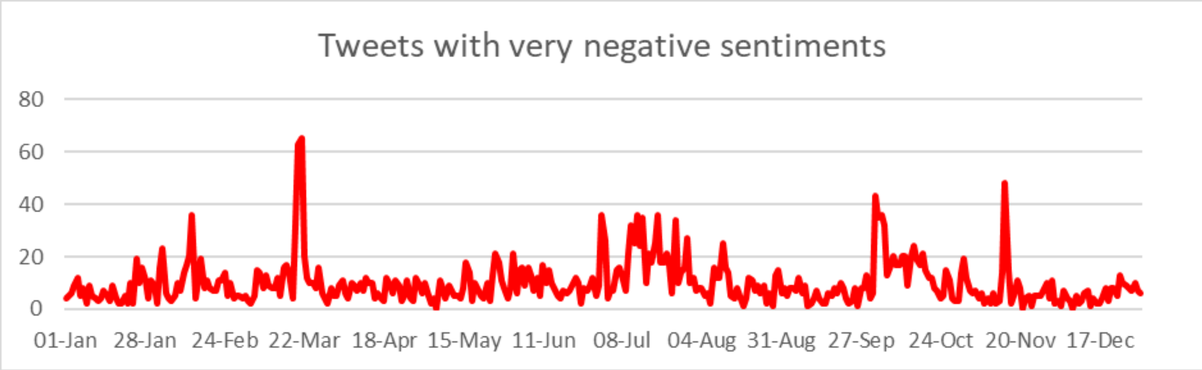

Figure 145: Variation of number of tweets with very negative sentiments by date

In addition to the above line-charts, the following descriptive statistics of the very positive and very negative tweets give us further insights.

Sentiment Score:	Very Positive	Very Negative
Mean	7	10
Standard Error	0	0
Median	5	8
Mode	3	4
Standard Deviation	6	8
Sample Variance	32	72
Kurtosis	7	11
Skewness	2	3
Range	39	65
Minimum	0	0
Maximum	39	65
Sum	2508	3639
Count	366	366

Table 15: Descriptive statistics of the number of very positive and very negative tweets

During the observation period the mean number of tweets with very positive sentiments was observed at 7 whereas for very negative sentiments, the mean number of tweets was observed to be 10.

4.3.3 Extended sentiment analysis

This section explains the output obtained through my custom-written R code. I used various packages and libraries to obtain the word cloud and WordCorpus, and then calculated the sentiments and emotions outputs discussed in detail here.

4.3.3.1 Word cloud analysis

The wordCloud function enabled me to calculate the WordClouds from the cleaned word corpus. Figure 146 shows the words that are predominant in the archive.

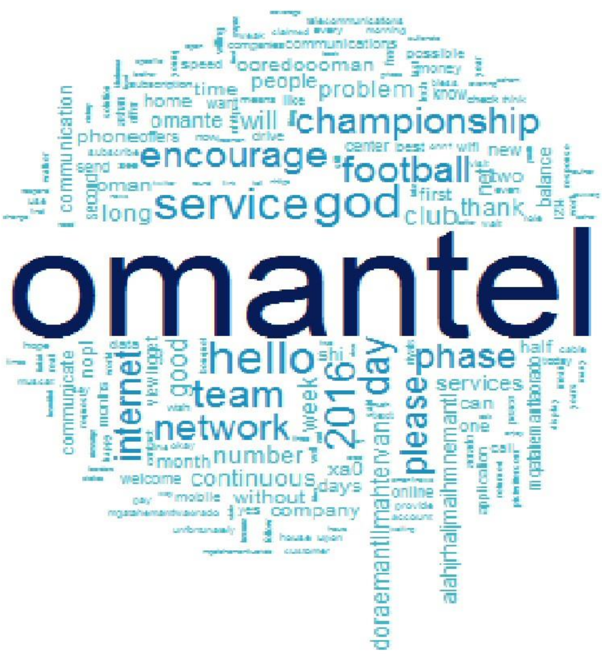

Figure 146: The Word Cloud of the entire archive

One can see that the word “OmanTel” influences the cloud to a great extent. Therefore, I tried to visualize the word cloud without the word “OmanTel” by adding this word in the lists of stop words, as shown in the following code:

```
wordCorpus <- tm_map(wordCorpus, removeWords, c(.., "OmanTel"))
```

The above code resulted in the following word cloud presented in Figure 147

Figure 147: Another Word Cloud without the top frequency word “OmanTel”

These word clouds illustrate various issues that are important for service providers to be aware of. Service, team, data, offers, etc., are all taken very seriously by the users. They seem to be following the offers and freebies made by the telecom providers, and comment about them. Their discussion not only covers calling plans but also constantly discuss data packages.

Now if we run another word cloud to remove the top user “OmanTel”, one can observe the word OmanTel is still dominating even after removing tweets from the user “OmanTel” (Figure 148).

Figure 148: The word cloud without the top user OmanTel

Once again from this list of words, I removed the top word OmanTel to see more words. Figure 161 shows rest of the words in the word cloud:

Figure 149: Word Cloud without the user OmanTel and the word OmanTel

The following word cloud (Figure 150) is formed of the users number of tweets, and shows their relative activity. We can see the user OmanTel being very active amongst others with highest number of tweets (also refer to Section 4.3.1.1).

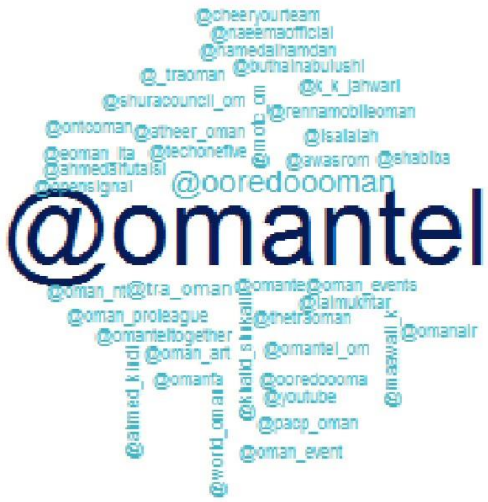

Figure 150: Word Cloud of Twitter users

All these word clouds illustrate that there are active discussions taking place with telecom providers on Twitter. The discussions range from the quality of service to the cost of various plans. All outages, offers and good business practices are actively analysed, and users post their comments without any hesitation and encourage everyone to follow or retweet.

4.3.3.2 Document matrices

As illustrated in Section 3.6.2, the "tm package" allow us to create a document matrix. The Tweets archive were converted into a document matrix with the following details:

Document Matrix Parameter	Value
Terms	62804
Documents	83981
Maximum Term Length	588

Table 16: Document matrix parameters of the tweet archive

In this case, "terms" refer to words and "documents" refer to tweets. The term "document matrix" helps us to keep track of tweets (documents) and their terms (words) in order.

4.3.3.3 Chi-squared tests for tweeting rates

Before inferring anything from the analysis, it is important to establish that the data contains non-uniform tweets. In cases of similar, or the same retweets or tweeting counts, affecting sentiments and emotions, I state the following hypothesis to test the data:

Null Hypothesis: Tweeting rates remain same over **i) weekly**
ii) monthly
iii) weekend or working days

I calculated the chi-square test using the R code shown below:

```
chisq.test(table(month(tweets$timestamp, label = TRUE)))
```

The above code was extended to calculate daily rates by replacing the function month () by wday (). The following were the outputs of running the code on the archive.

For Monthly:

```
Chi-squared test for given probabilities for monthly:
data:     table(month(tweets$timestamp, label =
X-squared = 18736, df = 11, p-value <
```

For Weekly:

```
Chi-squared test for given probabilities
data:  table(wday(tweets$timestamp, label = TRUE))
X-squared = 941.01, df = 6, p-value < 2.2e-16
```

Both these chi-squared tests illustrate that the distribution of tweets in the archive is highly unlikely to be uniform. Therefore, I reject the null hypotheses with a high degree of confidence.

In order to investigate whether there is difference between weekend and working days, the following expression was calculated:

```
chisq.test(table(wday(tweets$timestamp, label = TRUE)), p = c(4, 5, 5, 5,
5, 4, 4)/32)
```

This calculation resulted in the following output:

```
Chi-squared test for given probabilities
data:  table(wday(tweets$timestamp, label = TRUE))
X-squared = 839.11, df = 6, p-value < 2.2e-16
```

This output again results in a very low p-value; thus rejecting the hypothesis. It would not have been possible to arrive at this conclusion by looking at the data as there appeared to be another association. The following chart consolidates the results summary.

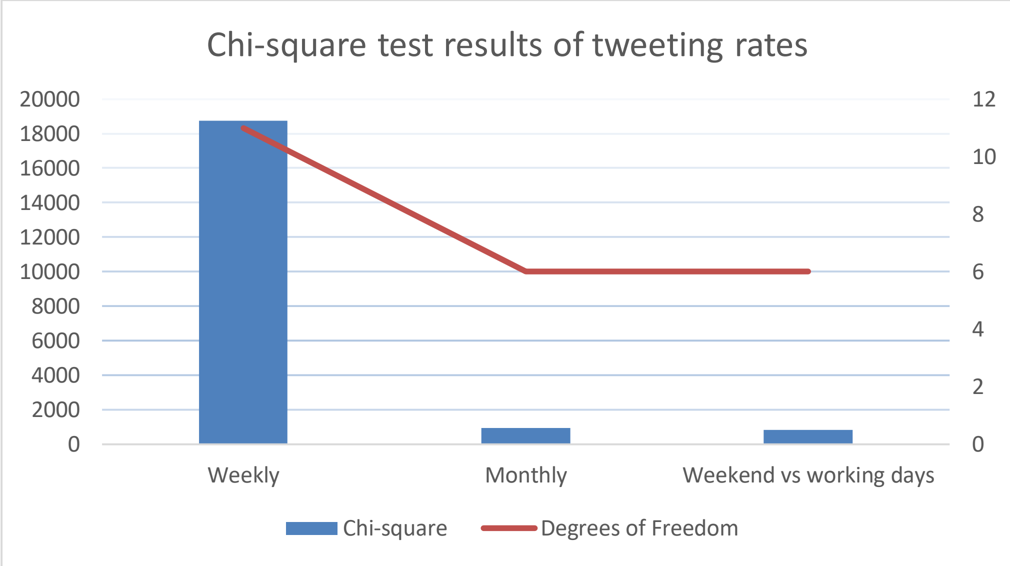

Figure 151: Visualising chi-square test results

4.3.4 Overall sentiments and the Wheel of Emotions

As described in the previous section, I calculated extended sentiment scores for all tweets. The following charts show how emotions are distributed in the overall archive.

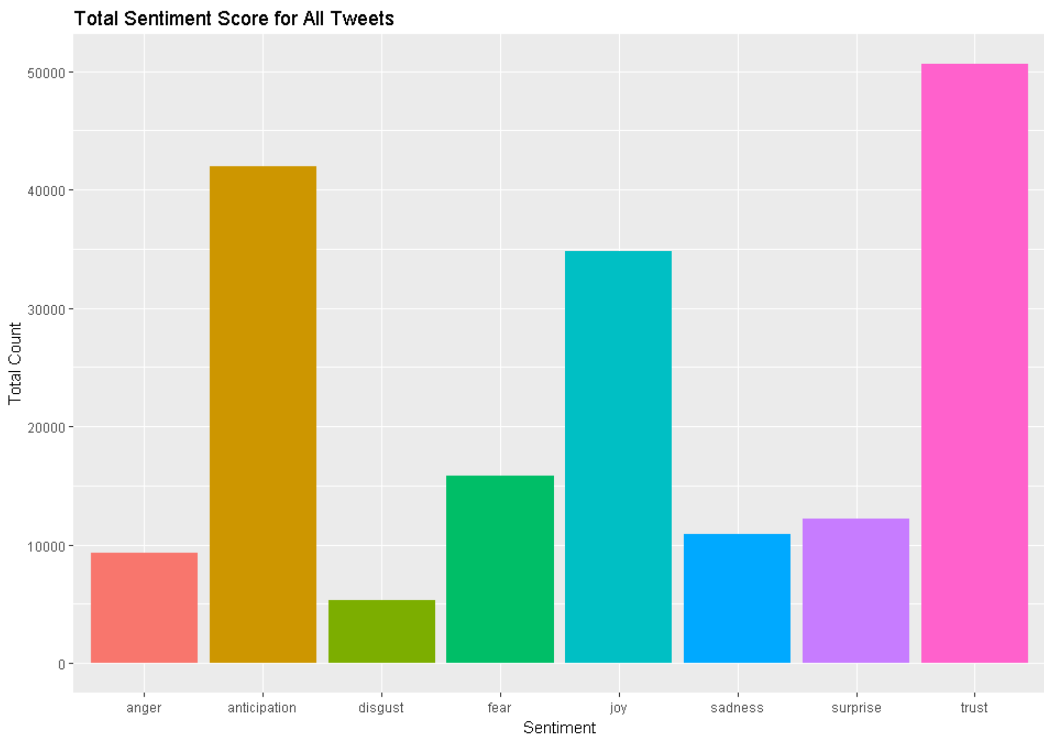

Figure 152: The total sentiment scores for tweets

The above histogram shows, interestingly, that the archive contains more than 50,000 counts of words expressing "trust". Followed by emotions including anticipation, joy, fear, surprise, sadness, anger and disgust (listed in the order they were expressed)

To further visualise emotions, I developed a visualisation methodology (explained in Section 3.6.3) to produce the following “Wheel of Emotions”.

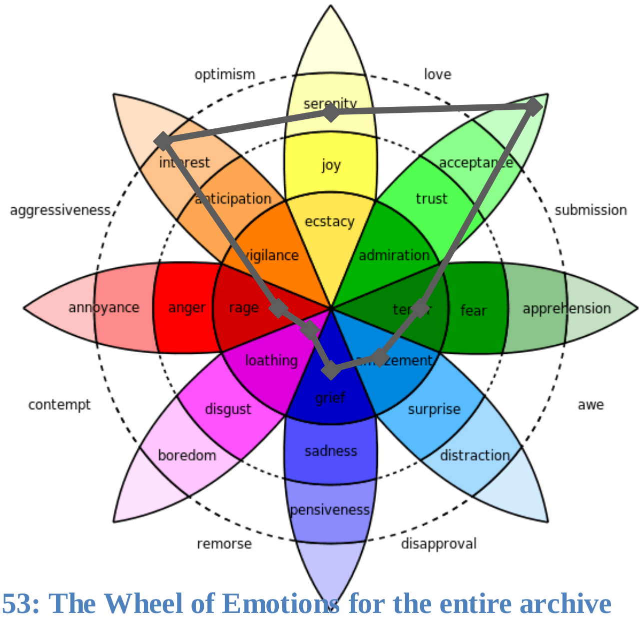

Figure 153: The Wheel of Emotions for the entire archive

This visualisation provides further insights of analysis. The following points are major interpretations from the Wheel of Emotions for the entire archive:

- The words “optimism” and “love” are both major mixed emotions obtained from the data. The combination of a high level of anticipation and joy produces optimism and similarly, a high level of joy and trust produces love. This could illustrate the loyalty of customers, and suggests a high probability of customer retention.
- Following optimism and love, “submission” seems to predominate. Due to the mixture of fear and surprise, submission appears to be an effective emotion. This illustrates that there are a lower number of players who offer less or no alternative choices for their customers’ when choosing an operator.
- “Contempt” and “remorse” seem to be the mixture of emotions observed the least. The tweets collected offer very little evidence that these emotions are prevalent.

As with the previous analysis, the top user “OmanTel” was removed to conduct the analysis again. Figure 167 and Figure 155 display the emotions of the archive.

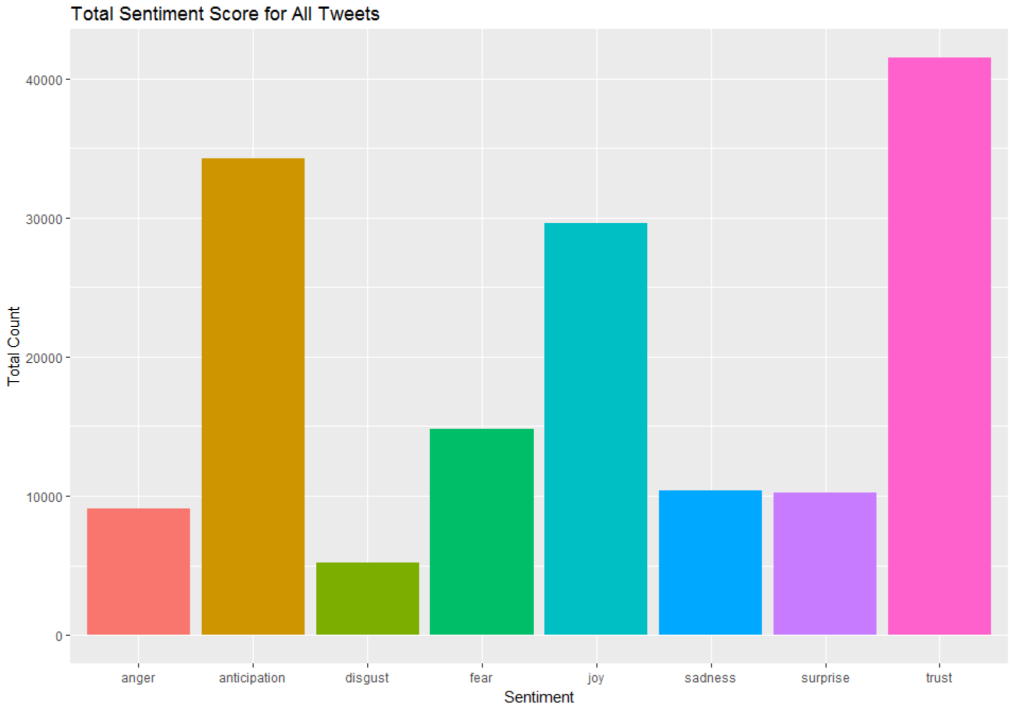

Figure 154: Variation of sentiments in the overall archive without the user "OmanTel"

Interestingly, even after removing the major users' tweets the emotion scores do not change. This could be due to the fact that the emotions obtained are not influenced by the top user
"OmanTel", who incidentally, is one of the major service providers in the country. This inference is further confirmed by the Wheel of Emotion chart displayed below (Figure 155).

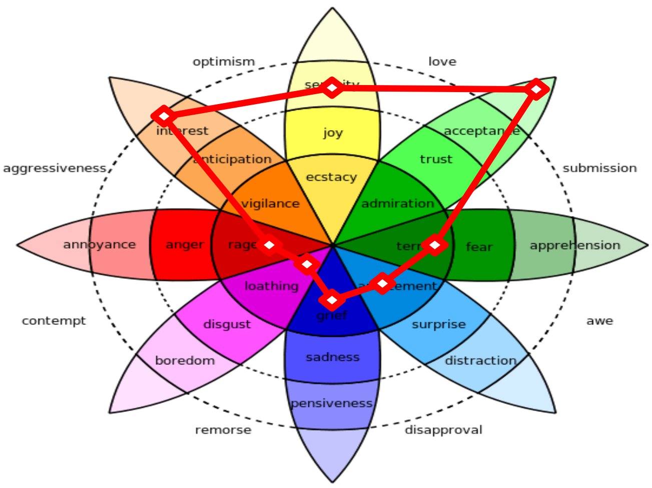

Figure 155: The Wheel of Emotion excluding the top user's tweets – "OmanTel"

Monthly, weekly and time dependent variations of emotions provide further insight.

4.3.4.1 The Wheel of Emotion in relation to days of the week

I also analysed the variation of emotions in relation to weekdays. Figure 168 shows how sentiments varied over the days of week. On most days, from Sunday through to Tuesday, the average sentiment score of eight emotions remained same. However, from Wednesday sentiment scores began to increase and they reached their peak on Friday, a public holiday; the scores then started to decrease on Saturday. I observed that on Fridays, “joy” overrides “anticipation”. During the second weekend, from Friday to Saturday the emotions of “fear” and “disgust” seemed to increase. In particular, “fear”, which was reduced on Wednesday, then started to increase on Thursday, and continued until Saturday.

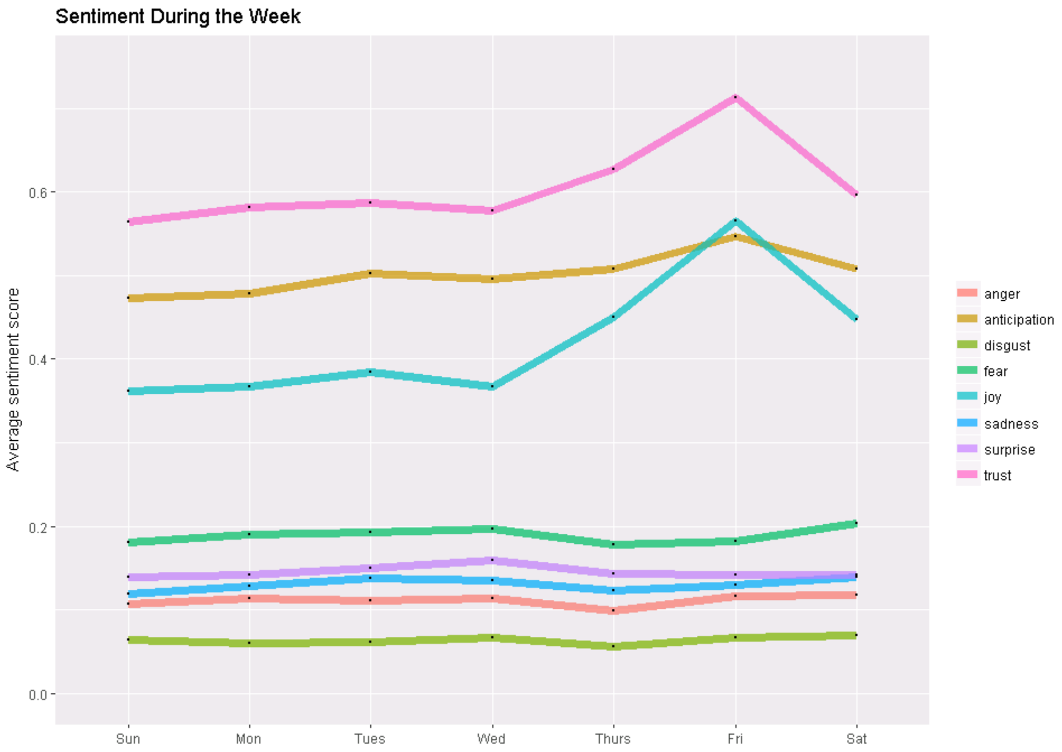

Figure 156: Variation of sentiments with respect to day of the week

In order to study this further, I used the Wheel of Emotion to display the values and obtained Figure 168.

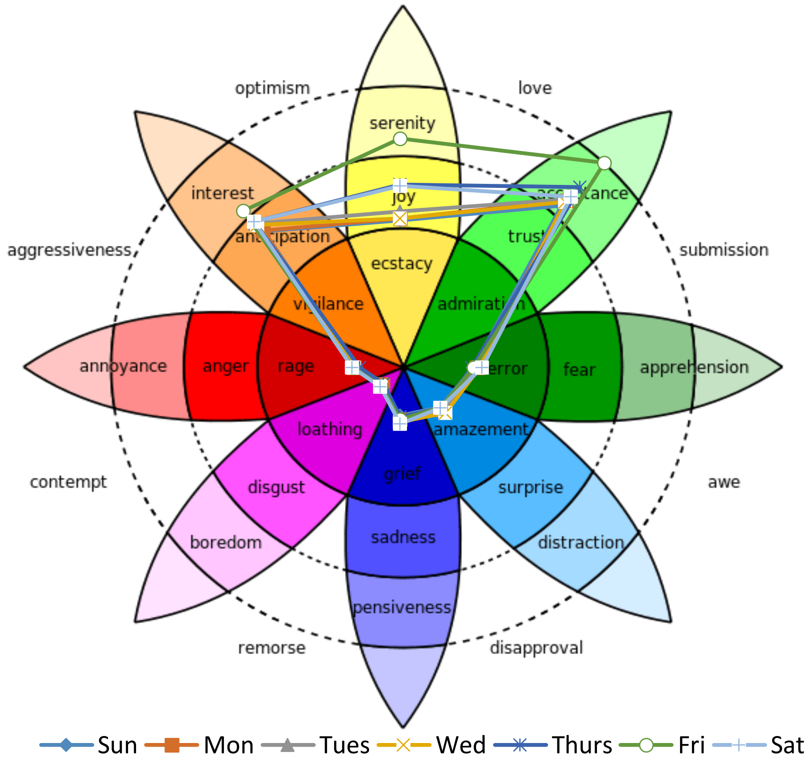

Figure 157: The Wheel of Emotion for the days of the week

We continued our analysis by removing the top user "OmanTel" and interestingly, the pattern remained the same. This illustrates the fact that the emotions of the data cannot be altered by a single user, irrespective of the frequency of his or her tweeting activity.

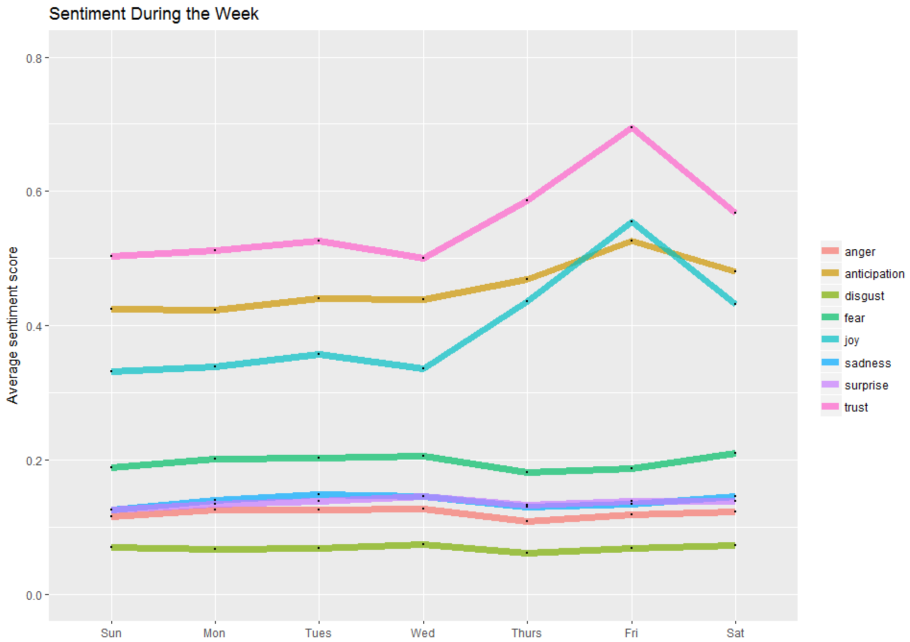

Figure 158: The variation of emotions with respect to day of the week, without the top user's contribution

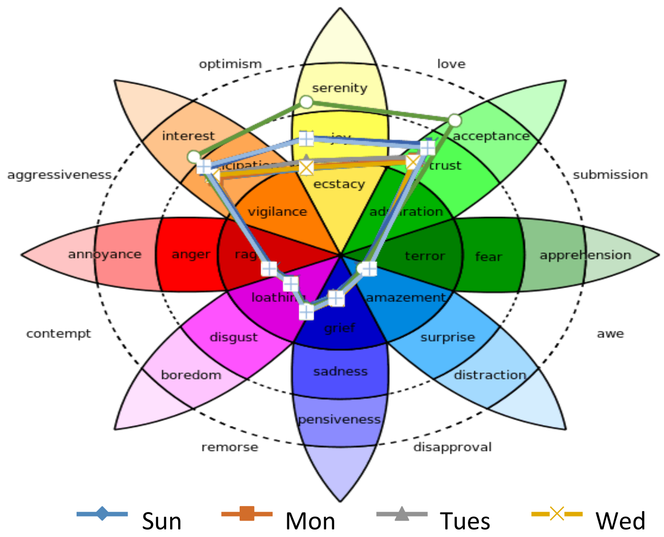

Figure 159: The Wheel of Emotion without the top user

The Wheel of Emotion for days of the week without top user (Figure 159) also confirms the same; that the tweets made by service providers, regardless of the number of counts, does not alter the emotion of the tweets.

4.3.4.2 The variation of emotions by month

I observed the sentiment pattern on a monthly basis with the aim of revealing some of the key events that take place over the course of the year. Figure 172 shows how the main eight emotions of the Wheel of Emotion change with respect to the month of the year.

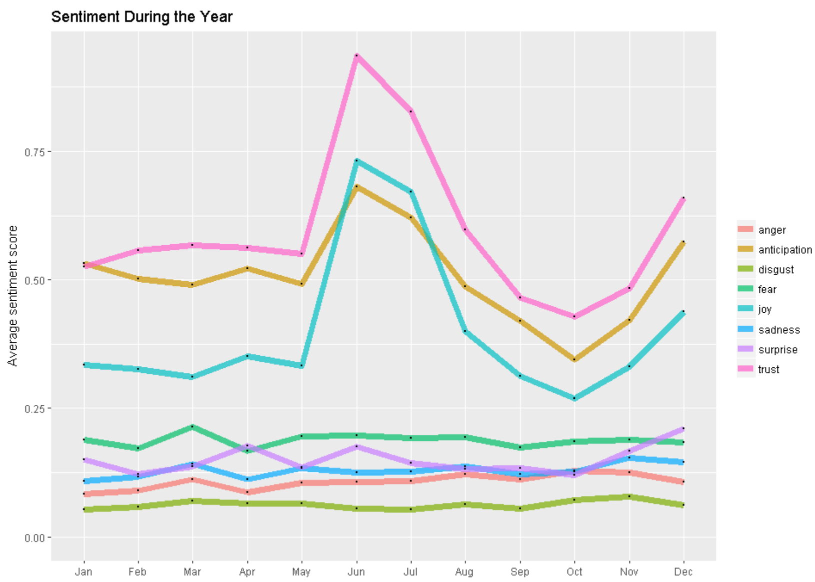

Figure 160: Variation of emotion by month

Emotions are at their peak during the month of June, which is similar to what happens on a

Friday during the week. Perhaps summer holidays and breaks have some relevance for this "outburst" of emotions. In particular, joy overrides disgust during the month of June; similar to what happens on Fridays. The emotion levels are at their lowest during the month of October. It is important to mention again, that the official boycott of services providers took place during the month of October and it was at this time when emotional levels are at a minimum. Moreover, it is also important to mention that despite the high number of tweets in the month of October, as shown in Figure 137, the low level of emotion in this month seems somewhat surprising.

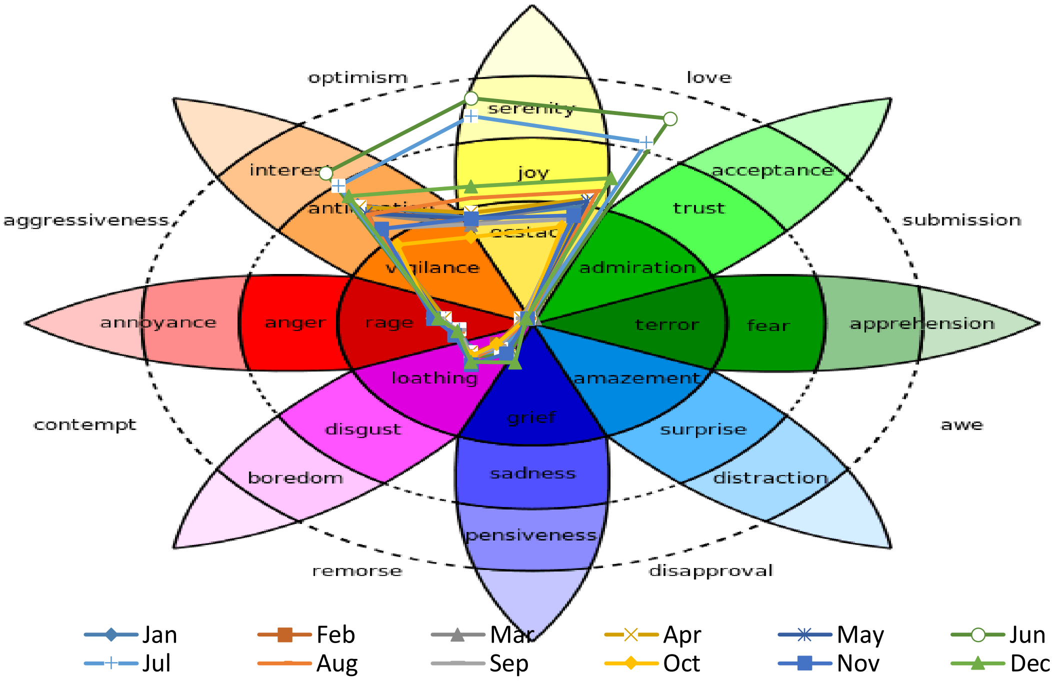

Figure 161: The Wheel of Emtion by month

The Wheel of Emotion displayed above shows the different months of the year. Once again the month of October shows the lowest emotional levels in this visualisation tool. When I extended this analysis to see how the top user "OmanTel" affects emotional levels on a monthly basis, as illustrated in Figure 163, again there was no difference; showing there is no contribution from the top user.

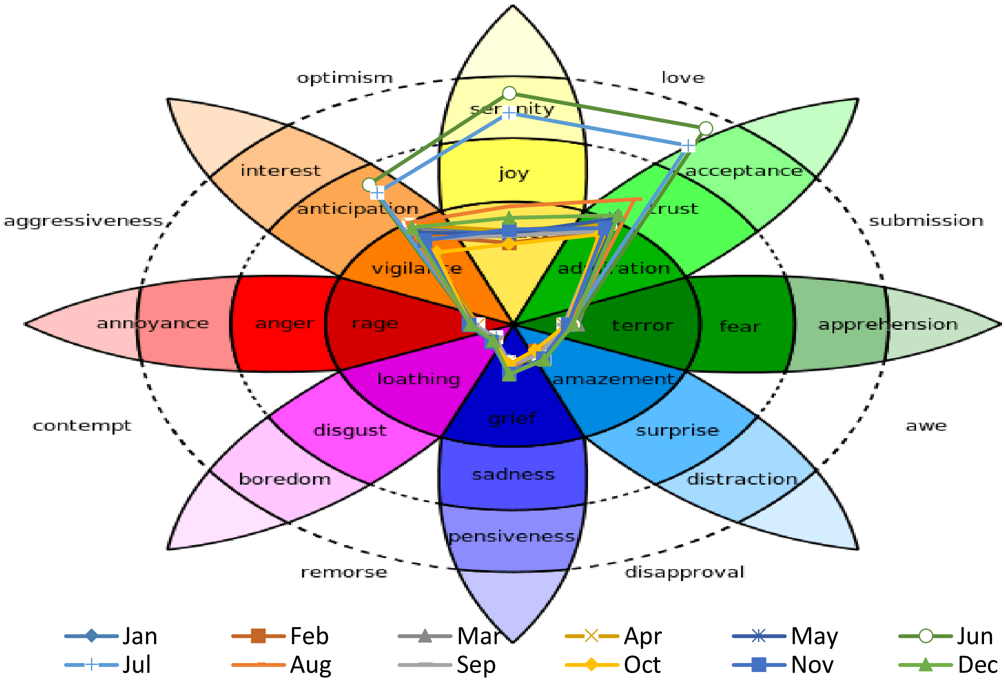

Figure 162: The monthly Wheel of Emotion without the top user's contribution

4.3.4.3 The Wheel of Emotion over time

A variation of emotions was observed over the whole year and has been represented in a dynamic motion chart available online. The online version of this animation illustrates how the Wheel of Emotions varies with respect to time, and is available at http://ms-ja.shinyapps.io/app1.

The following is the snapshot of the dynamic Wheel of Emotion to show that sentiments can be captured on a daily scale.

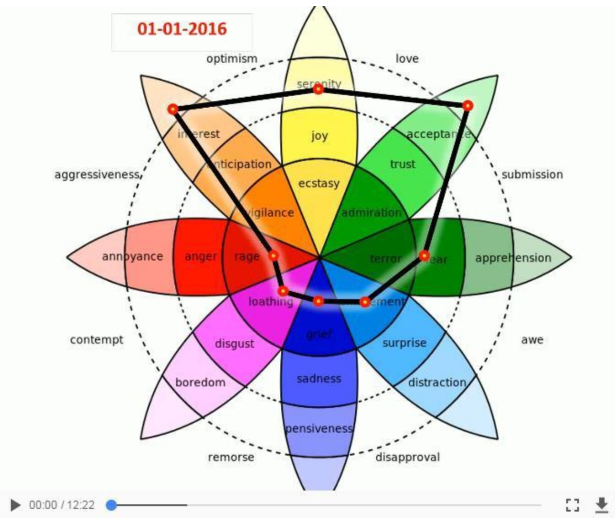

Figure 163: Snapshot of the Wheel of Emotion showing a daily variation of emotion.

The entire dataset for this study is represented in the line chart below (Figure 164).

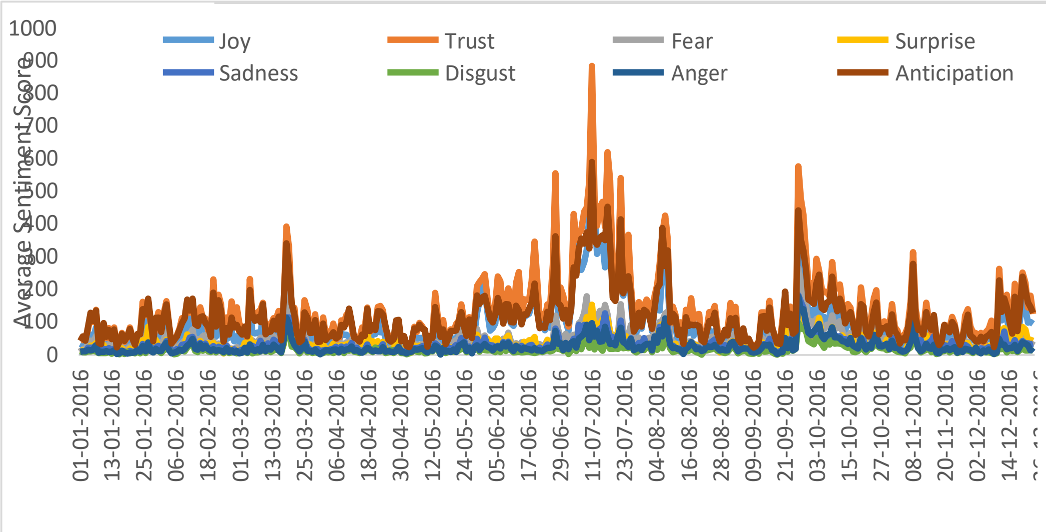

Figure 164: The variation of emotions with respect to date

The following points are worth mentioning:

- On 15th July 2016 the highest number of emotions recorded included the words “joy”, “trust” and “anticipation”. It is important to note that the state’s major telecom operator reported a 9% rise in H1 profit on July 14th.

- The emotions “fear”, “surprise”, “sadness”, “disgust” and “anger” were observed to be the highest on 2nd October 2016. As discussed earlier, this coincided with the boycott explained in the earlier section. This further fortifies I argument of the users’ fear, sadness and anger over the telecom issues experienced in Oman.

- Conversely, the emotions of “joy” and “trust” were at a minimum on 15th January 2016. It was on this day that the Omani Minister instructed the Telecom Regulatory Authority of Oman (TRA) to license a third telecoms operator.

- The emotions of “fear” and “anger” were the lowest on 18th May 2016. “Surprise” was the lowest on 25th February 2016 whilst “sadness” was the lowest on 6th May 2016. “Anticipation” was the lowest on 11th September 2016 whilst the emotion of “disgust” was observed to be the lowest on 24th September 2016.

These results evidence the close association between emotions and various events related to the telecoms sector at specific times in Oman.

4.4 Chapter four summary

This section discussed the outcome of social media data analysis. By using methods evolved from research methodology I conducted basic and extended sentiment analyses and reported these results.

I captured a total of 83,981 tweets during the period 01-01-2016 to 31-12-2016, a total of 366 days. I recorded an average of 229 tweets (per day) ranging from a minimum of 46 tweets collected on 06-05-2016 to a maximum of 1816 tweets collected on 2-10-2016. The median number of tweets (per day) totaled 180, and the more frequent count of tweets (mode) during this period was 85.

There were 17,331 unique users' tweets recorded during the search period. On average, every user tweeted at least 5 times during this one-year period. The top user, "OmanTel", tweeted 8,792 times which is around 10% of the total number of tweets. Next, users like "cheeryourteam" and "Oman_ProLeague" tweeted 4% and 2%, respectively. The rest of the users' tweets accounted for less than 1% of the total number of counts during the monitoring period.

In order to understand the tweeting patterns, we have investigated the hourly, daily and monthly tweeting activities which revealed the following facts:

1. On average, a total number of 229 tweets relating to a particular topic were tweeted every day.
2. Weekly and monthly average tweet counts were 1,615 and 7,000, respectively.
3. The maximum number of tweets 14,571 (17% of overall total of recorded tweets) were recorded during the month of October.
4. On 2nd October tweeting activity was observed to be the highest with 1,816 tweets; this figure is approximately 800% higher than the daily average.
5. The highest number of tweets were recorded on Tuesdays, followed by Sundays.
6. The peak times for the highest recorded tweeting activity were observed to be at 10 am followed by 6 pm.
7. There were 17,331 unique users actively tweeting during the monitoring period on my chosen topic.

Further examination of this illustrates that almost 77% of the captured data contained neutral sentiments, with negative sentiments representing 11% of the data. Positive sentiment was observed in 10% of the tweets. And there were about 2% of texts that contained mixed sentiments. During the observation period the mean number of tweets with very positive sentiments was observed at 7 whereas for very negative sentiments, the mean number of tweets was observed to be 10.

As described in the previous section I calculated extended sentiment scores for all our tweets. The following charts show how the emotions are distributed in the overall archive.

Interestingly, the archive contains more than 50,000 count of words expressing “trust”. Followed by anticipation, joy, fear, surprise, sadness, anger and disgust, in that order.

To visualise emotions further I developed a visualisation methodology (as explained in Section 3.6.3) which produced the following “Wheel of Emotions”:

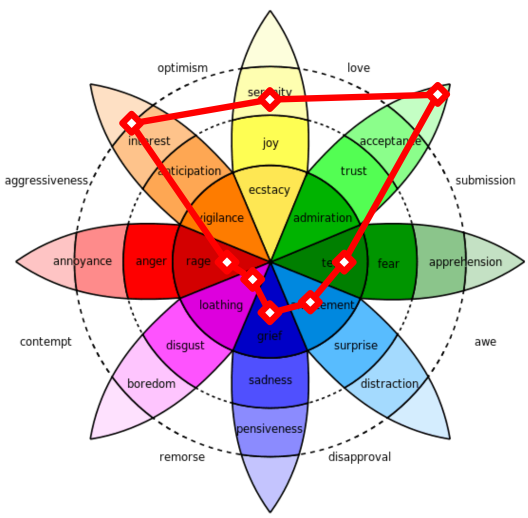

Figure 165: The Wheel of Emotions for our entire archive

The variation of emotions in relation to weekdays was also analysed. Figure 156 shows how sentiments vary over the days of week. On most days from Sunday through to Tuesday the average sentiment score of eight emotions remained the same. However, from Wednesday sentiment scores began to increase, and they reached their peak on Friday which was a public holiday; the scores then started to decrease on Saturday. I observed that on Fridays, “joy” overrides “anticipation”. During the second weekend, from Friday to Saturday emotions of “fear” and “disgust” seemed to increase. In particular, “fear”, which decreased on Wednesday, then started to increase on Thursday and continued to do so until Saturday.

In order to study this further, the Wheel of Emotion was utilized to display the values obtained. I continued the analysis by removing the top user “OmanTel” and, interestingly, the emotional pattern remained the same (Figure 159). This illustrates the fact that the emotions of the data cannot be altered by a single user irrespective of the frequency of his or her tweeting activity. Therefore, it is clear that the tweets from a service provider, however many counts there may be, do not alter the emotions of the tweets.

Observing the sentiment pattern on a monthly basis, I expected to reveal key events during the course of the year that Twitter users responded to emotionally. Figure 160 shows how the eight emotions change in respect to the month of the year. TEmotions are at their peak during the month of June, which is similar to what happens on a Friday during the week. Perhaps the summer holidays and breaks have some relevance to this outburst of emotions. In particular, again joy overrides disgusts during the month of June. This is also something similar to what happens on Fridays. Emotional levels are at their lowest during the month of October when the official boycott of services providers took place during the month of October (Fahad, 2016), and it was at this time when emotional levels are at a minimum. Moreover, it is also important to mention here that despite the high number of tweets in the month of October (as shown in Figure 137), the low level of emotion in this month seems somewhat surprising.

The Wheel of Emotion, displayed above, shows different months of the year. Once again, in this visualisation the month of October shows the lowest levels of emotion. I also extended this analysis to see how the top user “OmanTel” affects the emotions on a monthly basis; again there is no difference in emotional levels which confirms that they are not affected by contributions from the top user.

The following points are worth mentioning:

- On 15th July 2016 the highest number of emotions recorded included the words “joy”, “trust” and “anticipation”. It is important to note that the state’s major telecom operator reported a 9% rise in H1 profit on July 14th.

- The emotions “fear”, “surprise”, “sadness”, “disgust” and “anger” were observed to be the highest on 2nd October 2016. As discussed earlier, this coincided with the boycott explained in the earlier section. This further fortifies I argument of the users’ fear, sadness and anger over the telecom issues experienced in Oman.

- Conversely, the emotions of “joy” and “trust” were at a minimum on 15th January 2016. It was on this day that the Omani Minister instructed the Telecom Regulatory Authority of Oman (TRA) to license a third telecoms operator.

- The emotions of “fear” and “anger” were the lowest on 18th May 2016. “Surprise” was the lowest on 25th February 2016 whilst “sadness” was the lowest on 6th May 2016. “Anticipation” was the lowest on 11th September 2016 whilst the emotion of “disgust” was observed to be the lowest on 24th September 2016.

These results evidence the close association between emotions and various events related to the telecoms sector at specific times in Oman.

5 Discussion

Our case study approach to the Omani telecom sector illustrated how customer relations management (CRM) is maintained, and how important decisions are made based on available customer data. It is known to all firms here that providing the best customer service is of paramount importance.

As observed in the most relevant and recent studies, one of the main drivers in telecoms is customer retention. Studies like Premkumar and Rajan (2017) have shown that being in a competition rich and market saturated environment, telecom firms should keep finding ways to retain customers. In the social media era, where customers dissect every product and service available and companies can obtain real-time feedback, the challenges and complications of gathering, managing and analyzing this data are increasing. Therefore, firms should keep implementing possible innovations at every level.

Viriri and Phiri (2017) in their study on the Zimbabwean telecommunication industry, revealed that establishing and enhancing customer loyalty is vital for firms to grow and perform in this sector. Due to technological innovations and rapid developments, the communication sector is characterised as a sector that maintains a better perception of customer expectations, and this has resulted in the provision of high-quality services Mahajan et al. (2017).

The contribution of social media to enable customer involvement towards improving customer service is undisputable. One study on customer involvement for innovation in the telecom service has shown that such associations, via interaction between service providers and customers, become notable for others to follow (Corte et al., 2015). Processes necessitate customer involvement from the production or coproduction of services. As lots of limitations in service innovation exist under traditional processes, using production and coproduction with customer involvement can certainly help firms to obtain ideas for service innovations (Nyambu, 2013). Innovation can thus be reached by involving customers right from the service creation process; a level of interaction that could originate from social media interaction.

Influenced by recent studies, and facts learnt from the Omani telecom context, this research presents an interdisciplinary approach, building on that in the literature review that examined CRM. The review, in Chapter 2, focused on CRM, especially in the service sector, and the research methodology, in Chapter 3, described relevant concepts regarding information science, computer mediated communication, sentiment analysis, human structure interaction and social interaction. This enabled me to use sentiment analysis as an appropriate tool, in Chapter 4, to put the data into proper use at the organisational level.

Guided by the theoretical approach that offers a potential choice of strategy for this research through its method of enquiry, I have designed sampling methods for accessing and constructing measurements on social media. This research derived data not only from the extensive literature review but also from surveys and interviews with telecom users and social media managers. The research strategy of my study included surveys, interviews and data analysis, supported by interviews and prepared interview guides. All methods were piloted and further enhanced before the main data collection stage.

5.1 Discussion of the literature review

The literature review started from the marketing theory and discussed the evolution of CRM. The benefits and objectives of CRM were found discussed by many authors in different perspectives. In particular, the studies by Xu and Walton (2005) concluded that there are primary reasons for organisations to implement CRM which include: improved customer satisfaction, retaining a customer base, obtaining strategic information and enhancing the value of the customer lifetime. In addition, Nguyen et al.'s 2007 study, provided specific CRM objectives through increased customer loyalty, superior data collection and sharing, and knowing customers and providing a superior service.

In order to see how CRM works in the service sector we started by studying the product-service distinction. I have tabulated how marketing studies distinguish products and services in broader categories including: a wide ability to measure, perception, form, shelf life, delivery, flexibility and marketing (Evans and Berman, 2002). This resulted in a matrix being created, as recommended by them, for telecoms products and services which enable us to understand the nature of goods or services to be marketed (Figure 11).

Various theories and models of CRM have been reviewed, and this has highlighted how customer interaction and customer value play an important role in organisational success. Ways of measuring customer relationships, particularly in the service sector, were identified from that part of the literature review. I also reviewed how CRM and database marketing are related, and it is understood that such potential relationships will pave the way to a greater focus on customer segmentation. In particular, Xu et al. (2002) characterise a successful firm as one that has a system to implement their customer database wisely in order to deliver what the customer wants, every time. Nguyen et al. (2007) explain that such a process is continuous, and the process of digitising the employee's knowledge is vital.

In the literature review, I also consolidated different CRM strategies. Starting with Peelen (2005) and his illustration of different types of strategies, I explained the model proposed by Curry and Kkolu (2004) for customer management activity. This is a model that uses the customer life cycle as a process under consideration.

Marketing 3.0 is a methodology insists firms should consider customers as multidimensional entities and value-driven people. It is a holistic approach that an organisation should take into account (Kotler et al., 2019). And it is framework which necessitates organisations to consider customers as unique, and establish better interactions and relationships with them (Marques, 2018).

Relationship marketing is experiencing a recent change; one that considers the bigger roles of inter-organisational culture (Larentis et al., 2019). Social media provides customers with an interactive channel to voice their opinions. In turn, organisations can make use of the information on social media to serve their customers.

Cooperative practices, such as better conflict management and organisational integrity, can also influence relationship marketing at a result level. Weakening elements might also arise in communication between company's and customers, such as the non-availability of shared symbols and meanings (Larentis et al., 2019).

The review of information science enabled us to understand what information is and how it is transmitted from a source to a receiver. As the objectives of this research study was to extract certain specific and useful information from social media, as per Zins's (2007) description of information science, my task, therefore, was to focus on another knowledge domain of information science that is capable of handling multiple domains and can be very well applied. Thus, by gaining an understanding information's behaviour we are able to find a new approach to information that is unintentional, passive or even purposeful (Case, 2007).

According to Spink et al. (2006), more than the information on its own, the use and behaviour of the information enables us to enrich our knowledge base. The information process, therefore, has to coordinate a cognitive state, level of knowledge and individual understanding that results in a coherent series of activities (Kuhlthau, 1993).

Although various explanations of information science exist, human information coordinating behaviour seemed to be a suitable one for my study as it encompasses information finding and organising, and can be used for further analysis.

The main data source for this study came from a digital medium which contained the survey data from 16 social media managers, 455 customers, 83,981 Tweets (social media data) and also 19 interview transcripts. Therefore, it was necessary to review specific literature on computer mediated communication (CMC) which illustrated the dynamics of communication. Another notable point from the definitions of Kelsey Fragoso et al. (2008), is that information flow can be made to oneself, another person, a group or even to an imaginary audience. Thus, while looking for the data it was important to note the openness of receivers in the information flow. Furthermore, the mechanism that I employed should able to tap into information in real time (synchronous), time-delayed (asynchronous) or even super synchronously (with multiple users at a time).

Constraints and affordances, as explained by Clark (1996), Clark and Wilke-Gibbs (1986) and Clark and Brennan (1991), should be taken care of whilst analysing any communication. Social media usage needs to be analysed both via online interaction and by using the technology adoption dimensions of CMC.

The research methodology described an overview of sentiment analysis from both a historical and a technological perspective, and enabled me to justify the use of the right tools for this study. I established that the algorithms used in sentiment analysis are capable of extracting useful information from huge amounts of data, or real-time analysis would otherwise be impossible. As discussed by Mostafa (2013), the contribution of sentiment analysis for brand tracking is not only plausible but is also robust.

Although there are challenges to using sentiment analysis the tools of natural language processing offered promising solutions to overcome the constraints faced while extracting useful information from social media data. The seven step approach introduced by Tsytsarau and Palpanas (2010) explains the technicalities of sentiment analysis, and was indeed applicable for our case.

As widely noted in the literature (Greene et al., 2012, Max, 2013), in order to conduct sentiment analysis, we should:

1. Identify significant people and groups related with the telecom usage of the chosen organisation.
2. Archive social media data including tweets or posts pertaining to those identified in the previous step.
3. Calculate sentiment scores by using the most suitable tools available for the chosen sentiment analysis algorithm.

In order to investigate social media texts it was important for me to know how users interacted with social media applications. Therefore, my review of human computer interaction (HCI) enabled me to visualise the link between HCI within various disciplines, such as education, psychology, ergonomics, plus the efficiency of human-computer interaction (Dix et al., 2004). The theories of HCI appear to be highly fragmented and available without a single method or integrated approach. I understood that any approach should be tailored to the specific needs of the demands and situations where they were applicable. I studied three models of HCI and saw that Abowd and Beale's interaction model is refined and appears to have a suitable methodology in line with the methods of my study.

As pointed out by Poynter (2010), the huge potential of the expanding domains of social interaction becomes the driving force for organisations that see an opportunity for better marketing and profit making. This is one of the very important points that supports my methodology because by understanding and analysing the identity, conversations, shares, relationships and reputations of their product or services in social media, it is possible for organisations to implement a sophisticated social media strategy (Kietzmann et al., 2011).

At the same time, we can observe a steady increase in the literature of studies applying sentiment analysis to social media data. Social media users express their opinion for the reasons, including the need to belong, the need for cognition and self-presentation, and impression management (Carpenter et al., 2018). Some recent studies illustrate that social media posts expose the personality traits and motivational factors of the users (Ducange et al., 2019, Goswami et al., 2019). It has been shown that extraversion is a common attribute found across the active users of social media, and such people show their presence through a large number of friends, posts and responses (Goswami et al., 2019). Many authors opine that next to extraversion, another behaviour, those with neuroticism (tense, moody or irritable people) use social media as it is a safe and controllable space to self-express. So, there is great opportunity for sentiment analysis to be applied on the posts of social media users.

It is very clear from these points that sentiment analysis showing positive, negative and neutral sentiments, no longer helps organisations. There is a need to capture sentiments beyond these, i.e. emotions from social media datasets. When we consider the methods adopted by sentiment analysis, we can see diverse approaches are being used. One such remarkable approach involves using verb expression. Using linear regression optimised by particle methods, Jiang et al. (2019) have analysed verb expressions extracted from reviews These verb expressions are an accurate representation of customers' opinions and a direct way for firms to improve their products. Their study has shown that without manual training their methodology of sentiment analysis worked as proposed. Such verb expression methodology is unique, and has been demonstrated to be precise and efficient beyond relying more directly on sentiment. Second, another area of progress in sentiment analysis, goes beyond word frequency and the position of terms used in the overall discourse by using rhetorical structure theory. Kraus and Feuerriegel (2019) have proposed tensor-based, tree structured neural networks, and they have also proposed two methods of data augmentation: namely, training set and overfitting. Third, another notable recent development joins visual and textual sentiment analysis. In order to extract the sentiments about events or topics, Zhu et al. (2019) argue that visual and textual information are different components. Their model incorporates a cross modality attention mechanism with an embedded semantic learning network. By using these methods, they could obtain deeper insights and a more efficient classification of the dataset.

5.2 Discussion of the methods

The methodology chapter detailed my reasons for choosing the theories involved in this study and for choosing the Wheel of Emotions. This chapter also illustrated the challenges encountered during the research and their solutions. As deduced from the literature review, in order to find the difference between what managers think of the services they provide against what customers feel about the services they receive, I needed to carefully design the research study. My drafted research questions, therefore, needed to draw out answers about the behaviours of the subjects. This approach enabled me to design the study, collect data and interpret the data by providing a framework to carry out a study with interweaving, intangible facts.

The decision to use surveys, semi-structure interviews and employ sentiment analysis, are the result of the application of this theory. I also justified the chosen research methodology, its challenges and shortcomings, by comparing it with other methods. The right approaches were selected based on their suitability and relevance to this domain of research. This selection included making decisions regarding longitudinal versus cross-sectional study, both designs which involve survey research methodology.

A cross-sectional approach was found to be useful to study the present scenario, while a longitudinal approach was found to be more useful for studying changes and developments over time. Most research projects, such as mine, are time constrained and, therefore, they are cross-sectional. Hence, as the present study related to a snapshot of the social media engagement of Omani telecoms companies over a particular period of time obtained through questionnaires and interviews, my research was cross- sectional in nature.

The research methodology section also explained my philosophical stand and reason for ignoring other current understandings. Thus, I took into account the research strategy, as defined by Saunders et al. (2015). My research also employed a linkage between research philosophy and methodology for collecting and analysing the data. Figure 23, the Research Onion, illustrates the wide choices available for researchers to conduct research. The

Research Onion encompasses different layers consisting of different philosophies, approaches, methods, strategies, time horizons, data collections and analyses.

My choice of an appropriate research strategy was strictly guided by my research questions and objectives and their linkage to philosophy, approach and purpose. Moreover, the research philosophy depended heavily on existing knowledge, availability of time, resources and data. Saunders et al. (2015) rightly describes grounded theory as an incorporation of methodology and method; in other words, a theory that is grounded in the data collected. This enabled me to understand the importance of what type of questions to include in the study. Therefore, I employed various questions that started with "what" in the present study.

As this study is about contemporary events (social media usage) without actual control over users' behaviours, it was felt that a survey strategy was deemed to be suitable for the research. By using survey instruments social media managers and customers were asked for meaningful data. As discussed, data from questionnaires enables a researcher to propose a relationship amongst the variables under investigation. For this purpose, I also used quantitative research methods. This resulted in a detailed cross-sectional and longitudinal study and enabled me to select samples, measure data and conduct semi- structured interviews. Questionnaires were also developed and piloted. After the pilot study, improved surveys were administered to social media managers and customers. Social media data pertaining to the Omani telecom sector were collected for a year and subjected to basic sentiment and emotional analysis, as explained in Chapters 3 and 4.

5.3 Discussion of the research findings

This section discusses the results of survey and interviews for social media managers, the customers' survey, and sentiment analysis of the social media data. The analyses of these three domains enabled me to triangulate my discussion on CRM from the combined perspective of firms, customers and the sentiment analysis tool.

5.3.1 Discussion of the data collected from the social media managers

This part of the discussion focuses on the outcomes of the social media managers. As the data were collected through questionnaires and semi-structured interviews, both of these methods brought out some salient features of the current status of sentiment analysis tools, and whether they are effective CRM tools for use in the Omani telecom sector.

5.3.1.1 Survey results

Both surveys for social media managers and customers were administered through Qualtrics provided by the University of Strathclyde. The first survey contained 20 questions to collect demograpic details and social media usage patterns (Appendix 1). Responses were recorded in Qualitrics from 8:18 pm on 21st May until 09:04 am on 31st May 2016.

More than 50% of the survey respondants had been in their current position for the last 15 years or more, 40% for the last 1 to 5 years, and 10% over the last 10 to 15 years. This enabled me to obtain accurate results from the perspective of the senior managers of the firms that participated in the research. The majority of managers (80%) were aged between 30 and 50 years old; 20 to 30 year-olds, and those aged 50 years and above, represented 10% of the respondents.

When asked how actively organisations participated on social media: 80% of managers agreed that their firm was very active on social media, and only 20% of the respondents said that their firm did not use social media at all. Twitter was the most sought after social media platform with 30% of managers endorsing it; followed by Facebook, LinkedIn and, finally, Google+. Four respondents (16.67%) also opted for Instagram which was observed as an active platform used less than LinkedIn but more than Google+.

When asked about the frequency of updating social media content, 40% of respondents said that their organisation's social media profile was updated every day, and 10% of respondents said that their firm updated social media content bi-weekly. Amongst the other respondents, 10% said that their organisation updated its profile on a monthly basis, or only when there was a product launch or special offers.

When asked about the maintenance of their company profile page revealed that 29% of managers mentioned that the profile is maintained just for the basic details of the organisation, whereas 25% said it is used for showcasing promotions or advertising products and services. Another 25% opined that their profile page was to contact customers whilst recruiting for jobs, and measuring supporters or followers was observed by another 10%, respectively.

When asked about the most significant social media platform, using a Likert scale, Twitter was considered to be the most significant social media platform by 70% of managers, followed by Instagram with 67% and Facebook 44%.

The next part of the questionnaire focused on marketing strategy. Firstly, I asked about whether there was a link between marketing strategy and social media coverage, and 90% of the managers agreed that there is a clear link between marketing strategy and social media coverage. This clearly indicates that Omani telecom firms make deliberate attempts to link their marketing strategy with their social media coverage. However, despite this approximately 10% of managers were not aware of any such linkage.

Secondly, I asked an open-ended question in an attempt to obtain further clarification on this issue. I received further input from the second manager who described this connection as being innovative. He went on further to state that: "*The link is in stimulating some innovative ideas from the audience, as well as getting some good insight into how the customer(s) perceive*

the company". This shows that firms are open to their customers and are keen to understand what their customers think of the firm and its services.

Another manager enunciated, *"Social media is becoming the most important channel for approaching the clients and customers and understanding their behaviours and needs; these types of information are very critical in establishing and implementing the organisation's [marketing] strategy".* This is in accordance with what the studies of Xu and Walton (2005) concluded as being the best customer relationship strategies, which are:

- improved customer satisfaction;
- retaining a customer base;
- getting strategic information; and
- enhancing the value of the customer lifetime.

Another manager also reflected this view by confirming such alignment opens two-way communication channels, and by doing so creates lower costs and a wider customer reach. Therefore, it was commonly agreed amongst the managers that social media is a powerful vehicle for transferring strong messages to targeted audiences. They also agreed that such platforms are suitable for immediate feedback on promotions and offers.

According to Nguyen et al. (2007) one of the most important objectives of CRM is better customer support. Therefore, our next question in this regard was aimed at finding out whether the Omani telecoms firms provide online customer support. 80% of the managers informed us that their firm provides online customer support with 10% saying that they don't provide online customer support services. The remaining 10% of managers did not know or were unsure if their organisation provides online support.

According to Xu and Walton (2005) keeping in touch with the customers is essentially continuous, analytical and strategic; in addition, the process of identifying potential customers should be built-in and proactively integrated within the processes of the business. It is important that customers are in touch in real-time and that their feedback on every service and/or a firm's offers, are obtained from time to time.

Thirdly, I asked whether there was any mechanism available for managers to monitor the current topics (trends or discussions) pertaining to the organisation. For this question, 70% of the managers agreed that their firms follow trends and discussions to get a feel for what messages have been reaching their customers; 10% said they don't have any such mechanism in place, and another 20% were not aware of such mechanisms in their organisation.

Monitoring trends and discussions is vital; it provides a vast amount of rich information which enables firms to cater for different segments of their customer base, that should result in increased profitability (Leventhal and Zineldin, 2006). This type of analysis provides current and in depth information which can be of great benefit to the organisation. For example, it can be used to draft effective marketing strategies, as well as providing insight and knowledge of the limitations of competitors. Firms can then capitalise on these limitations to lure new customers. Leventhal and Zineldin (2006) pointed out that the main use of CRM is to engage in defensive marketing which enables firms to understand why their customers leave and thereby initiate a suitable customer retention program. They suggest that such retention program implementation not only improves customer retention but also increases customer satisfaction, and hence profitability.

When I asked social media managers whether they were aware of any sentiment analysis tools in their firms, 71% of the managers said that they are aware of sentiment analysis tools and about 29% said they did not know of the existence of any such tools. Further to this, those mangers who knew about sentiment analysis were asked about the presence of any such tools in their firms. Thirty-eight percent of the managers agreed that they have seen such tools in their firms, and about 25% said they have not seen any tools in their firms. Out of those mangers that were aware of sentiment analysis, 25% did not know or were unsure about such tool use in their organisation, and about 12.5% were aware of the name of the tools used in their organisation.

I asked further questions to understand how sentiment analysis tools were built, i.e. in-house or outsourced. About 63% of the managers said they outsourced both the development and management of sentiment analysis tools, and 25% of the managers said they were in-house built. About 12% of the managers were not sure how this is implemented in their organisation.

When I asked if there were any issues with the present tools, 62.5% of the managers were not sure and 25% of the managers informed us that there were no issues with the present tools. Only 12.5% of the respondents said that there was a problem with the existing tools.

The next question was open-ended and asked about the contribution that sentiment analysis made to the organisation, the answers to which revealed many details. One respondent reflected that *"It helps the organisation to assess the existing strategy, bridge the gaps and rectify the challenges"* while another said, *"… it is very important as it gives an insight into the voice of the customer"*.

Another respondent aptly said that sentiment analysis tools are useful *"… to analyse consumer concerns and behaviours"*. The next manager agreed that these tools are *"… very effective in getting instant feedback and proactively resolving issues with unhappy customers"*. Overall mangers accepted that sentiment analysis tools are *"… very useful tools to support the high level managements in their decision making"*.

5.3.1.2 Outcomes of the semi-structured interviews

The semi-structured interviews used a custom developed user guide (Appendix 1) and brought out various qualitative data. The interviews were structured in such a way that a range of information was collected pertaining to the interviewee: their background, current sentiment analysis practices in his or her organisation, and their familiarity with sentiment analysis tools. I also gathered qualitative information about the problems encountered when using such tools. I tried to correlate how these practices will affect profitability and share price. Finally, I asked them about the fitness of sentiment analysis as a promising customer service or marketing tool.

Open-ended discussion on the presence of social media brought out further details to supplement what was obtained through the questionnaires. The question on social media presence highlighted how seriously the presence of social media is considered by the different organisations in the Omani telecom sector. The discussion further demonstrated that various state of the art tools are present within their respective organisations. This trend was clearly felt across all the Omani telecom firms which focus on social media. They tended to use social media at different times to coincide with when users are active on social media, so that they can post their content at that time across different platforms. Organisations even adopt different updating intervals, i.e. frequency changes or switching between different channels. For example, a firm's may be less frequently on Facebook, but more frequently on Twitter because the latter is a fast-moving channel.

This evolution of social media use is very useful for us to understand exactly how vital organisations in Oman consider social media to be. We can observe that this transformation towards the accelerated usage of social media is in line with my findings in the literature review. Kumar and Reinartz (2005) provide a timeline of CRM to show how its practices shifted from transactional marketing to relationship marketing to raise the economic value of a customer for the firm. They reiterate the importance of customer value which emphasises the value of long-term customer relationships instead of short-term sales goals.

Thus, it is obvious to conclude that the scenario in the Omani telecom industry is very well into the third generation, where customer service is approached as an integrated service.

The question on SA tools and their familiarity brought out various facts. All four managers shared their experiences in their respective organisations and this resulted in gaining a better understanding. Furthermore, as discussed in the literature review, the use of sentiment analysis for tracking the image of corporate branding is vital and exists in the Omani telecoms sector. Therefore, by using the discussions taking place in social media, according to Mostafa (2013), it is possible to put sentiment analysis into practice, and obtain an opinion about how healthy brands image is.

The outcome of discussions with the managers reiterated that their firms use social media to:

- identify that potential customers are being proactively integrated within the processes of the business (Xu and Walton, 2005);
- collect information from customers as well as competitors to enable firms to cater for different segments, ultimately resulting in increased profitability (Leventhal and Zineldin, 2006);
- to understand trending discussions and use this information to draft targeted marketing strategies and lure new customers (Leventhal and Zineldin, 2006).

Finally, all of the above steps are deliberately being taken by Omani telecom firms to gain a better understanding of why their customers are leaving. This knowledge can also facilitate the initiation of a suitable customer retention programme. The implementation of such retention programmes will not only improve customer retention rates but will also increase customer satisfaction and profitability.

It is clear that all of the above benefits are tapped in a firm, particularly as the managers confirmed that they are following both their customers and their competitors. Thus, the answers from the social media managers on this topic reflect that there is a deliberate attempt to capitalise on the use of sentiment analysis in their respective organisations.

The sentiment analysis of the interview scripts fortified the above arguments. The word cloud enabled me to understand how discussions progress, and the Tree Map enabled me to see how the terms “social” and “media” branch out and offer insights to the subject being discussed.

On one hand, the hierarchy chart was arranged based on the topics of the semi-structured interviews and offers further insight about interview discussions in terms of the weight of the entire text. Almost all the topics were discussed equally with additional thrusts of sentiment analysis related topics explained in Figure 67. The comparison diagram, on the other hand, offers additional insights into the discussions in terms of the interviewer and the interviewees. The discussion clearly seems to connect sentiment analysis with social media. The codes and nodes chosen in the analysis direct me to conclude that the interviewees were equally contributing to build relationships between the topical terms. Further to this the sentiment scores of the social media managers were almost skewed towards moderately positive or very positive (Table 17).

Cases	**A : Very negative**	**B : Moderately negative**	**C : Moderately positive**	**D : Very positive**
1 : Internals\\SM1	1	1	15	7
2 : Internals\\SM2	1	3	10	10
3 : Internals\\SM3	1	6	8	1
4 : Internals\\SM4	3	6	9	3

Table 17: The sentiment scores of each manager’s dialogues

5.3.2 Feedback on the customer survey

In order to understand what the customer thought I used a different survey for the customers (Appendix 4: Questionnaire for customer). This survey contained 24 questions that collected both quantitative and qualitative data: demographic details, the customer usage pattern of telecoms services, their providers, and their acquaintance with social media.

The demographic details of the customers are presented below:

- The majority of the customers (72.2%) were male.
- 49% of the customers were aged between 30 and 40 years old.
- 25.3% of the customers were aged between 40 and 50 years old.
- 21.2% of the customers were aged between 20 and 30 years old.
- 2.41% of the customers were aged 19 years or under.

- Only 1.9% of the respondents were aged above 50 years.

It is interesting to note here that the distribution is close to an ideal normal distribution with the bell-shaped curve perfectly showing a good sample of the population of Oman.

- The majority worked in the government sector (53%).
- 26.6% were employed in the private sector.
- 7.9% were students.
- 6% owned their own business.
- The remaining 6.5% were mainly comprised pensioners and job seekers, etc.
- A 50% majority were from the Muscat region which is the capital region of the country.
- The Al Batinah North region was represented by 31.4% of respondents.
- The rest of the regions were represented by less than 7%.
- And about 60% of the respondents were from urban areas and the rest were from rural areas.

This distribution typically reflects the Omani population and is therefore reliable and represents the actual scenario.

The survey questions focused on obtaining details about the service providers and their level of customer service. From the responses it could be seen that OmanTel was considered to be a major service provider by 64.8% of the customers; the second most popular service provider was Oredoo with 34%; other resellers such as Renna and Friendi represented less than 1%.

The literature review identified that the most important reason for effective CRM is that it provides firms with an ongoing relationship with their clients. One that establishes a sense of trust, control and security (Grönroos, 2007). Gummesson (2008) also adds that CRM enables corporations to build relationships in order to reach and maintain a prosperous market share. He divides the other benefits into the following two categories:

- Retentions: knowledge about customers, such as their names, habits, likes, dislikes and expectations, information which will facilitate customer retention.

- Intimacy and profits: information technology which helps firms to create intimacy with their customers. This can also increase the degree of mutual trust between the customer and the organisation, and ultimately leads to an increase in profits.

In line with the above arguments, It is clear that the majority percentage (34.2%) of the respondents were taking a neutral stand: neither strongly disagreeing nor strongly agreeing. However, the average score of all the respondents was 3.2 which represents "Agree" on the Likert scale (Figure 79). When broken down further by gender, age, region of residence, type of place and service provider, this revealed additional information. The most notable and interesting facts are listed below:

- With a score of 3.4, which is higher than the overall average score, females were more satisfied with their customer experience.
- The >50 and 30-40 age groups gave a higher than average score of 3.3.
- The younger age group, i.e. <19 years and 20-30 years old, gave a score of 3 which is less than the overall score.
- Regions like Muscat, Al Dhahirah, Al Batinah, Al Buraimi, Ash Shaqriya South and Dofar surpassed the median score. The remaining regions gave a score of less than 3.
- Those privately employed and those categorised as "others" gave a high score of 3.3.
- The lowest score, of 3.1, was given by students and government employed customers.
- Customers who lived in urban areas (city/town) gave a score of 3.3, whereas, customers living in rural areas were slightly less satisfied with a score of 3.

For the question pertaining to customers' perceptions of the various service providers, OmanTel's customers gave a maximum score of 3.2, followed by Oredoo's with a score of 3.1. The next question focused on whether service providers treated their customers as valuable assets. A majority (32.5%) of customers gave a score of 3. The distribution for whether customers were considered to be valuable assets was too close to the previous question on retention; this distribution gave an average score of 3.1 at the halfway mark. It is important to note that 3.1 is the average score from 415 respondents (with a maximum of 5 and a standard deviation of 1.2).

On further classifying the responses of the customers on the grounds of gender, age group, region, place of stay and service providers, I obtained further insights about whether customers thought that they were regarded as a valuable asset, as follows:

- Again, females were very positive with a score of 3.2 whereas males gave an average score of 3. Age group categorisation did not provide any significant difference as they were all close to the average score of 3.

- Similar to the previous question, private sector employees gave a higher score than the others. Those employed in the government sector gave a score of 3 which is less than the average.
- Further classification by service provider illustrates that OmanTel scored highest (with a score of 3.1) followed by Oredoo (with a score of 3).
- Again, as seen for the previous question, respondents from urban areas gave a slightly higher score of 3.1, whereas respondents from rural areas gave a score of 3.
- When I compared scores by region, respondents from Muscat, Al Batinah North, Musandam and Dofar gave a higher score than the other regions.

Thus, I conclude that it is important for firms to understand their customers' social media usage patterns, and to attempt to interpret social media data by organisation. For instance, focusing on service provider and social media usage I found that OmanTel users were active on WhatsApp, while the Oredoo users relied on Snapchat. This is useful information for companies to be aware of to reach their customers. When I asked which social media platform was actively used overall by respondents, WhatsApp was considered the main medium, with 90% of the respondents supporting it; following this was Instagram and Twitter. While Facebook was used by 24% of the respondents. The other respondants (4.2%), mentioned Snapchat as their preferred social media platform.

In order to dissect this further, I grouped respondents based on their gender. This catagorisation revealed further differences: specifically, that the male group preferred Twitter as their preferred choice of social media platform, whereas the female group preferred Snapchat.

The next question was about finding out which social media sites were being actively used by the service providers. Overall the majority of respondents felt that Twitter is actively used by service providers. To cross validate this, I combined this response with the service provider respondents were using; this confirmed that customers using OmanTel and Oredoo were also using Twitter very actively.

The next question asked customers whether they followed their service provider on social media. Fifty-seven percent of the respondents said that they do not follow their service providers on social media, and 43% said that they do follow their service providers on social media. This information did not alter when I grouped this answer based on their service provider which indicates a similar trend across the sector. Amongst those who follow their service providers on social media, Twitter is an active platform where many customers will follow. It is interesting to note that both the leading providers, OmanTel and Oredoo, have a similar percentage of followers on social media.

When I asked if respondents have ever used social media to share any information, 62% said they have never used it to share any information. This implies that they receive and read the information but do not share any of their own content. Amongst those who use social media to share information, 21% of the respondents said they shared news or live feeds, 15% said they shared information regarding social networking, and the remainder indicated that they shared photos and videos, etc. When asked what they considered to be the most important function of social media, the results indicated:

- News or live feeds (57.34%)
- Social networking (39.61%)
- Micro-Blogging/Twitter (37.67%)
- Sharing photos (31.30%)
- Sharing videos (27.15%)

Our next question focused on whether service providers conducted any market search on social media. The majority of respondents (36.3%) agreed that their provider did not conduct market research. This amounted to an average score of 2.9 which is below the halfway mark. Grouping the above response in relation to service providers did not result in any further interpretation as trends remained the same across the major service providers.

We asked if their service providers ever asked for their preferences through social media, 33.2% of respondents mentioned that they neither strongly disagreed nor strongly agreed that their service provided did, indeed, collect any such data. When asked whether they felt that their service providers identified current trends being discussed via social media, this question also resulted in a similar pattern as that obtained for the previous one–an average of 3 on the Likert scale score, exactly in the middle of the halfway mark.

When asked about whether service providers resolved their problems and complaints through social media, in this case too, a score of 3 represented the majority representing (26.8% of respondents). The Likert scale produced an average score of 2.8 slightly below the halfway mark. This did not change across providers, whose customers all displayed similar trends. The major providers, OmanTel and Oredoo, obtained similar scores of 2.8 with Trendi obtaining the slightly higher score of 3.

When asked if "social media is a good tool for conducting research, collecting customer preferences, identifying industry trends and resolving complaints?" the response was very interesting as the majority of respondents strongly agreed with this question. The results revealed a very high value score of 3.8 which indicates that customers prefer their service providers to conduct research through social media.

I showed in the literature review that customer loyalty is an important attribute that effective CRM should take a note of. Wallin Andreassen and Lindestad (1998) define loyalty as an "intended behaviour triggered by the service" while operational loyalty is "a re-purchase intention" and a "willingness to provide positive word-of-mouth" recommendations. Therefore, firms should focus more on loyalty as it results in increased revenues and lowers the costsof attracting new customers, all of which lead to higher profitability.

When customers were asked about their intention to stay with their present service provider, 27.5% of the customers gave a score of 3 and, interestingly, 26.4% of the respondents gave the next highest score of 5. These Likert-scale responses produced a very good average of 3.5. When this score is segregated in terms of gender females agreed to stay for longer than males (with a score of 3.7 compared to 3.4, for males). It is also interesting to note that the retention score was observed to be the highest in the 50+ years age group, who gave a score of 4 indicating their intention to stay for a long time.

The age group of 20-30 years gave the lowest score of 3.2 which is still above the halfway mark. As observed in earlier cases, those employed in the private sector expressed higher retention scores than other respondents with different employment statuses. Students and business owners gave a lower score of 3.3. A higher expectation of retention was observed in the respondents from urban areas (3.6) compared to those living in rural areas (3.2). Comparing respondents using different service providers those using OmanTel gave a slightly higher score of 3.5 compared to those using Oredoo who gave a score of 3.4.

The next question about loyalty provided a mixed response, unlike in the earlier cases, with 26.3% giving a score of 3 and 21.2% of the respondents giving a score of 5. This gave rise to an average score of 3 which is exactly halfway. As in the previous cases I grouped these average scores based on gender, age group, employment status, region, type of place and service provider. This analysis provided the following results:

- Females were more loyal than males (with scores of 3.4 and 2.9, respectively). The age group segregation reflected that respondents aged <19 years old and 30-40 years old scored above the halfway mark (higher loyalty) with scores of 3.4 and 3.2, respectively.

- The respondents from urban areas exhibited more loyalty than those living in rural areas (with scores of 3.2 and 2.8, respectively).
- Respondents from Muscat and Al Buraimi showed high loyalty scores (of 3.3 and 3, respectively).
- Respondents employed in the private sector gave loyalty scores of 3.3, which were higher than those employed in the government sector or running their own business who gave a score of 2.9.
- Grouping loyalty scores in relation to service provider showed that OmanTel customers had a higher loyalty score than Oreedoo customers.

Customer satisfaction is a very important factor in maintaining effective CRM. The last question asked customers how satisfied they were with the services they had received from their providers:

- The majority of respondents gave a score of 3 which is positioned midway between strongly disagree and strongly agree.
- This Likert scale response produced an average score of 2.8 which is below the halfway mark and is skewed towards the negative.
- Breaking this down further to include various additional factors reveals more insight about customers' satisfaction. Female respondents showed more satisfaction than male respondents, with scores of 3 and 2.8, respectively.
- The age group breakdown revealed that respondents aged between 30-40 years and above 50 years of age were more satisfied than other age groups.
- The last segregation by service providers illustrated that OmanTel and Oredoo obtained a satisfaction score of 2.9 and 2.7 respectively, both below the halfway mark.

The next section discusses the outcomes of the sentiment analysis conducted in this research study.

5.3.3 Outcome of sentiment and emotional analysis

Sentiment analysis is undoubtedly a robust tool that can be used in real-time for brand monitoring and sentiment detection. Sectors such as the telecom sector involve extensive social media usage, and customer satisfaction is heavily relied on for customer opinions and perceptions. Indeed, just one dissatisfied customer can open up a huge discussion on social media, and has the potential to sway many satisfied customers into his or her line of thinking. Therefore, continuous, careful and in-depth real-time monitoring of social media discussions will undoubtedly produce various benefits to telecom operators about the changing brand perception of customers. For example, positive, negative and neutral emotions can, temporally, provide salient information about an organisation's moves and how these are received by the customers. It is possible for telecoms operators to take a cue from these variations and adapt their behaviour.

Tweets are popular mode of social media exchange which offer a wealth of information and can easily be subjected to sentiment analysis. Proprietary software, such as NVivo and open source software packages (e.g. the "tm-package"), can handle tweet streams and make real-time monitoring possible. In this study, I monitored tweets for a period of one year (from 01-01-2016 to 31-12-2016) and captured more than 83,000 tweets. With an average of 229 tweets per day, the Omani telecoms sector has been very actively discussed on social media during this period of data collection. At times the number of tweets have been as high as 1816 tweets in one day, at other times as low as 46 tweets.

Observing the top 10 active users enabled me to understand and map current trends related to important announcements or events related to the telecoms sector. The monthly, daily and hourly distribution of tweets helped me to view tweeting patterns as they can enable telecoms companies to select the most/least sensitive times to make decisions or announcements.

In order to map social media trends, using software like NVivo provides an easy to handle platform to manage and extract sentiments (e.g. from tweets). On one hand, extracting positive and negative sentiments from Twitter data provides ways to deeper understand customer sentiments and to receive feedback from customers on various announcements and offers. On the other hand, more than positive, negative or neutral sentiments can be extracted using state-of-the-art text mining packages (e.g. tm-packages). Hence, by using a purpose-built R-code, I was able to extract the emotions of tweets in real-time.

By combining the popular Emotion Wheel with sentiment detection, for the first time, to my knowledge, I have been able to show a choreography of tweets in real-time. More than positive, negative or neutral tweets, this display of emotion can be used to display customers' feelings about various events taking place in the telecoms arena, as well as other areas. Thus my research is applicable to other areas of marketing and academic research.

6 Conclusions & Recommendations

6.1 Conclusions

Events are forcing the world's telecoms players to redesign their approach towards their customers: rapidly advancing technological breakthroughs, the affect of the economy (e.g. in lowering the cost of gadgets), and an increasing number of active players in the telecoms sector; all of these things have redefined the norm for the telecom sector. Across the globe telecoms firms are facing fierce competition amidst these rapid technological advancements. Retaining and satisfying loyal customers remains a challenge, and influences a firm's ability to sustain itself in the business arena and remain profitable. Providing superior services to the customers who are socially connected with each other has changed the landscape of customer relationship management (CRM). This study, positioned in this fast changing arena, has carried out a detailed review on CRM and established what constructs are critical for customer satisfaction; in particular, in the Omani telecom sector.

An in depth literature review suggested that the primary reason for organisations to implement CRM is to improve customer satisfaction, retain their customer base, obtain strategic information and enhance the value of the customer lifetime. Collecting data about customers' interests, habits and interactions enables organisations to provide a superior level of service specifically tailored to meet the needs of each customer.

In the literature review I also discussed possible tools that can be used to enhance CRM from the perspectives of the service sector. In an age of social media, interpreting social media data without manual intervention becomes an obvious and potential option. Sentiment analysis (SA) is an efficient tool that has evolved through machine learning algorithms to provide efficient and robust mechanism to watch customer sentiments in real-time. And SA is very useful for CRM data collection. Throughout this study, have demonstrated how such data will help to enhance CRM at Omani telecom firms. Ultimately, positive, negative or neutral sentiments cannot be used to make strategic marketing decisions. Therefore, for the first time to my knowledge, I have extended existing sentiment analysis to emotional analysis. My novel visualisation tool demonstrates the choreographic emotion of tweets, and is applicable to other large sources of social media data.

Therefore, my study started with the following objectives:

1. Apply sentiment analysis to collected data related to CRM which pertains to the Omani Telecom Sector through social media (SM) platforms.

2. Survey SM departments to gauge their SM experience and behaviour when interacting with customers.
3. Survey customers and gauge their feedback about their experiences of using SM.
4. Develop a SM policy/model for companies to use in the Omani context.

The research thus aimed to investigate the applicability of SA and its potential for establishing better CRM processes in Omani telecom companies.

These objectives were translated into research questions so that a scientific, evidence based investigation could be carried out. I commenced with a literature review that enabled me to understand the factors affecting the relationship between service quality and customer satisfaction – as this research involved measuring the impact of service attribute importance on performance. In addition, I wanted to investigate the relationships between customer satisfaction, service quality and customer behavior, as switching probability and word of mouth was another very important factor uncovered through the literature review.

Therefore, this research tried to answer the following questions:

1. What are the parameters that have to be measured to understand the extent of customer satisfaction?
2. How can these factors be measured from social media discussions or any other datasets available?
3. How can the results of the sentiment analysis of these datasets be applied to developing a better CRM policy for the Omani telecom industry?

In order to answer these identified research questions, I conducted a further review of the literature that focused on the features of marketing theory, evolutions of CRM in the service sector, and methods to analyse social media data.

The literature review enabled me to conclude that the primary reason for organisations to implement CRM is to improve customer satisfaction, retain their customer base, obtain strategic information and enhance the value of the customer lifetime. I further discovered that the specific objectives of CRM can be met by obtaining information about customers and sharing this information across the organisation with the intended outcome of increased customer loyalty. In addition to this, collecting data about customers' interests,

habits and interactions, enables organisations to provide superior services tailored to the needs of each customer.

On these grounds collecting information from social media becomes imperative and compelling. Sentiment analysis, which is an efficient tool evolved through machine learning algorithms, provides an efficient and robust mechanism to watch customer sentiment fluctuating in real-time. Considering the importance of data, ultimately positive, negative or neutral sentiments cannot be used to make strategic marketing decisions. Therefore, my novel visualisation tool, an adapted Wheel of Emotion becomes a potential tool to capture emotional snapshots from social media data.

I triangulated the collected dataset from social media managers, customers and social media data to arrive at meaningful conclusions. Although 80% of social media managers insisted that their firms are very active on social media, only 36% of customers felt that their service providers conducted any useful market research to better their services. It is important that customers are made aware of how firms get to know about their requirements. The Emotional Wheel tool draws out emotions so that we can observe how a combination of high level anticipation and joy produces optimism in customers, and, similarly, how a high level of joy and trust produces love in customers. Achieving and maintaining such states in a firm's customer base will certainly lead to better customer offerings with the scope to retain customers.

It is also important to note that only 40% of social media managers admits that their firm's profile page is updated every day. The rest say that it is done either monthly or from time to time. It was also noted by 29% of social media managers that a profile page shows very basic information. This is a challenge, as an expired offer or a non-existing discount may frustrate customers and affect loyalty and retention. Therefore, maintaining an updated profile page becomes imperative to achieve an organisation's CRM objectives. In order to keep customers happy (with less remorse and less disapproval – as seen in the Wheel of Emotion), an updated and detailed profile page can affect the customer's experience with service providers.

It is very positive to note that 90% managers agreed on the linkage between marketing strategy and social media coverage. This gives a clear sign that such a linkage becomes a driving force to sustain all CRM objectives as such methods provide rich information to firms that can pave the way to increased customer segmentation. Recall the study of Ahn et al. (2006), conducted on the Korean mobile telecommunications service industry that demonstrated that a traditional marketing strategy was not able to meet the demands of the modern telecoms sector. To prioritise customer demands is possible only with the help of segmentation, as without such processes firms will never be able to recognise the individual needs of their customers.

The next point of triangulation is to enlighten us about online customer support. Whilst 80%

of managers confirmed that they offered active online customer support, customer responses regarding customer support remained neutral: 34.2% of customer respondents took a neutral stand, neither strongly disagreeing nor strongly agreeing. This clearly shows that customer support outreach remains questionable. Although female customers were satisfied with the support they were provided, male customers were not satisfied with customer support. Similarly, the younger age groups, <19 years and 20-30 years gave lower scores than other age groups. In addition, students and government employees have given lower scores on customer support. These facts have to be taken into account during resolution management and customer segmentation. Considering this scenario further with the Wheel of Emotion, it becomes apparent that a customer who received better customer service, may have feelings of surprise, happiness, etc.; however, when a customer is not satisfied, the emotion shown on the Wheel of Emotions can include disappointment, anger, irritation or anxiety. I have mapped this information on Figure 166.

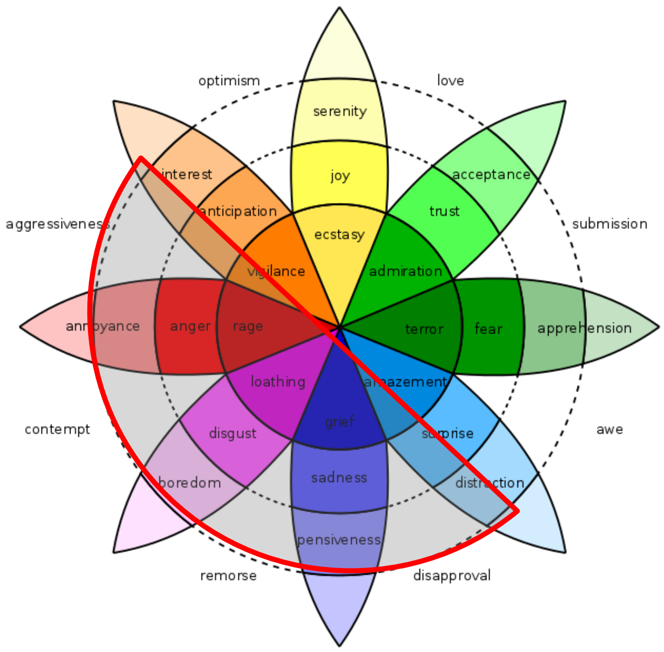

Figure 166: Wheel of Emotion after worst customer service highlighted

Therefore, organisations should strive to calculate customer emotion after every customer interaction or customer support resolution outside of the shaded area in the above figure.

The survey with social media managers established that their firms follow trends and discussions on social media to understand what customers think of their products and/or services (70% agreed in favour of this question in the survey). However, only 43% of customers followed their service providers. These contrasting results illustrate a huge gap between firms and their customers: firms follow customers but less customers follow firms' social media trends although an increased level of interaction with customers is important for effective CRM.

The research purpose of this study has been addressed by answering research questions based on identified methods supported by the literature review. The triangulation of the collected data enabled me to justify my interpretations and conclusions. Such conclusions enabled me to arrive at potential recommendations for Omani telecom firms.

Considering the research questions in turn, the first part of the literature review enabled me to answer the first research question about the parameters that needed to be measured to understand the extent of customer satisfaction. It was found that the most important characteristics of CRM help firms to organise customer information and provide it across the organisation very quickly where it is needed. Therefore, any technology-based solution that enables organisations to obtain data in real-time is vital. Measuring opinions across the users of the system enables organisations to measure the extent of customer satisfaction.

The very objective of using CRM is to store, process and deliver customer information when and where required. Such an efficient organisation of data leads to increased loyalty, satisfaction and retention. As loyalty, satisfaction and retention are all related quantities, the timely management of data flow becomes imperative. Such an objective can be realised using appropriate strategies that include accessing important information about customers, plus creating value and customising products for customers. It is important that all this information is transferred as quickly as possible as time is an important factor.

While addressing the second research question, how to measure social media discussion and other datasets pertaining to this research domain, the literature review on CRM theories and research methods insisted the importance of obtaining a triangulation of data: from social media managers, who are instrumental in handling social media in Omani telecom firms;from customers who are the end users; and the obtainable data about customer opinions from social media.

It was clearly evident from the literature review that social media plays a very important role in communication; its correlation with CRM increasingly becomes important. The rapid development of machine learning algorithms, language technology, and better monitoring tools means that telecoms tools can start using the information on digital platforms effectively. It was clearly understood from the data collected from social media managers and customers that social media platforms play a vital role in connecting customers and firms, and thus the formation of a digital communication landscape.

It is the third question that brought vital conclusions for this study. Basic sentiment analysis does not provide the best possible overview to gauge customer emotion in the digital communication landscape. Having found that the information flow across an organisation and its timing is critical, from the first research question, I determined that a better tool was needed than basic sentiment analysis. A tool that could provide more than just positive, negative and neutral sentiments, with which to measure customer satisfaction from social media discussions. My novel visualization methodology, based on the Wheel of Emotion provided a timely, functional and detailed display of emotion leading to the better measurement customer satisfaction.

6.2 Recommendations

It is evident from the results of this study, that Omani telecoms firms are aware of the transformed marketing landscape where social media bears a predominant role. The adoption of such digital media by marketing managers in these firms reiterates the fact that they obtain valuable information which is crucial to realise their CRM objectives. However, the availability of such information across the organisation is much more vital than simply holding information about customers. Therefore, organisations should constantly update their strategy based on the data provided by sentiment and emotional analyses. Making sure that the appropriate data is available, when, where and how it is required by various teams within a company transforms the present system into a robust one.

This study also reiterates the fact that Omani telecom firms should develop their CRM capabilities further by making use of all social media platforms. More than just gathering information, firms should be actively involved in disseminating and responding to each piece of information obtained through such analysis. As the increased linkage of data across the organisation is vital to increase customer satisfaction, organisations should strive for data integration. A real-time analysis of social media data is more useful than analysing social media periodically and intermittently; therefore, creating a system where all layers of the organisation have access to such rich information in a timely manner is crucial.

It is also strongly recommended that conducting market research periodically, to get to know what customers are looking for, is an another area where improvement is needed. Although it has been discovered in this study that some firms continuously engage in market research, many customers contradict that market research is occurring as they are not aware of it. Therefore, appropriate marketing surveys should be conducted with the knowledge of customers so as to obtain more information for organisations and pave the way for better

CRM initiatives.

It is also recommended that online support should be enhanced with an age-group related approach. As customer satisfaction, remarkably, differs across age groups, organisations should set up a mechanism to address each particular age groups' need. Knowing that one age group is under satisfied makes it possible to address them using a targeted approach. Having seen data plans and mobile tariffs targeted to specific age groups (for example, Ozone from OmanTel or Shabibiah from Oredoo that are for teens with special data and calling plans), it becomes imperative that any customer service approach is also stratified to its specific age group. Such a targeted approach can also be extended to gender, employment status and region, which may be suitable for specific firms.

It is important to note that Wailgum (2007) cautioned us that CRM cannot just happen by buying and installing software; CRM can be effective only if firms realise the value of customers with respect to time. Nguyen et al. (2007) advised that any CRM initiative should start with building an effective model based on every customer's profitability, and then the model can further be developed.

My study has revealed the importance of CRM for telecom firms in Oman. Under growing social media usage, the importance of obtaining customer feedback in real-time has been proven to be critical to survive severe competition in the market. Sentiment analysis enhanced by emotional analysis is displayed in my concept of the emotional wheel. This tool can pave the way for real- time monitoring.

In order to facilitate organisations' use of this new tool, I developed a framework which involves the following steps:

I. **Collection of live social media data:** This becomes the starting point of a system where live social media data is analysed in real-time. Based on organisational requirements the data could be Tweets, Facebook posts, etc.

II. **Analyse sentiment and emotion through our custom code:** Our custom developed code will help organisations to clean and analyse the collected social media data and make it ready for further analysis.

III. **Detecting sentiment scores and emotional catagories:** I recommend conducting basic and advanced sentiment analysis to calculate sentiment and emotional scores.

IV. **Real-time logging with time, ID, sentiment and emotional scores:** As the core idea of this recommendation is to showcase everything in real time, it is important to tag each activity with a unique ID, sentiment and emotional scores. This information then has to be archived for further inspection and reference. All users of the system have read-access to this archive, and able to preview or print reports based on their queries or filters.

V. **When a set critical value is surpassed, identified issues are allocated with a department:** A centralised control to fix a critical value of sentiment or emotional score to flag up for further action is required. My analysis of a one-year dataset has shown that variation occurs in emotional and sentiment scores. Based on need or time it is possible to fix a threshold score. During product release or special offers, it is possible to alter these settings and observe their influence on customers over a fine window of time to feed back this information to the appropriate department.

VI. **Live, real-time follow up of issues, as action statuses are tracked through a centralised unit:** A display unit showing sentiment and emotional scores through the Wheel of Emotion should be displayed in every department or unit of the organisation. This is expected to help staff members identify on-going issues and give attention to those issues.

VII. **All social media data is archived and made available for further future research:** This will help managers to observe historical trends or investigate the features of any trends.

The above 7-point approach is recommended for Omani telecom firms. As discovered from the social media managers' survey, sentiment analysis usage already exists amongst Omani telecom organisations but incorporating it back into the organisation is an approach that does not exist. Hence my recommendation of real-time, feedback-looped, adaptive and responsive social media analysis is expected to further realise the objectives of CRM.

Collating the findings from the literature review, customer and social media managers' surveys, and my own methodology of the emotional wheel display of Twitter data in real time, I present my recommended approach in the following flowchart (Figure 167).

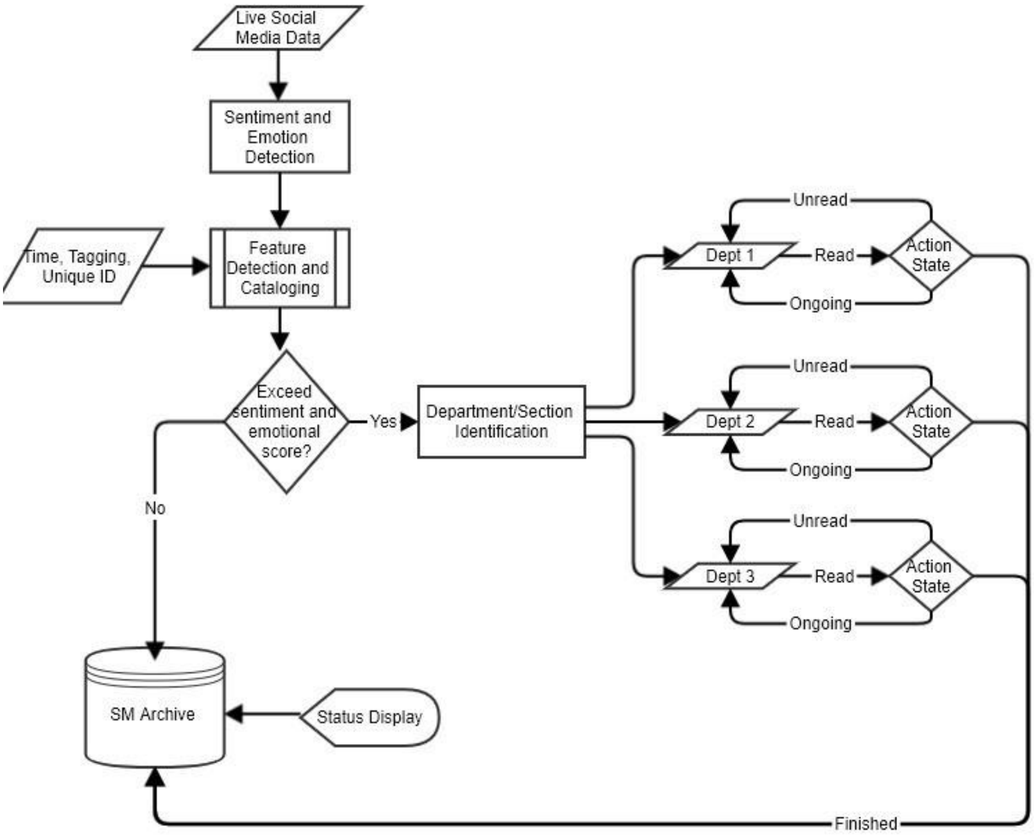

Figure 167: Recommended approach to implement SA for enhancing customer satisfaction

Following up the whole process through a centralised administration team is recommended, plus the use of several monitors to display sentiment and emotional scores in the organisation. Employees should be able to see live feeds of scores everywhere so that they are reminded that their actions and responses decide these overall scores.

As illustrated in the above flowchart, at the heart of this implementation is centralised administration, and the holistic dissemination of information. There are several layers on which activities like tagging, emotion detection, archiving, and department identification occur. These layers are needed in order to achieve the objective of classification: tracking and archiving. The following figure shows the recommended layers and their functions.

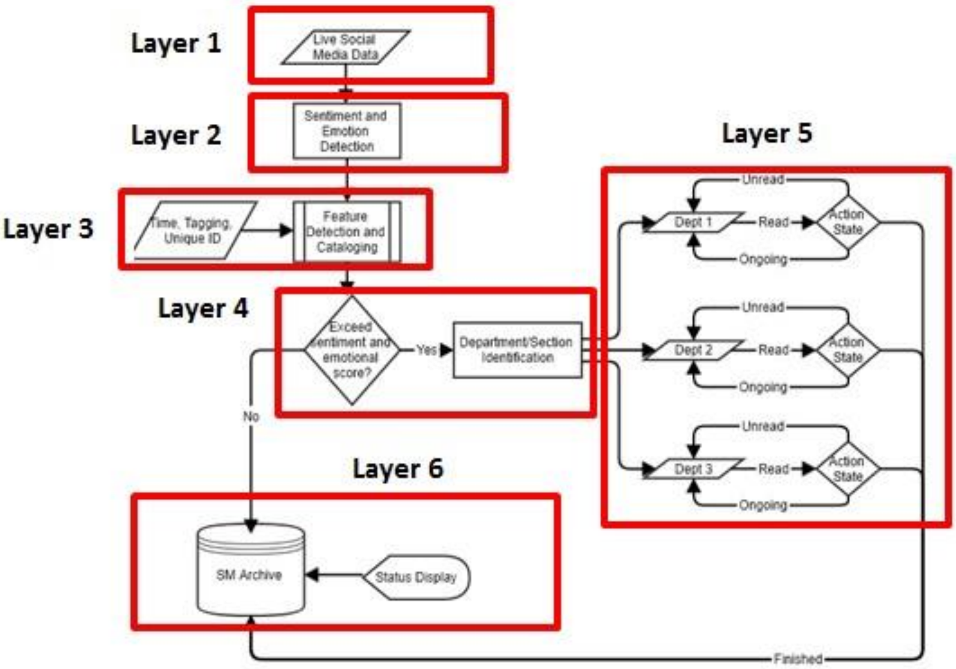

Figure 168: Different layers in the proposed recommendation

A real-time social media data feed enables the system to capture the data as and when it happens, and all important features are detected and catalogued with their time and a unique ID. It is possible to set thresholds for sentiment and emotional scores to be monitored. My collection of data over a year showed the variation of sentiment scores and emotional scores over time, and based on organisational requirements an appropriate threshold can be set for that organisation. This can be done at any time based on requirements. It is also possible to set a lower threshold in the aftermath of a significant event like a new product release or offer announcement. Such an observatory period will enable firms to capture subtle changes of sentiment or emotional scores.

All these cataloguing and feature detections should be displayed across an appropriate department to allow for manual intervention. In order to identify the required department, it is possible to use machine language tools to extract specific terms or words. A status display across the organisation will enable staff to recognise on-going sentiment or emotional scores, their associated issues and what actions to take. We envisage that real-time displaying of choreography of social media data through the Wheel of Emotion in every department will result in a radical change in each staff member's approach towards customers.

The beauty of centralised administration is that it is possible to constantly monitor and detect emerging patterns/sentiments/emotions. Any changes to the machine learning algorithm can be effectively fed into the system without affecting the overall flow of the process. This is expected to address the issues of intricate complexities of feature detection. For example, as explored in the literature review, the detection of sarcasm or similar symbolisms. Any updates to this detection mechanism can be fed to the system and will improve the system over time, and make sure company objectives are met.

Such co-ordination to address issues is expected to help an organisation to deliver the best CRM practices possible, and thereby capitalise on the latest tools and technologies. This integrated approach can help organisations to be competitive and serve demanding customers at the right time and in the right place.

6.3 Contributions to existing knowledge and practice

My attempt to address the existing gap in current CRM practices at Omani telecom firms enabled me to produce findings that can be considered as a contribution to existing knowledge and practice. This study was undertaken with the aim of finding ways to enhance CRM practices at Omani telecom firms. Various areas of CRM from the perspective of the service sector and methods of sentiment analysis have been critically reviewed to identify their current state, and existing gaps. My attempt to address bridging a gap to improve sentiment analysis has been formalised through appropriate research methods.

My review of the literature confirmed that the primary reasons for organisations to implement CRM are to improve customer satisfaction, retain their customer base, obtain strategic information and enhance the value of the customer. It was also established that by collecting pertinent information on customers, such as their interests, habits and interactions, organisations can provide a superior service which is specifically tailored to meet the individual needs of each customer. Sentiment analysis, which is particularly useful for CRM data collection, is an efficient tool that has evolved through machine learning algorithms and provides an efficient and robust mechanism to observe customer sentiment in real-time.

6.3.1 Contributions to Knowledge

- Social media data are information-rich and available in real-time. My investigation of such data brought out the fact that social media can act as a mirror to provide instant feedback to a company about customer relations. I established that by incorporating the outcome of such data analysis, firms can improve their CRM. It was further demonstrated that this exercise could improve customer satisfaction, retain a customer base, obtain strategic information and enhance the value of a customer's lifetime. It was also established that collecting data about customers' interests, habits and interactions enables organisations to provide a superior service which is specifically tailored to meet the needs of each customer.

- SA is applied at various levels at present, but unfortunately the binary outcome of such analyses is used for decision-making. Most existing SA tools draw out positive or negative sentiments by customers and using such binary outputs for making non-trivial decisions is, therefore, questionable. The perceptions customers have towards a firm need not be binary, but can go beyond binary thoughts. Therefore, my extended SA method, involving emotion, can bring out in-depth facts making SA a meaningful tool to help firms make strategic decisions. My custom-coded SA tool is capable of extracting sentiments for better decision-making.
- I realised that there no direct way to visualise customer emotions existed in the literature. Therefore, I created a new method to visualise emotion. To my knowledge, this is the first time that a novel visualisation tool has been used to demonstrate the choreographic emotion of tweets.
- I named this visualisation method the 'Choreography of Emotion'. It was observed that customers who received better customer service may have experienced feelings such as "surprise" and "happiness". Conversely, when customers were not satisfied, the emotions shown included "disappointment", "anger", "irritation" and/or "anxiety". These findings were mapped on the Wheel of Emotion.
- This study, therefore, lead to developing a model that can integrate the SA of social media data along with the CRM processes of telecom firms in real-time. This involves horizontal and vertical integration of the outcomes of emotional analyses across the organisation.

6.3.2 Contributions to Practice

- Moving from binomial sentiment analysis to multinomial or emotional analysis is a way to proceed in the world of social media rich data.
- My new visualisation method, the "choreography of tweets" visualises emotions in real-time.
- Feeding back the emotional states of the day, the week, the month or any particular duration of interest to the relevant department of an organisation is expected to influence decision-making in a robust and meaningful way. For example, during promotional or offer periods the sales department can get real pulse for how they are perceived by customers.
- I recommended that organisations implement my 7-step approach in order to

capitalise on the robustness of machine learning algorithms to obtain a choreography of emotions from live stream social media data. This can equip firms which are striving to prosper amongst competitors and rapidly advancing technology with a tool to improve their CRM processes.

6.4 Limitations and Further Research

As in the case of any research study, a number of limitations exist. I observed the following three limitations. Firstly, the data collected from social media managers are solely from their perspective and does not necessarily represent that of their organisations. It should also be noted, in the interest of managers, organisations, competitors and their rights to convey the information that they choose, their contribution to this study may be limited.

Secondly, I collected data from the perspective of the service sector and that of telecom service providers. A wider range of data collection would have reflected different regional, cultural or social stances. Different products and services may have different features and, therefore, collecting data from other users would have shed light on the expectations of a typical customer. So, although I collected a huge social media dataset for one complete year, and included it in our analysis, real-time capturing would have changed the scenario and decision-making processes across the organisation that could have led to different outcomes. In the world of social media, many events take place like a chain reaction (for example "viral phenomena"). To capture the effects of such incidents, observing reactions during particular windows of time may provide further insights on the mechanisms and dynamics of specific incidents and their impact on customer satisfaction, loyalty and retention.

Thirdly, I translated all Arabic social media data into English using an automated approach. Although the translations were cross checked, it would have been better if I had developed a sentiment and emotion analytic tool that can support the Arabic language. Doing so, I expect, would have resulted in the capture of more detailed sentiments and emotions. I made every attempt to verify the machine translation, at times I encountered slang, phrases and cynicisms that were not able to be completely translated into English, and hence their contribution to the final sentiment or emotional scores was limited.

As future research enables such limitations to be overcome, I make the following future research recommendations from the present study:

- **Extending this approach to other services and product sectors:** The study at present focused only on the telecom sector. It is possible to extend the research further into various industries and sectors. Various products and services are often vehemently discussed in social media and therefore such an extension will help business owners to survive fierce competition by providing better customer service than their counterparts.
- **Developing and using a core Arabic-based sentiment and emotion analysis algorithm:** I relied on Google translate to translate Arabic words into English and then subjected the translated data to analysis. It is also possible to conduct the entire analysis entirely in Arabic without translating. For this we need to build an Arabic corpus containing sentiment scores and emotional scores. This exercise appears to be a big project, but it can potentially be used to serve various domains as there is vast user base for the Arabic language.
- **Exploring other popular and potential social media platforms:** The present analysis only included data captured on Twitter. It is also possible to collect social media data from other social media platforms, such as Facebook, Instagram, YouTube, etc. I discovered through the survey that Twitter is used widely by Omani mobile users, but it may not be same with the users of other products and services.

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Appendices

Appendix 1: Interview Guide (Social Media Managers) for semi-structured interviews

Based on Jayachandran et al. (2005), Srinivasan and Moorman (2005) and Harrigan et al. (2015).

1. **Customer Relationship Orientation:** Scale as per the works of Jayachandran et al. (2005) this section focuses on:
   a) How does your firm measure its customer priorities?
   b) How is customer focus identified?
   c) What are the valueable assets for the company for a better customer relationship?
2. **Social Media Usage:** Scale provided by Jayachandran et al. (2005):
   a) What social media tools does your firm use and why?
   b) How interactive are your tools?
   c) In particular, how do any of these tools facilitate better CRM?
3. **Social CRM capabilities:** Based on the scale by Jayachandran et al. (2005):
   a) How is market research conducted through social media within your firm?
   b) To what extend are they useful in finding customer preferences?
   c) How is info. on market trends, customer needs, and satisfaction collected using social media?
   d) How is social media used to tackle your competitors' activities?
4. **Customer Relationship Performance:** Based on the scale by Harrigan et al. (2015):
   a) How is customer satisfaction achieved?
   b) How are current customers retained?
   c) How is customer loyalty increased?

Appendix 2: Modified Questionnaire (Social Media Managers)

Usage of Social Media in Omani Telecoms

INFORMATION SHEET FOR PARTICIPANTS

Dear Colleague,

We would like to invite you to participate in this research project. You should only participate if you want to; choosing not to take part will not disadvantage you in any way. Before you decide whether you want to take part, it is important for you to understand why the research is being done and what your participation will involve. Please take time to read the following information carefully and discuss it with others if you wish. Please ask if there is anything that is not clear or if you would like more information.

Introduction

Social media remains an active tool to remain in touch with customers. Telecom companies, as main service providers, should capitalise on the advantages of social media for their business development. This project mainly revolves around the usage of social media in Omani telecom firms.

Who will be recruited for this research project?

We are inviting the employees of Omani telecom firms, particularly those in charge of social media management staff to aid us to understand how social media plays a role in marketing and strategic decision-making.

What will happen if you agree to take part?

No sensitive or personal information will be sought from you. Participation, or choosing not to participate, will in no way affect you in any way. And you are free to withdraw from the study at any time.

Who is funding this study?

This study is being undertaken as a part of my PhD research work.

What will happen to the information?

The findings will be presented to my research supervisor at the University of Strathclyde. They will also be presented through peer reviewed journals, an internal report, a public report, and conference/seminar presentations.

Should you wish to have a copy of the final report, please ask.

Benefits to participants

This study is expected to provide some insights about how the usage of social media enables telecom firms to better handle customer relations.

Anonymity and confidentiality

All data will be anonymous and kept confidential, and only the researcher will have access to them. My reporting of the data will ensure that individuals cannot be identified.

If you have any questions or require more information about this study, please contact me directly using the following contact details.

Thank you for reading this information sheet and I hope that you will agree to take part in this study.

Yours sincerely,

Jihad Al-Ansari
jihad.al-ansari@strath.ac.uk

Q1. Job title, please specify:

- ❍ Manager – Social Media(1)
- ❍ Manager - Advertisement (2)
- ❍ Manager - others (3)
- ❍ Others. Please specify (4)____________________

Q2. Length of experience in current position (years):

- ❍ 1-5 (1)
- ❍ 5-10 (2)
- ❍ 10-15 (3)
- ❍ More than 15 (4)

Q3. Gender:

- ❍ Female (1)
- ❍ Male (2)

Q4. Age Group (years):

- ❍ Below 20 (1)
- ❍ 20-30 (2)
- ❍ 30-40 (3)
- ❍ 40-50 (4)
- ❍ Above 50 (5)

Q5 Is your firm active on social media?

- ❍ Yes (1)
- ❍ No (2)
- ❍ Don't Know/ Unsure (3)

Q6 Which of the following social media actively is used in your organisation?

(Please select that all apply)

- ❑ Twitter (1)
- ❑ Facebook (2)
- ❑ Google+ (3)
- ❑ LinkedIn (4)
- ❑ Others. Please specify: (5) ____________________
- ❑ Don't Know/ Unsure (6)

Q7 How long has your organisation been active in social media?

- ❍ Less than 1 year
- ❍ 2-5 years
- ❍ 5-10 years
- ❍ More than 10 years
- ❍ Don't Know/ Unsure (5)

Q8 What frequency is your organisation's social profile updated?

- ❍ Weekly (1)
- ❍ Bi-weekly (2)
- ❍ Every day (3)
- ❍ Other. Please specify: (4) ____________________
- ❍ Don't Know/ Unsure (5)

Q9 What is the purpose of your corporate profile page on these social media platform(s)?

- ❑ Basic details of the organisation (1)
- ❑ Promotion or advertising product/service (2)
- ❑ Contact customers (3)
- ❑ Job recruitments (4)
- ❑ measuring supporters/followers (5)
- ❑ Other. Please specify: (6) ____________________
- ❑ Don't Know/ Unsure (7)

Q10 How would you rate the advantage due to the online presence of the following social networks?

	5: Significance (1)	4: Some advantage (2)	3: neutral (3)	2: very few advantage (4)	1: No advantage (5)
Twitter (1)	❍	❍	❍	❍	❍
Facebook (2)	❍	❍	❍	❍	❍
Google+ (3)	❍	❍	❍	❍	❍
LinkedIn (4)	❍	❍	❍	❍	❍
Others. Please specify: (5)	❍	❍	❍	❍	❍

Q11 Is there a link between marketing strategy and social media coverage?

- ❍ Yes (1)
- ❍ No (2)
- ❍ Don’t Know/ Unsure (3)

Q12 Could you please elaborate on the link between social media coverage and marketing strategy? (Discussion through open question)

Q13 Do you offer any customer support online?

- ❍ Yes (1)
- ❍ No (2)
- ❍ Don’t know /Unsure (3)

Q14 Is there any mechanism to monitor the current topics, trends or discussions, that are relevant to the organisation?

- ❍ Yes (1)
- ❍ No (2)
- ❍ Don’t know / Unsure (3)

Q15 Sentiment Analysis / opinion mining is a tool that uses natural language processing or machine learning to extract information from huge data sources such as social media data. Without reading vast data, this tool enables us to identify positive, neutral or negative sentiments available in the source data. Are you aware of sentiment analysis/sentiment detection/opinion mining?

- ❍ Yes. If selected this option, please proceed to next question (1)
- ❍ No. If selected this option, thanks for your response. You have completed the questionnaire (2)

Q16 Is there any tool in place to perform such analysis? If so please name.

- ❍ Yes (1)
- ❍ No (2)
- ❍ Name of the tool used: (3) ____________________
- ❍ Don't know / Unsure (4)

Q17 If such analysis is conducted is it?

- ❍ In-house (1)
- ❍ Outsourced (2)
- ❍ Don't know / Unsure (3)

Q18 Are there any problems with the current tool?

- ❍ Yes (1), if yes, Please list the potential issues: 1. ________, 2.__________, 3._________
- ❍ No (2)
- ❍ Don't know / Unsure (3)

Q19 What do you think the contribution of sentiment analysis is so far for the organisation? (Open-ended question for discussion)

Q20 Out of the following options what do you think sentiment analysis may achieve for your organisation?

- ❍ To know about positive or negative comments about campaigns (1)
- ❍ To know about the popularity of the organisation on social network (2)
- ❍ To increase profit (3)
- ❍ To analyse and compare your firm against competitors (4)
- ❍ Others. Please specify: (5) ____________________
- ❍ Don't know / Unsure (6)

Appendix 3: Transcripts of Interview with Omani Telecom Managers

Interview with SM1:

J.: Hi, I'm really appreciating the time you are giving me to complete my survey. As I briefed you, I am a researcher at Strathclyde University doing a PhD in Computer Science. Basically, my research is looking into the impact of social media on the telecom sector in the country, which, in my case, is Oman. If you can just give me a brief summary about your role, your experience, and the background of social media in your organisation.

SM1: Thank you very much, Jihad. It's my pleasure. Actually, my current role, I'm the general manager of projects in one of the utility providers for the telecom services. But previously, I used to be in one of the biggest telecom operators in Oman which is OmanTel, and I was managing their access network planning and design. Now, so I have moved from the planning department into the project department in one of my new roles.

As you know, social media has been a really powerful tool, and it has made a complete change in the way a company communicates and interacts with their customers. And so far, I can see that most telecom operators in our country have really made some quite substantial uses of social media, and it has really strengthened the way they positioned their brands, the way they communicate the product and services, the way they manage their customer service and customer relations. And it has also been a powerful tool in communicating proactively any incidents: cable cuts, the service goes down, and so on.

J.: Okay. So do you think that higher management can capitalise from this tool as… I mean, can they capitalise on it as a sentiment analysis tool in the future? Do you think it is a promising tool?

SM1: I can't comment precisely on whether it's a promising tool, but this is how they have been… we have already been using it in that way. I mean, today most of the CEOs and top executive management, they get most of their analysis from social media. It's one of the tools that they are using to judge how they are perceived in the market, and if there is a new launching of products, if they want to get a sense of reactions, the sense of how they are getting rated compared to their competitors, and so on. So today this is big news. To what extent that will be a powerful analysis tool, maybe it has some sort of [unclear] (3:25) because the feedback you get is more slightly emotional feedback, so you cannot use it precisely as a judgement.

J.: Okay. Do you think that social media as a tool or sentiment analysis as a tool, in general, can contribute towards the profit of organisations? I mean, in telecom organisations for example? Even directly or indirectly, maybe?

SM1: It could be. I mean it depends on how you…

J.: Utilise.

SM1: …utilise the social media tools, and what are the innovative ideas that you can implement as part of using all the rich data that comes out from the social media. Maybe we've seen in some of the cases where some of the social media, they give you some sort of an idea, on some of the product and services, and those ideas can be profitable ideas if they could implement them in the right manner. So it can be.

J.: How about the share price? Do you think these is a relation with social media, it can increase your share price? If it is listed, I mean, in the stock market?

SM1: Brand image and brand perception has a value in general. And so the stronger the rating you get as a brand, the more valuable the company can become. So, yes.

J.: What do you think if, for example, an organisation starts publishing that they are introducing a new project which is coming up in the second quarter of the year? So maybe, I don't know, maybe it can increase the profit or the price of the share, you know, the share price.

SM1: It could be, but not necessarily.

J.: Not necessarily.

SM1: Not necessarily.

J.: Okay. How do you think that social media can be used as a customer service tool, and what do you think are the boundaries of it, if it's there?

SM1: I will answer this from the view of my previous company, because I've just recently been in this post so, if I speak from my previous experience, OmanTel are providing pre-paid and post-paid services. And I would say maybe more than eighty per cent of our subscriber base comes from the pre-paid. And most of these pre-paid subscribers are teenagers. So these teenagers today are so familiar and excited, and they love using social media. So from a customer service perspective, it is very easy for them to communicate back to the company if they have any issues or concerns, or if they want to complain about something, or even if they want praise a specific service.

And I think OmanTel, my ex-company, has really made some good use of that communication, that is used by these teenagers. So, I would say it is quite a substantial proportion of our subscriber base today, getting managed and used through social media for any customer service or any customer relations.

J.: So maybe, I'm not sure if you have it in this company, because you are still new in this company, so… I'm talking about something called sentiment analysis, so have you heard the word sentiment analysis as a tool? Either here or in your previous company which is OmanTel?

SM1: What is it? What is expected by sentiment analysis?

J.: Okay, sentiment analysis is an opinion mining tool, which will gather your data from different social media streams. For example, Instagram, Twitter, Facebook, LinkedIn. And for example, somebody mentioned OmanTel positively so it will tie together all this information, analyse it, and compare it with a competitor, or you can put your filters and your keywords over theirs, so it can really capture that data.

SM1: My answer as I said, in general, yes. My current company today, our customer is basically the existing operators. So we don't have a big subscriber base like the normal operators. We actually provide infrastructures to the operators, and they arrive on that infrastructure and provide services to their customers. So maybe in my current company, I don't see that, unless we start printing a new revenue stream where we interact directly with bigger paying subscribers so that can be of use.

J.: Right. So from your experience, do you think that there will be some challenges and problems with these kinds of tools? I mean the social media sentiment analysis tools.

SM1: I think there is. That's what I mentioned earlier, there is an element of emotional and subjective feedback that you get which sometimes you need to do some filtering to ensure that you get the right feedback that you can use. And you are talking to a big subscriber base, where people have different mindsets, different views, different opinions. So, I think, if this tool can become smart enough to eliminate some of the nonsense feedback or nonsense information by one way or another, maybe it can be powerful. But I think if you take it as it is, you need to somehow do some sort of filtering.

J.: So, I'm not sure, again my questions might relate to your ex-company always, and feel free to answer it. If such a tool is available, do you think analysis is happening in-house or it is outsourced to another company outside the organisation?

SM1: I think it can happen in-house. It just depends on the algorithms that you might need to use to analyse this rich information, and maybe you need to categorise things. With my ex-company, I think they have the capabilities to do it in-house, especially when I left they were already in the process of doing business intelligent tools and so on, so maybe this can be a source of input into those tools and then it can be developed further, you know.

J.: Do you think that there will be some problems with the integration of this tool within other platforms? Technically I mean.

SM1: I don't honestly see that.

J.: So it is just a normal plug and play tool which can gather the information using some PPIs maybe?

SM1: It may not be a just plug and play. It is not also too complex.

J.: Okay. If you compare it to a billing system, it's not like a billing system?

SM1: Not like a billing for sure.

J.: Because I know you are a billing guy, so… great. So those are my questions. Do you have any questions for me?

SM1: Just before I would like to thank you for the interview. And since you are doing this PhD outside the country, have you come across some companies that have really made some good use of the social media?

J.: Well yes actually, I had interviews with Bader al Hinai the social media guy with OmanTel. And I was really happy and glad to see the tools they are using, it's really an intelligent tool.

It is, I think, called Gangaro, the tool is called Gangaro which they are using. And it's smart enough to gather all the mentions on all different platforms. And they have also like a white-list library where they can introduce, as you said, some thank you words that are used by Oman social media fans, and it will keep listening to those mentions, it will gather this information, analyse it. And also this tool is intelligent enough to compare all mentions against the competitor to which they have set it. So it will have a dashboard where it will display all the mentions of OmanTel. And also they have a tool which really has a twenty-four seven support.

Their support agent runs twenty-four seven, in case there is any support required or needed, they will provide it on spot. So yes, it's well used in OmanTel I can see. And, I think, even in Ooreedoo to some extent, but since I am working for OmanTel they didn't disclose this information to me. But yes, they are having as well.

SM1: I wish you all the best and I'm looking forward to seeing your PhD thesis.

J.: Thanks a lot for your time. I really appreciate that. I wish you all the best in your role.

SM1: Thank you very much.

Appendix 4: Questionnaire for customer

Questionnaire for customers إســــتـبـيـان الـعـمــلاء

The social media remains an active tool to be in touch with customers. Telecom companies as the main service providers, should capitalise the advantages of social media for their business development. This project mainly revolves around usage of social media in Omani telecom firms. This study is being undertaken as a part of my PhD research work. The findings will be presented to research supervisor at University of Strathclyde. They will also be presented through peer reviewed journal, internal report, public report, and conference/seminar presentations. This study is expected to bring some insight on how the usage of social media enables telecom firms for better handling of customer relations. All data will be anonymous and kept confidential and only the researcher will have access to them. Reporting of the data will ensure that individuals cannot be identified from the data. على لزاماً وكان عملائها، مع للتواصل والمؤسسات الشركات تستخدمها فعّالة أداة الإجتماعي التواصل شبكات تعتبر خدماتها وتطوير مصالحها يخدم بما الإجتماعي التواصل شبكات من تستفيد أن الرئيسية الخدمات لأحد كمزوّد الإتصالات شركات الإجتماعي التواصل لشبكات العماني السوق في الإتصالات شركات توظيف مدى حول المشروع هذا ويتمحور .العملاء على والحفاظ المحصّلة النتائج كافة تقديم يتم وسوف ستراثكلايد، جامعة من الدكتوراة درجة لنيل المقدم بحثي من جزء عن عبارة الدراسة هذه إن . الدولية، المؤتمرات بعض في عرضها أو العالمية الدوريات بعض في نشرها سيتم كما ، الدكتوراه رسالة على للمشرف الدراسة هذه من مدى على الضوء بتسليط الدراسة هذه تقوم أن المؤمل من إنه .الجامعة نطاق ضمن منها والإستفادة إستخدامها إمكانية إلى إضافةً أفضل بشكل التعاطي في الإجتماعي التواصل لشبكات عمان سلطنة في الإتصالات شركات إستخدام عن ينتجان اللذان والتأثير الإستفادة تخويل يتم ولن السرية بمنتهى الإستبيان هذا في بها تشاركون التي المعلومات كل تعامل وسوف .العملاء مع جيدة علاقات على والحفاظ واقع من شخص أي تحديد أو /على التعرف يتم أن الأحوال من حال بأي يمكن لا أنه كما الباحث، عدا عليها بالإطلاع شخص أي بها المشارك المعلومات.

Q1 Gender الجنس :

- a. Male ذكر (1)
- b. Female أنثى (2)
- c. Rather not say أحتفظ بالإجابه (3)

Q2 Your age group الفئة العمرية:

- a. >19 (1)
- b. 20-30 (2)
- c. 30-40 (3)
- d. 40-50 (4)
- e. <50 (5)

Q3 Employment status الوظيفية الحاله:

- a. Student طالب (1)
- b. Employed in Govt. حكومي موظف (2)
- c. Employed in Private خاص قطاع موظف (3)
- d. Own business حره أعمال (4)
- e. Others, please specify أخرى ، الرجاء تحديدها (5) ____________________

Q4 Region of living السكن \ الإقامه منطقة تحديد الرجاء:

- a. Muscat مسقط (1)
- b. AL Dakhiliyah الداخليه (2)
- c. AL Dhahirah الظاهره (3)
- d. Al Batinah North شمال الباطنه (4)
- e. Al Batinah South جنوب الباطنه (5)
- f. Al Buraimi البريمي (6)
- g. Al Wusta الوسطى (7)
- h. Ash Sharqiyah North شمال الشرقيه (8)
- i. Ash Sharqiyah South جنوب الشرقيه (9)
- j. Dofar ظفار (10)
- k. Musandam مسندم (11)

Q5 The area you live in is الإقامه مكان تحديد الرجاء:

- Urban (city/town) العاصمه / مدينه (1)
- b. Rural (village) قريه (2)

Q6 Which of the following is your mobile phone service provider المحمول الهاتف خدمة مزود هو يلي مما أي بك الخاص:

- a. Omantel عمانتل (1)
- b. Oredoo أوريدو (2)
- c. Samatel سماتل (3)
- d. Renna رنه (4)
- e. Friendi فريندي (5)

Q8 The service provider you selected above in question1 place a high priority on retaining customers: العملاء على الحفاظ في متقدمه مكانه السابق السؤال في أعلاه حددته الذي الخدمه مزود يحتل :

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Strongly Disagreeلاأوافق بشدة:Strongly Agree أوافق بشدة (1)	❍	❍	❍	❍	❍

Q9 The service provider treats customers as valuable assets: . يعامل مزود الخدمة عملاءه كأصول ذات قيمة:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Strongly Disagree لاأوافق بشدة:Strongly Agree أوافق بشدة (1)	❍	❍	❍	❍	❍

Q10 Which of the following social media is actively used by you? (Please select that all apply) أي من وسائل التواصل الإجتماعي التالية تستخدمها بكثرة: (الرجاء إختيار كل ما ينطبق عليه السؤال)

❑ a. Twitter (1)
❑ b. Facebook (2)
❑ c. Whatsapp (3)
❑ d. Instagram (4)
❑ e. Others. Please specify أخرى؟ يرجى ذكرها (5) ____________________
❑ f. Don't Know/ Unsure لا أعرف/ غير متأكد (6)

Q11 Which of the following social media is actively used by the service provider you selected? (Please select that all apply) أي من وسائل التواصل الإجتماعي التالية يستخدمها مزود الخدمة الذي تتعامل معه: (الرجاء إختيار كل ما ينطبق عليه السؤال)

❑ a. Twitter (1)
❑ b. Facebook (2)
❑ c. Whatsapp (3)
❑ d. Instagram (4)
❑ e. Others. Please specify أخرى؟ يرجى ذكرها (5) ____________________
❑ f. Don't Know/ Unsure لا أعرف/ غير متأكد (6)

Q12 Do you follow your service provider through social media? هل تتابع مزود الخدمة الخاص بك من خلال وسائل التواصل الإجتماعي؟

❍ a. Yes نعم (1)
❍ b. No لا (2)

If b. No لا Is Selected, Then Skip To If yes, specify which of the followin...

Q13 If yes, specify which of the following social media you use to follow the service provider? (Please select that all apply) إذا كانت الإجابة بـ "نعم"، أي من وسائل التواصل الإجتماعي التالية التي تتابع عليها مزود

(السؤال عليه ينطبق ما كل إختيار الرجاء) :بك الخاص الخدمة

- ❑ a. Twitter (1)
- ❑ b. Facebook (2)
- ❑ c. Whatsapp (3)
- ❑ d. Instagram (4)
- ❑ e. Others. Please specify ذكرها يرجى أخرى؟ (5) ____________________
- ❑ f. Don't Know/ Unsure لا أعرف /غير متأكد (6)

Q14 Have you ever used social media to interact or share information with the service provider you selected: . هل سبق لك إستخدام وسائل التواصل الإجتماعي للتفاعل أو تبادل المعلومات مع مزود الخدمة الذي حددته؟

- ❍ a. Yes نعم (1)
- ❍ b. No لا (2)

Q15 Which of the following functions of social media do you consider important? أي من إستخدامات شبكات التواصل الإجتماعي التالية تعتبر ذات أهمية من وجهة نظرك:

- ❑ a. Sharing photos تبادل الصور (1)
- ❑ b. Sharing videos تبادل مقاطع الفيديو (2)
- ❑ c. News or live feeds الأخبار الحية والمباشرة (3)
- ❑ d. Blogging المدونات (4)
- ❑ e. Twitter التغريدات (5)
- ❑ f. Online conferencing الإجتماعات عن طريق الإنترنت (6)
- ❑ g. Social networking الشبكات الإجتماعية (7)
- ❑ h. Professional networking الشبكات المهنية (8)
- ❑ i. Social analytics التحليلات الإجتماعية (9)
- ❑ j. Community or groups المجتمعات و المجموعات (10)

Q16 Your service provider always conducting market research? مزود الخدمة الخاص بك يقوم بإستمرار بإجراء أبحاث تسويقيه ؟

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Strongly Disagree لاأوافق بشدة:Strongly Agree أوافق بشدة (1)	❍	❍	❍	❍	❍

Q17 Your service provider gathered any information about your product or service preferences through social media? هل تعتقد أن مزود الخدمة قد قام بجمع معلومات من خلال وسائل التواصل الإجتماعي عن منتجاته

الخدمات؟ هذه من المفضلة خياراتك عن وكذلك بها، بالإشتراك قمت التي وخدماته

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Strongly Disagree لاأوافق بشدة:Strongly Agree أوافق بشدة (1)	❍	❍	❍	❍	❍

Q18 Your service provider use social media to identify the trends in the industry? الخدمه مزود يقوم الإتصالات سوق في جديد هو ما وكل التوجهات بتحديد الاجتماعي التواصل وسائل استخدام طريق عن وذلك بك الخاص

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Strongly Disagree لاأوافق بشدة:Strongly Agree أوافق بشدة (1)	❍	❍	❍	❍	❍

Q19 Your service provider use customer interaction through social media to resolve problems and complaints? والشكاوى المشاكل لحل العملاء مع للتفاعل الإجتماعي التواصل وسائل بإستخدام يقوم بك الخاص الخدمة مزود الخاصه

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Strongly Disagree لاأوافق بشدة:Strongly Agree أوافق بشدة (1)	❍	❍	❍	❍	❍

Q20 Do you think social media is a good tool for conducting research, collecting customer preferences, identifying industry trends and resolving complaints? هل تعتقد أن وسائل التواصل الإجتماعي والتفاعل العملاء رغبات جمع وكذلك والصناعة، السوق توجهات وتحديد البحوث، وإجراء المعلومات لجمع المناسبة الأداة تعتبر والشكاوى؟ المشاكل وحل معهم

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Strongly Disagree لاأوافق بشدة:Strongly Agree أوافق بشدة (1)	❍	❍	❍	❍	❍

Q21 I am planning to stay with my service provider for long period of time? مزود مع للبقاء أخطط أنا

الزمن؟ من طويلة لفترة الحالي الخدمة

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Strongly Disagree لاأوافق بشدة:Strongly Agree أوافق بشدة (1)	❍	❍	❍	❍	❍

Q22 I am loyal to my service provider? بي الخاص الخدمة مزود تجاه بالولاء أشعر أنا

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Strongly Disagree لاأوافق بشدة:Strongly Agree أوافق بشدة (1)	❍	❍	❍	❍	❍

Q23 I am satisfied with my service provider? الحالي؟ الخدمة مزود عن راض أنا

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Strongly Disagree لاأوافق بشدة:Strongly Agree أوافق بشدة (1)	❍	❍	❍	❍	❍

Q24 Do you have any comments regarding your satisfaction with your service provider? لديك هل أي تعليقات إضافية عن مدى رضاك عن خدمات مزود الخدمة الحالي؟ (الرجاء ذكرها إن وجدت)