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Application of convolutional neural network algorithm in sentiment analysis for evaluating customer satisfaction

A case study for mobile and fixed internet service providers in Zimbabwe

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APPROVAL FORM

The undersigned certify that they have supervised the student Praise Tapera's dissertation entitled, "*Application of convolutional neural network algorithm in sentiment analysis for evaluating customer satisfaction. A case study for mobile and fixed internet service providers in Zimbabwe"* submitted in partial fulfillment of the requirements for a Bachelor of Information Technology Honors Degree at Bindura University of Science Education.

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DEDICATION

This research project is dedicated to all those who have supported and inspired me throughout my academic journey. To my family and loved ones, who have been my pillar of strength and endless source of encouragement, thank you for always believing in me and supporting me through thick and thin. To my supervisor and mentors, who have imparted their knowledge and expertise, thank you for shaping me into the individual I am today and for guiding me towards the pursuit of knowledge. To my colleagues and friends, who have stood by me and shared in my struggles and triumphs, thank you for your unwavering support and for making this journey an unforgettable one. I hope that this research project will contribute to the betterment of society and serve as a testament to the dedication and hard work of all those who have been a part of our journey."

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ABSTRACT

This research topic aims to evaluate customer satisfaction using sentiment analysis for mobile and fixed internet service providers in Zimbabwe. The study is significant because it recognizes the growing importance of customer satisfaction in the telecommunications industry and the need to measure it systematically and continuously. The research methodology will involve collecting data through surveys and sentiment analysis tools and analyzing the data using statistical and sentiment analysis techniques. The expected outcomes of the study include providing insights into the factors that influence customer satisfaction in the mobile and fixed internet service providers in Zimbabwe, evaluating the effectiveness of sentiment analysis in measuring customer satisfaction, and proposing recommendations for improving customer satisfaction in the telecommunications industry in Zimbabwe. The study's relevance to the mobile and fixed internet service industry in Zimbabwe lies in its potential to provide a systematic and objective way of measuring customer satisfaction and identifying areas for improvement, ultimately leading to long-term profitability and success.

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Chapter 1

1.0 Introduction

Leading reviews is the noticeable strategy most associations are utilizing to gauge consumer loyalty. Asking your clients, the right inquiries is the way to estimating it. Without the right inquiries, the reactions may not show you the right information. You won't be able to find areas in your business where you can make improvements and then take action based on those areas. This chapter introduces the research by explaining the background of the research problem, the research objectives, significance, scope and limitations.

1.1 Background to the study

Managing the experience of customers has been identified as an integral part of enhancing business performance (Makudza, 2020). The need for customer experience management has been more pronounced in the services sector where quality of a service is determined by the strength of the service interaction Cajetan, 2018; Zeithaml et al., 1990). Given the increasingly large number of consumers using social media, most businesses globally have embraced social media to engage with current and prospective customers. These social networks have given them the ability to communicate with consumers in real time. There are using social media monitoring techniques to gauge how people are talking about their brand, products and services online. Because information spreads fast in social media, most organisations have strategically positioned their customer service departments to utilise social media since it helps them identify issues early, monitor and predict their growth. Customer service centres strive to improve customer experiences across the customer journey, from evaluating a product purchase to the after-sales support needed. The need to ensure customers are happy is an ongoing priority for any business that wants to survive.

1.1.1 Active Mobile Subscriptions

The Zimbabwean technology landscape has experienced positive transformations at the backdrop of an underperforming economy. While performance of the sector is dependent on the economic environment, the mobile telecommunications industry has experienced significant growth for the past 2 decades. The economic environment impacts the sector through service demand and consumption levels, operating costs, investment et.al. According to POTRAZ (2017) annual sector performance report, demand for mobile telephone services has been consistently growing.

1.1.2 Data & Internet Subscriptions

According to the Performance Report by the Postal and Telecommunications Regulatory Authority of Zimbabwe (POTRAZ) in 2022, the total number of active internet subscriptions increased by 3.7% to reach 6,971,617. In 2020, active internet and data subscriptions grew by 5.6% to reach 8,726,904, resulting in an increase in the internet penetration rate by 3.2% to reach 59.9%. Mobile internet and data usage also increased by 43% to record 14,878 Terabytes from 10,407 Terabytes in the second quarter of 2022. The mobile telecommunications industry in Zimbabwe is dominated by three players, namely Econet Wireless, Telecel Zimbabwe, and Net One. According to the POTRAZ report, Econet and Telecel gained 8.9% and 0.1% market share, respectively, whereas Net One lost market share by 9%. The industry has seen a lot of competition among the three service providers, with most subscribers subscribed to all three mobile providers, switching between them depending on use case. However, the customer retention rates of all three providers have been decreasing, with businesses now focusing on improving customer experience across a product or service lifecycle to reduce churn, increase revenues, and ultimately become profitable. POTRAZ has defined a framework that enables them to collect metrics from telecommunications providers to determine the quality of service, and sentiment analysis is an important pillar of social media analytics.

1.2 Statement of the problem

The COVID-19 pandemic has caused a rise in mobile internet subscriptions in Zimbabwe. Due to the pandemic, governments around the world enforced lockdowns which affected businesses. In response, organizations in Zimbabwe turned to teleworking to maintain operations. The Postal and Telecommunications Regulatory Authority of Zimbabwe reported a 43% growth in mobile internet and data usage, with all mobile operators seeing growth. The surge in mobile internet traffic has caused a strain in customer service departments within mobile service providers. However, the pandemic has highlighted the importance of telecommunications infrastructure in keeping businesses, governments, and societies connected and running. As a result, many telecom companies have benefited from a surge in data traffic. Data and internet services will continue to drive industry growth as more businesses adopt teleworking. Mobile service providers in Zimbabwe are product-focused rather than customer-focused, which has affected current customer experience processes. Customer retention will be crucial for operators going forward. The surge in teleworking has forced businesses to rethink their IT strategies through digital transformation initiatives. Mobile telecommunications providers such as Econet and Netone have enabled businesses to enable their employees to work from home.

1.3 Research objectives

The study aims to achieve the following objectives:

1. To measure customer satisfaction by analysing customer sentiment from tweets
2. To extract the most prevalent words that contribute to a negative or positive sentiment.
3. To develop a twitter sentiment predictive model

1.4 Research questions

1. The research sought to answer the following questions:
2. How do we measure customer satisfaction using sentiment analysis?
3. What words can be used to improve customer engagement?
4. How do we measure customer sentiment from words?
5. What is the general customer sentiment towards services on offer?

1.5 Research propositions

H1: Tracking customer satisfaction using sentiment analysis yields better results than using NPS or CSAT scores

H2: Analysed customer sentiments show a true picture of the quality of your service or product

H3: The effect of certain words during customer engagement influences how customers perceive your product /service

1.6 Significance of the study

The study will help the researcher broaden his knowledge on how sentiment analysis can be used to evaluate and measure customer experience. The industry being studied will also benefit from the study through in-depth research of how they are currently measuring customer satisfaction. The research will also make recommendations on how the model can be implemented better to get the desired benefits. The research will also present the industry with additional knowledge on sentiment analysis and how it can be effectively implemented. The study will also be used as literature by the academic community. The study will be accessible to anyone in the academic community who would like to know more about the subject. Customer satisfaction is fundamental to business growth. The telecommunication industry in Zimbabwe plays an important role in enabling business in other industries. Evaluating customer satisfaction through sentiment analysis provides cheaper and quicker results as compared to other alternatives NPS and CSAT. Findings from this study will benefit all telecommunication companies in incorporating twitter sentiment analysis in their customer experience programs. Sentiment analysis presents an efficient and effective evaluation of consumer opinions in real time.

1.7 Delimitations of the study

There are multiple sources of customer data that can be augmented with social media data such as call records, data from incident management systems and market research data from surveys but the research was focused on data from twitter. This may not be sufficient for the purposes of generalisation (Yin, 2009). Many Zimbabwean businesses have embraced digital transformation initiatives mainly focusing on a widely spread online digital footprint. However, the study will be limited to mobile and fixed internet companies that have an online presence on twitter. Also due to time constraints, the model will not be multilingual. The model will not cater for Native Zimbabwean languages Shona and Ndebele within its language model. Data collected from tweeter that the researcher will encounter in the stream will not be stored to disk so that the researcher can refer to it and perform offline analysis. The decision to store the data in-memory during extracting and analysis forces the researcher to concentrate on the research objectives rather than the nuances of setting up storage servers which adds to the complexity of the architecture. Natural Language Processing (NLP) still struggles with the inability to discriminate between different meanings of words and sentences and identifying sarcasm or ironic statements. Current methods are still based on the degree of correlation rather than the intended meaning which translates into poor practical applications whereas word ambiguity refers to the same word but with different meanings.

1.8 Chapter summary

This research topic aims to evaluate customer satisfaction using sentiment analysis for mobile and fixed internet service providers in Zimbabwe. The study is significant because it recognizes the growing importance of customer satisfaction in the telecommunications industry and the need to measure it systematically and continuously. By using sentiment analysis, the study proposes a rigorous and comprehensive technique to interpret data in this challenging and new context, removing subjectivity and individual biasness.

Chapter 2 Literature Review

2.0 Introduction

In this section, the researcher presents the review of previous studies done on various methods used to evaluate customer satisfaction. The work done by several researchers was reviewed in line with the objectives and the methodology of this study. The review was guided by already existing theories in customer satisfaction and sentiment analysis techniques. Literature on how organisations approach customer engagement exercises was reviewed. The popularity of social media was analysed particularly how it has necessitated organisations to find ways to tap into the vast amounts of data to improve customer satisfaction.

2.1 Related work – Sentiment analysis

Sentiment analysis is a field that has gained significant attention in recent years. Researchers have conducted extensive studies on predicting sentence polarity using classifiers such as Naive Bayes, SVM, and Decision Trees, along with word embeddings. Most of the research has focused on social media data. Giachanou et al. conducted a comprehensive analysis of popular approaches for Twitter sentiment analysis, including SVM and Naive Bayes, as well as data sets like Edinburg Twitter corpus, Stanford Twitter Sentiment, Sanders corpus, and sentiment lexicons such as SentiWordNet and MPQA. Da Silva et al. presented hybrid models that combine SVM, Naive Bayes, Decision Trees, etc., to achieve an accuracy of 81.06%. They also compared feature hashing and bag-of-words and concluded that feature hashing is suitable for computational efficiency, while bag-of-words is more appropriate for accuracy. Hassan et al. proposed bootstrapping models to bring consistency in results for imbalanced data obtained from Telco and Pharma tweets. Araque et al. combined traditional models that use manual feature extraction as surface models with deep learning techniques for sentiment analysis using word embeddings. Muhammad et al. used the term frequency-inverse document frequency searching model to examine the polarity of a sentence and the sentiment of the whole document in Bangla text. Se et al. used supervised machine learning techniques such as SVM, Maxent classifier, Decision Trees, and Naive Bayes to classify Tamil movie reviews as positive or negative, with SVM outperforming all other models. Uma et al. used the SVM classifier to retrieve information from Tamil and English tweets and classify each sentence as positive, negative, or neutral, with an F-measure of 0.741. Phani et al. performed sentiment classification on the Sentiment Analysis of Indian Languages (SAIL) 2015 data, achieving excellent results in two-class and three-class classification experiments using stratified 10-fold cross-validation on training data.

2.2 What is customer satisfaction?

Karim and Chowdhury (2014) explain that customer satisfaction refers to a person's feelings of pleasure or disappointment resulting from the comparison of a product's perceived performance in reference to expectations, while Angelova and Zekiri (2011) define it as the outcome felt by those who have experienced a company's performance that has fulfilled their expectations. Naik, Gantasala, and Prabakar (2010) emphasize that satisfying customers is one of the main objectives of every organization, as keeping current customers is more profitable than having to win new ones to replace those lost. Management and marketing theorists stress the importance of customer satisfaction for business success (McColl-Kennedy and Schneider, 2000, cited in Naik, Gantasala & Prabakar, 2010). Zamil and Shammot (2011) argue that customer satisfaction is critical for public sector organizations, as the customer needs services that satisfy them and equilibrate with their expectations. If customer satisfaction is not achieved, the customer will feel that their satisfaction is ignored, leading to more complaints. Similarly, continuous systematic measurement of satisfaction levels is necessary, as a satisfied customer is a real asset for an organization that ensures long-term profitability even in the era of great competition (Chakraarty et al., 1996, cited in Karim & Chowdhury, 2014). The International Social Security Association also notes that when people are empowered to access the social security system in the way that best suits their needs, their level of satisfaction with the system and their level of trust in the system rises commensurately (Lee-Archer, 2013). The current study evaluates customer satisfaction in mobile and internet service providers.

2.3 Evaluating customer satisfaction Zimbabwe Case studies

Customer churn in Zimbabwe's mobile telecommunications sector include customer dissatisfaction, low switching cost, lack of customer support, lack of sufficient or adequate advertising, and increased security/ethical concerns of customers. This study was conducted by (Hwambo, Shamhuyenhanzva, & Sandada, 2017). Meanwhile, (Makanyeza & Chikazhe, 2017) conducted a study that investigated the mediators of the effect of service quality on loyalty among bank customers in Zimbabwe. The study revealed that service quality, satisfaction, and corporate image all have positive direct effects on loyalty. Satisfaction and corporate image also mediate the effect of service quality on loyalty. Another study by (Chitura, Dube, & Chari, 2007) found that network performance had the greatest impact on both service quality and customer satisfaction based on p-levels alone. The study also found a positive correlation between mobile phone quality and customer satisfaction. These studies were conducted to explore how various organizations evaluate their customer experience journeys, loyalty to the brand, and satisfaction with service quality. The findings of these studies can help service providers prioritize customer retention initiatives and develop business strategies aimed at improving customer satisfaction, ultimately leading to improved profitability.

2.4 Evaluating customer satisfaction using sentiment analysis - International case studies.

Customer satisfaction is a vital measure of how well a company's products and/or services meet or exceed customer expectations. Several studies have been conducted to measure customer satisfaction using sentiment analysis. (Al-Otaibi et al., 2018) and (Anastasia & Budi, 2016) used sentiment analysis to measure customer satisfaction on Twitter. Meanwhile, (Feine, Morana, & Gnewuch, 2019) proposed an automatic and objective approach to using sentiment scores as a proxy to measure chatbot service encounter satisfaction (CSES). (Kang & Park, 2014) developed a new framework for measuring customer satisfaction on customer reviews of mobile application services. They found that a customer-review-based approach not only saves time and effort in measuring customer satisfaction but also captures the real voices of customers. (Gitto & Mancuso, 2017) also used sentiment analysis to improve airport services, recognizing that measuring the level of customer satisfaction of airport passengers provides valuable feedback to airport managers. Finally, (Miranda & Sassi, 2014) proposed a tool for aiding the evaluation of customer satisfaction in a Brazilian online job search company using sentiment analysis. They found that sentiment analysis served as a support tool to enrich the customer satisfaction evaluation process. These studies demonstrate the usefulness of sentiment analysis as a tool for measuring customer satisfaction and providing valuable insights for improving products and services.

Besides the traditional methods of targeting customers, social media presents its own set of opportunities. Consumers share their opinions about services and products in public and with their social circles. This valuable data can be used to support business decisions. However, it is huge amounts of unstructured data that is difficult to extract meaningful information out of them. Social Media Analytics is the field which makes insights out of social media data and analyses its sentiment rather than just reading and counting text.

2.5 The SERVQUAL Model of Customer Satisfaction

Gibson (2009) notes that SERVQUAL was developed by Parasuraman, Berry and Zeithaml in the 1980s. SERVQUAL is a multi-item scale developed to assess customer perceptions of service quality in service and retail businesses. The SERVQUAL model was originally made up of ten dimensions of service quality, namely, tangibles, reliability, responsiveness, communication, credibility, security, competence, courtesy, understanding the customer, and access (Daniel & Berinyuy, 2010). Later these dimensions were reduced to five because some dimensions were overlapping (Daniel & Berinyuy, 2010). The five dimensions are as follows:

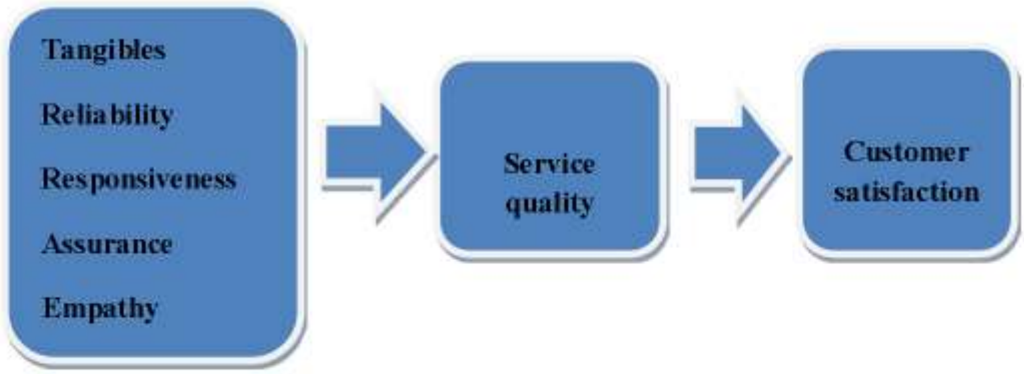
Tangibles - For example, physical facilities, equipment and staff appearance.
Reliability - Ability to perform service dependably and accurately.
Responsiveness - Willingness to help and respond to customer needs.
Assurance - Ability of staff to inspire confidence and trust.
Empathy - The extent to which caring individualized service is given.

As Shahin (2006) notes, the SERVQUAL approach, which was adopted in this study, is the most common method for measuring service quality. Shahin (2006) notes that SERVQUAL is a generic instrument with good reliability and validity and broad applicability. Its purpose is to serve as a diagnostic methodology for uncovering broad areas of a company’s service quality shortfalls and strengths. As Shahin and Janatyan (2011, p.101) put it, SERVQUAL dimensions and items represent core evaluation criteria that transcend specific companies and industries, hence it has been used to measure service quality in a wide variety of service environments.

2.5.1 Conceptual Framework

The SERVQUAL model is the conceptual framework for this study and is represented diagrammatically in Figure 3. As part of the conceptual framework the five dimensions of quality identified by Parasuraman, Berry & Zeithaml in the 1980s under the SERVQUAL model were used to assess service quality and customer satisfaction. The dimensions are as follows: tangibles, reliability, responsiveness, assurance and empathy.

Figure 1 Servqual Model



Social Media Analytics

According to Guy (2012), social media, derived from the social software movement, are a collection of Internet websites, services, and practices that support collaboration, community building, participation, and sharing. Kaplan and Haenlein (2010) defined it in a similar manner, they said it is "a group of internet-based applications that allow the creation and exchange of user-generated content". It promotes interaction between different people using the internet. Kapoulas and Mitic (2012) further noted that what began as an array of platforms for online interactions with focus on entertainment quickly escalated into a global phenomenon where connectedness to the online networks is everything and the aptitude to "follow," "like" or "share" means power. This alone indicate that social media has gained global popularity. Mayes (2011) also highlighted this growth in social media by noting that it is developing rapidly and new platforms are developed daily. This according to Mayes (2011) has made it necessary for companies to not only be familiar with those platforms, but also know how to reach the consumer through them. According to Laroche et al. (2013), people spend more than one third of their waking day consuming content on social media. Levinson and Perry (2011) noted that the social media is now referred to as ''new media'' to differentiate social media from the other two types of media. As Levinson and Perry (2011) summarizes, ''old media'' includes TV, newspapers and magazines. These types of media highlight the top-down control approach; they are produced and managed by professionals. The second type is called ''new media'', which includes email, websites, online message boards, chat rooms, etc. As a result of internet technology, ‘‘new media’’ transcends the time and space of ‘‘old media’’ (Zhou and Wang, 2014). According to Ruddell and Jones (2013)‘‘new new media’’ includes blogs and micro blogs (e.g., Twitter), Wikis (e.g., Wikipedia), picture sharing sites (e.g., Flicker) and video sharing websites (e.g., YouTube), BBS (e.g., Tianya in China), SNS (e.g., Facebook) and internet communities (e.g., Maopu in China). Despite this growing popularity and the general agreement on the influences of social media, a systematic understanding by organisations and customer services managers on how to make use of the social media to evaluate customer experience remains elusive.

2.5.2 Social Media Analytics and Sentiment Analysis.

When customers engage with organizations by leaving feedback, there is always an underlying emotion. With sentiment analysis, you can capture this subjective information to understand your customers better. Questions like why are they feeling negative about customer service or product in general? Which product features do they like the most? Understanding and acting on the information that can be provided by sentiment analysis can boost customer satisfaction and loyalty. Sentiment analysis can help track a customer sentiment on social media in real time which can help an organization instantly spot a critical issue affecting customers and, in the process, take immediate action. Most organizations in Zimbabwe have already embraced social media when engaging their customers. Social media offers raw and unfiltered customer feedback as compared to data gathered from call logs or net promoter score (NPS) surveys. According to (Stelzner, 2013) Social networks engulf everyday life; they represent a place to share news, ideas and information of all kinds.

2.6 Sentiment analysis techniques

The literature on sentiment analysis primarily focuses on developed countries, and there is a lack of research on the use of sentiment analysis for evaluating customer satisfaction in Zimbabwe. This study aims to address this gap by conducting a case study on the effectiveness of sentiment analysis in evaluating customer experience for mobile and internet service providers in Zimbabwe. The study investigates the use of social media as a means of measuring customer satisfaction and enhancing customer experiences in this industry. Sentiment analysis, also known as opinion mining, is an emerging field with many practical applications. It explores people's sentiments, opinions, behaviors, attitudes, and emotions toward individuals, organizations, products, and services. The objective of this research is to extract opinions of users on Twitter, analyzing the data for user sentiments, and eventually creating a model that can be used to evaluate and measure customer satisfaction by telecommunications providers in Zimbabwe. When applied to customer experience, the resultant model aims to provide deep insights into how customers perceive products and services, which cannot be established using traditional methods. Traditional approaches, such as analyzing call logs or conducting customer surveys, are subject to researcher presence and small sample sizes, which can present biases in the analysis of the data. Sentiment analysis addresses these problems by systematically collecting and analyzing online sentiments as emotions expressed on that product or service. This presents an efficient and effective evaluation of consumer opinions in real-time, and marketers gather feedback on attitudes and opinions as they occur without having to invest in lengthy and costly market research activities. According to Rambocas (2013), sentiment analysis has become popular due to the proliferation of microblogging sites such as Twitter. Businesses have realized the value in sentiment analysis as it provides insights that speak to the inner views of the audience. The results enable businesses to tailor their services or products based on their clientele preferences. Sentiments can be categorized into three categories, positive, negative, and neutral. Consumer sentiment is of value for marketers gathering market intelligence but greater value for consumers who need to gain a quick overview of the collective opinion about a provider or product/service/experience. Perumal (2010) notes that opinion mining is a sub-field of Natural Language Processing (NLP) that deals with the analysis of text data to determine polarity and uses sentiment analysis as a part of opinion mining. Sentiment analysis is widely used in mining subjective information from internet content using various techniques, including NLP, statistical techniques, and machine learning methods. Any opinion/review given by an individual through which feelings, text messages, attitudes, and thoughts can be expressed is known as sentiment (Tyagi, Chakraborty, Tripathi, Choudhury, 2019). Due to the vast amount of consumer-generated content available, extracting sentiment manually has become impractical, encouraging research into the applications of sentiment analysis.

According to (D’Andrea, Ferri , Grifoni , Guzzo, 2015) , there are three types of techniques for sentiment classification:

Machine learning approach,

Lexicon based approach and

Hybrid approach.

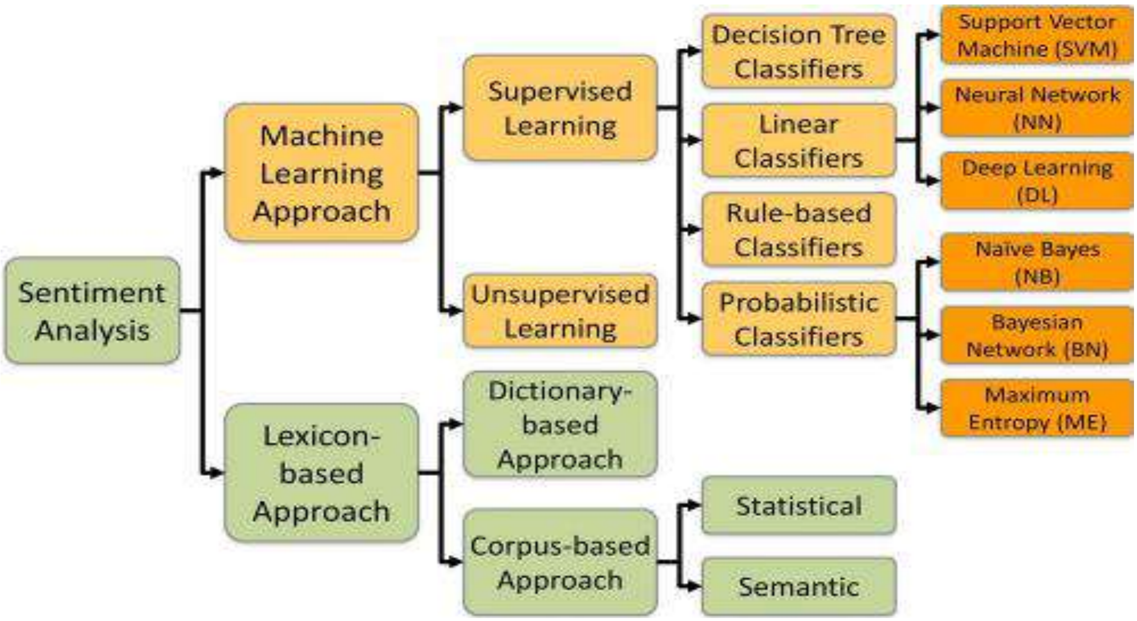


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Figure 2 Sentiment Classification techniques (Medhat et al.2014).

2.6.1 Machine learning approach

The machine learning approach is used for predicting the polarity of sentiments based on trained as well as test data sets. It applies the ML algorithms and uses linguistic features. The main advantage of this method is the ability to adapt and create trained models for specific purposes and contexts while its main disadvantage is the low applicability of the method on new data because its dependant on the availability of labelled data that could be costly or even prohibitive. It can use supervised and unsupervised methods. The machine learning approach uses a supervised approach when there is a finite set of classes (positive and negative). This method needs labelled data to train classifiers. In a machine learning based classification a training set is used by an automatic classifier to learn the different characteristics of documents, and a test set is used to validate the performance of the automatic classifier. The unsupervised methods are used when it is difficult to find labelled training documents. Unsupervised learning does not require prior training to mine the data. Unsupervised approaches to document-level sentiment analysis are based on determining the semantic orientation (SO) of specific phrases within the document. If the average SO of these phrases is above some predefined threshold the document is classified as positive, otherwise it is deemed negative. Among the machine learning approaches the most used are:

(i) **Bayesian Networks**: it is a probabilistic approach that models' relationships between features in a very general way. It is based on directed acyclic graph in which nodes are variables and arcs represent the dependence between variables.

(ii) **Naive Bayes Classification**: it is an approach particularly suited when the dimensionality of the inputs is high. Despite its simplicity, it can often outperform more sophisticated classification methods.

(iii) **Maximum Entropy**: this method is mostly used as alternatives to Naive Bayes classifiers because it does not assume statistical independence of the random variables (features) that serve as predictors. The principle behind Maximum Entropy is to find the best probability distribution among prior test data.

(iv) **Neural Networks**: this model is based on a collection of natural/artificial neurons uses for mathematical and computational model analysis

(v) **Support Vector Machine:** SVM is a supervised machine learning algorithm that can be used for both classification or regression challenges. Classification is predicting a label/group and Regression is predicting a continuous value. SVM performs classification by finding the hyper-plane that differentiate the classes we plotted in n-dimensional space. It finds an optimal solution.

2.6.2 Lexicon based approach.

While the lexicon-based approach does not need any prior training to mine the data. It uses a predefined list of words, where each word is associated with a specific sentiment. They are based on the counting of positive and negative words. These methods vary according to the context in which they were created. Lexical do not need labelled data but is hard to create a unique lexical-based dictionary to be used for different contexts. For example, slang used in social networks is rarely supported in lexical methods. The lexicon-based approach uses sentiment dictionary with opinion words and match them with the data for determining polarity. There are three techniques to construct a sentiment lexicon: manual construction, corpus-based methods and dictionary-based methods. The manual construction is a difficult and time-consuming task. Corpus-based methods can produce opinion words with relatively high accuracy. Finally, in the dictionary-based techniques, the idea is to first collect a small set of opinion words manually with known orientations, and then to grow this set by searching in the WordNet dictionary for their synonyms and antonyms.

2.6.3 Hybrid approach.

Finally, in the hybrid approach, the combination of both the machine learning and the lexicon based approaches has the potential to improve the sentiment classification performance. There are some advantages and limitations in using these different approaches depending on the purpose of the analysis. We provide an overview of the main. The main advantage of machine learning approaches is the ability to adapt and create trained models for specific purposes and contexts, while the limitation is that it is difficult integrating into a classifier, general knowledge which may not be acquired from training data. Furthermore, learnt models often have poor adaptability between domains or different text genres because they often rely on domain specific features from their training data. Lexicon-based approaches have the advantage that general knowledge sentiment lexicons have wider term coverage; however, these approaches have two main limitations. Firstly, the number of words in the lexicons is finite, which may constitute a problem when extracting sentiment from very dynamic environments. Secondly, sentiment lexicons tend to assign a fixed sentiment orientation and score to words, irrespective of how these words are used in a text. The main advantages of hybrid approaches are the lexicon/learning symbiosis, the detection and measurement of sentiment at the concept level and the lesser sensitivity to changes in topic domain. While the main limitation is that reviews are with a lot of noise (irrelevant words for the subject of the review) are often assigned a neutral score because the method fails to detect any sentiment.

2.6.4 Comparison and Consolidation

The comparison and consolidation of the three main approaches used in sentiment analysis. Performing sentiment analysis by various approaches will produce different results. Each approach has its own pros and cons. By considering the key factors like performance, efficiency, and accuracy, the machine learning approach yields the best result and most of the work has been done in this approach.

2.7 Chapter summary

This Chapter reviewed work done by several researchers in the past with regards to customer satisfaction and sentiment analysis and also seeks to provide a literature review on sentiment analysis techniques and how its applied in the field of market research. It also aims at highlighting some of the challenges of the different sentiment analysis techniques that remain in advancing current approaches. It gave the researcher room to evaluate this research in terms applicability in other domains. Past research was evaluated in terms of weakness and strength in the current environment.

Chapter 3 Research methodology

3.0 Introduction

This section explains and justifies methods the researcher used to extract and analyse data for this study. The section focused on the research philosophy, research design, research instruments, research population, sampling, validity and reliability, data analysis, ethical considerations undertaken throughout the research.

3.1 Research Philosophy and Paradigm

This research followed the pragmatism approach because of its potential to allow the mixing of methods given the nature of the research problem that was being investigated. This case study outlined the methods used to both quantitatively analyse Twitter data for overall public sentiment and qualitatively analyse the same data to discover details in the changing discourse when customers are engaged in a certain way. It was necessary to understand the content posted on social media and adopt comprehensive analytical techniques to predict and evaluate relevant information within the same context it was posted. Analysing data through sentiment analysis using lexical signifiers of emotion, to determine if the data leans towards positive or negative emotions justifies why both quantitative and qualitative approaches were required. Qualitative analysis was applied on text extracted from twitter where the researcher had to determine the subjectivity (our emotions) and explaining it using some abstract representations. Qualitative was used to detect semantic patterns and context of user tweets while quantitative was used to determine the percentage of negative and positive tweets.

3.2 Research design

The researcher adopted the descriptive observational research design where tweets or customer behaviour on twitter were closely observed without influencing them in any way. Customers on Twitter share information about their preferences or opinions on products and services voluntarily. Thus, they are honest in their views which fits well into the characteristics of this design. The researcher adopted the lexicon-based approach, the most primitive method. The main objective of the study sought to justify why mobile and fixed internet service providers need to adopt sentiment analysis in evaluating customer experience given the increase in reported tickets.

3.3 Sample size and sampling method

The amount of data streaming from twitter is defined as big data which is complex to analyse due to its volume, variety and velocity. Streaming data is data that is continuously generated and has no discrete beginning or end. It varies from time to time. Scalability, continuous availability, diversity, data security and manageability are the challenges in streaming data. Rather than analysing the entire streaming dataset, sampling provides an alternate solution to analyse in an efficient manner and thereby minimizing the computation time. The Reservoir sampling (RS) technique was used to extract batch samples of size 200.

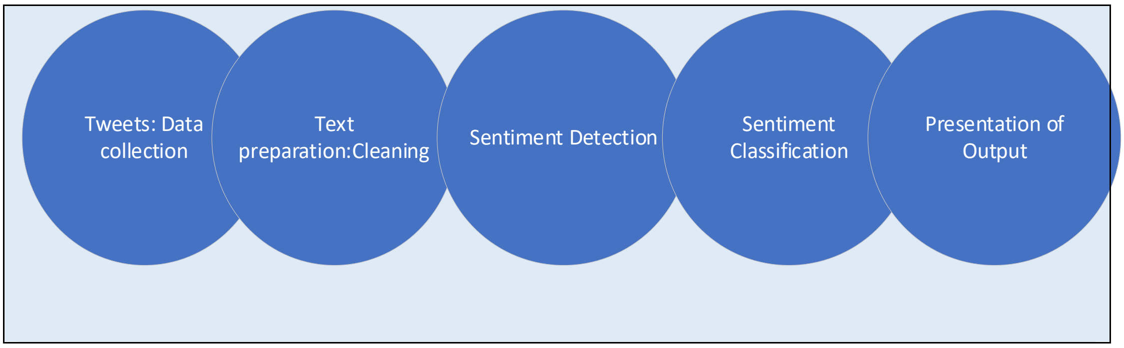
3.4 Research instruments

The Twitter API and the Tweepy python library was used to extract data from Twitter and stored in memory for further processing using python and data analytics libraries such as pandas and NumPy.

Python Library	**Description of libraries**
textblob	Textblob is a Python library for processing textual data. It provides a simple API for diving into common natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more.
NLTK	The Natural Language Toolkit (NLTK) is a platform used for building Python programs that work with human language data for applying in statistical natural language processing (NLP). It contains text processing libraries for tokenization, parsing, classification, stemming, tagging and semantic reasoning.
NumPy	This library is going to be used for calculations in multidimensional space.
Pandas	Library used for data manipulation and analysis
Matplotlib	Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python.

Table 1 Research Instruments

Figure 3 Sentiment analysis pipeline



3.5 Data collection procedures

Data was collected through the official Twitter Application Program Interface (API) using python and then imported into a Jupyter notebook for data cleaning and analysis.

Figure 4 Data Collection

```
from IPython.display import display
screen_name="econet_support"
posts = tweepy.Cursor(api.user_timeline,screen_name, count = 200, lang ="en", tweet_mode="extended" ,include_rts=False)

for tweet in (posts.items(5)):
    display(tweet.full_text)
```

```
'Hey @sircarta_. Please check your other post for our response. ^SC'

'Hey @sircarta_ @nico_lasi. We want you to have the connection you need. Do you mind sharing your mobile number, loca
tion, and the type of device you are using, so that we may assist? We look forward to hearing from you. ^SC'

'Hey @thatgirlRieRie. Please check your DM for our response. ^SC'

'Hey @thatgirlRieRie. Please check your other tweet for our response. ^SC'

'Hey @thatgirlRieRie. Please check your DM for our response. ^SC'
```

Twitter provides a streaming API that developers can use to download data about tweets in real-time. The researcher obtained Twitter API credentials (API key, API secret key, Access token, and Access token secret) and used the Tweepy library to connect to the Twitter API in real time. Looking at the service provider timelines, there were tweeter engagements between customers and service providers. The researcher chose to store collected data in memory, running analysis as the data was streaming rather than converting the data and storing it into disk. The choice of data collection method was based on the premise that the resultant model will be run on continuous streaming data in production providing analysis that can be used in real time. However as highlighted on the delimitations of this study the researcher chose not to include data streaming mechanism as part of this study as that would have added complexity.

Mobile and fixed internet service providers such as Econet Zimbabwe, Net one Pvt Ltd, ZOL Zimbabwe and Telone Pvt Ltd all have an online presence on Twitter as identified by their twitter handles below.

- @econet_support
- @Telone
- @Zol_support
- @netone

The researcher measured customer satisfaction using twitter data from customers who have an account on twitter and were engaging with the service providers. The researcher also worked with the assumption that the samples used in this research would fairly generalise the overall customer satisfaction scores for the service providers even though not all customers are on twitter. The resultant sentiment analysis model can be used on other data such as customer call records, incident management systems or live chat data where customers who are not on twitter could be catered for.

Exclusion criteria included

(1) Selecting tweets that are written in English, based on the "language" field provided by the Twitter API. We chose to only consider English tweets and focusing on one language allows us to abstract away the nuances associated with sentiment analysis based on different languages.

3.6 Data cleaning (Text preparation)

Data cleaning involved checking the data for any missing values, errors, and outliers in all variables. All errors must be corrected; outliers must be identified at this stage. Duplicates, wrong symbols must be removed. Text preparation involved cleaning the extracted data before the analysis was performed. Any content that was not deemed relevant to the area of study was removed from the textual dataset. In the case of streaming data, Twitter data is often messy and contains a lot of redundant data which needs to be cleaned before analysis. Non-textual contents and contents that were irrelevant for the analysis were identified and removed using the panda's library.

a) Removing Twitter Handles (@user): Twitter handles do not contain any useful information about the nature of the tweet, so they can be removed.

b) Removing Punctuations, Numbers, and Special Characters: The punctuations, numbers and even special characters are removed since they do not contribute to differentiating tweets.

c) Tokenization: We split every tweet into individual words or tokens which is an essential step in any NLP task. The following example shows a tokenization result,

Input: [their service is poor]

After tokenization: [their service is poor]

d) Stemming: It is a rule-based process of stripping the suffixes ("ing", "ly", "es", "s" etc) from a word.

For example: "play", "player", "played", "plays" and "playing" are the different variations of the word – "play". The objective of this process is to reduce the total number of unique words in our data without losing a significant amount of information.

Figure 5 Sentiment detection

In [108]:
```
# Create a function to clean the tweets

def cleanTxt(text):
    text = re.sub('@[A-Za-z0-9]+', '', text) #Removing @mentions
    text = re.sub('#', '', text) # Removing '#' hash tag
    text = re.sub('RT[\s]+', '', text) # Removing RT
    text = re.sub('https?:\/\/\S+', '', text) # Removing hyperlink
    text = text.lower()


    return text

# Clean the tweets
df['Tweets'] = df['Tweets'].apply(cleanTxt)

# Show the cleaned tweets
df.head()
```

Out[108]:

	Tweets
0	hie _ . _ we have responded. ^nza
1	hie , our apologies for the experience. may yo...
2	hi , we have reversed the transaction back to ...
3	hi , may you please dm us your mobile number a...

Sentiment detection: The extracted sentences of the reviews and opinions were examined. Sentences with subjective expressions (opinions, beliefs and views) were retained and sentences with objective communication (facts, information) were discarded. Sentiment detection is done at different levels either single term, phrases, complete sentences or complete document with commonly used techniques such as:

- **Unigrams**: This is a classic approach where each element is represented as a feature vector based on frequency of a single word. It is often described as a bag of words approach
- **N-Grams**: In this approach the features of a document is represented by multiple words in sequence (e.g.: words in pairs, triplets) which captures more context

- **Lemmas**: This involves the use of synonyms rather than the literal word. For example: better -> good, best → good. This method reportedly makes the classification task easier as well as facilitates generalization. However, Kushal et al. (2003) argued that meanings are not necessarily synonyms and provided evidence through his experiment that suggested that the accuracy of sentiment classification was reduced when words are linked to their thesaurus meanings.
- **Negation**: This is basically an extension to the n-gram methods where the phrases "I like this book" and "I do not like this book" would have considered similar under most classification techniques, but with negation, both terms are forced into opposite groupings. However, negation is not always easy to model. For instance, Pang and Lee (2008) reported that it is difficult to identify negation when sarcasms and ironies are used in a sentence. Additionally, the negation term does not always reverse the polarity. For example, it will be considered incorrect to attach the word NOT to BEST in the sentence "No wonder this is considered to be the best book".
- **Opinion words**: These are basically words that are used to describe people feelings and opinions (nouns, verbs, adjectives, adverbs). These words are incorporated into a feature vector where they represent the presence of absence of a word. These words are good indicators of subjectivity in a document.

It is not uncommon to find textual sentences referring to several objects, features and attributes. Through mathematical algorithms, sentiment analysis can be used to extract these objects, features and attributes and form categorize. This assists in the analysis stages and enhances precision in classification and data summarization.

Figure 6 sentiment classification

```python
# Create a function to get the subjectivity
def getSubjectivity(text):
   return TextBlob(text).sentiment.subjectivity

# Create a function to get the polarity
def getPolarity(text):
   return  TextBlob(text).sentiment.polarity


# Create two new columns 'Subjectivity' & 'Polarity'
df['Subjectivity'] = df['Tweets'].apply(getSubjectivity)
df['Polarity'] = df['Tweets'].apply(getPolarity)

# Show the new dataframe with columns 'Subjectivity' & 'Polarity'
df
```

	Tweets	Subjectivity	Polarity
0	Hie , our apologies for the experience. May yo...	0.500000	0.000000
1	Hi , we have reversed the transaction back to ...	0.071429	0.000000
2	Hi , may you please DM us your mobile number a...	0.000000	0.000000
3	Hi , our apologies for the experience. Kindly ...	0.641667	0.350000
4	Hi 48697166, kindly provide us with the error ...	0.900000	0.600000
5	Hi 1, our apologies for the late response. Kin...	0.750000	0.150000
6	Hey , may you please let us know your location...	0.000000	0.000000
7	Hey _mhaps @263lod. Kindly note there was no d...	0.725000	0.475000
8	_AK47 Hi 50834056, did you buy the airtime vi...	0.700000	0.300000
9	3, thank you for getting in touch. Please note...	0.450000	0.025000
10	Thank you for your continued support _dhliwayo...	0.758333	0.425000

Sentiment classification: in this step, subjective sentences are classified in positive, negative, good, bad; like, dislike, but classification can be made by using multiple points.

Create a function to compute negative (-1), neutral (0) and positive (+1) analysis

```
def getAnalysis(score):
    if score < 0:
      return 'Negative'
    elif score == 0:
      return 'Neutral'
    else:
      return 'Positive'

df['Analysis'] = df['Polarity'].apply(getAnalysis)

# Show the dataframe
df.head()
```

	Tweets	Subjectivity	Polarity	Analysis
0	Hie , our apologies for the experience. May yo...	0.500000	0.00	Neutral
1	Hi , we have reversed the transaction back to ...	0.071429	0.00	Neutral
2	Hi , may you please DM us your mobile number a...	0.000000	0.00	Neutral
3	Hi , our apologies for the experience. Kindly ...	0.641667	0.35	Positive
4	Hi 48697166, kindly provide us with the error ...	0.900000	0.60	Positive

The fourth stage is polarity classification which classifies each subjective sentence in the textual dataset into classification groups. Usually, these groups are represented on two extreme points on a continuum (positive, negative; good, bad; like, dislike). However, classification can also involve multiple points like the star ratings used by hotels, restaurants and retailers. A wide variety of machine learning techniques are used in binary and polar classification. Machine learning is linked to the field of artificial intelligence and aims at building computational models from past experiences and observation. It fundamentally promotes the use of computer programming to learn and understand fundamentals a particular data set and then use that knowledge acquired to predict or optimize some future criterion. The general objective is to generate a predictive function capable of predicting a target outcome - y (dependent variable) using predefined input criteria or attributes - x (Gama and Carvalho, 2009). When the target is known, this type of learning is called "supervised learning". Using a supervised leaning approach in sentiment analysis requires training document of textual content or a data corpus, which serves as a preparation document for classification learning. The three basic functions available for classification includes: Naive Bayes (NB), Support Vector Machines (SVM) and MaximumEntropy (ME). A Naive Bayes classifier is a probabilistic classifier based on applying Bayes' theorem assuming that features are independent given the class label. This classifier is constructed based on the frequency of occurrence of each feature per class in the training data set. Support vector machines are based on the statistical learning theory (Vapnik, 1995). Binary classifiers show high generalization capability by looking for a hyperplane that maximizes the separation margin between observations from different classes. The use of kernels allows their use for nonlinear problems. Under ME a number of models are constructed where each feature correspond to a constraint on the model. The model with the maximum entropy over all models is selected for classification. Although all three classifiers are validated in the literature (Pang and Lee 2008, Li and Liu, 2012), they require pre-tagged training data or a data corpus which is not always available, or will take a considerable amount of resources both in terms of time and human resources to build. In addition, the language of the data cannot be ignored. Most literature, tools and techniques available on sentiment analysis are written in English language. This presents a problem for 9 multilingual translation. While there is a stream of research focusing on aligning other languages to the domain of interest, cross lingual adaptation remains a challenge especially when cultural idiosyncrasies are taken into consideration (Kim and Hovy, 2006; Blitzer et al. 2007). The most basic is the bag of words method where a score or weight is assigned to each word based on the nature of the word (good or bad) and the frequency of the word in the text document. Once the score for each term is calculated, a score for the whole document is calculated by taking the arithmetic sum or mean. The simplest scoring method involves the subjective assignment of scores to opinion documents from which a "pseudo-expected" value is computed. Although this method is statistically grounded and simple to comprehend, it is criticized as not providing an efficient alternative to categorize large volumes of data. Additionally, because it relies on human categorization, the reliability of the classification has also been questioned given the diverse nature of human beings (Li and Liu, 2012). Another technique involves the use of lexicons. A lexicon acts as a bridge between a language and the knowledge expressed by that language. It is a list of all words and meanings in a specific language. A variety of lexicons have been created for use in sentiment analysis. WordNet is a lexical database for the English Language. Created in 1985 by Princeton University, this database gives general definitions of words, group words into sets of synonyms known as synsets, and record relationship between synonymy sets through conceptual-semantic and lexical relations. In 2004, Kamps and Marx used this synonym relationship to measure the distance between words based on their similarities and differences based on graph theory. They first classify each adjective on a good-bad (+,-) spectrum and then compute the distance between words based on the length of the spectrum with closer words having shorter distances. Web Search is another scoring method introduced by Turney (2002). This method recognizes the contextual problems with single word classification. For instance, the word "unpredictable" might have negative reviews in an automobile review but might be a positive review for a movie. To accommodate this problem, Turney (2002) used "tuples" which consist of adjectives combined with nouns, and adverbs combined with verbs. The process of word search involves a series of stages. Firstly, tuples are extracted from reviews. Secondly, semantic orientations of the extracted tuples are determined and finally, the average semantic orientations are calculated for the whole document. To determine the semantic orientation of tuples, Turney (2002) used the 10 search engine AltaVista and ran two queries. One that looked that the number of documents that considered the tuple "excellent" and another with the number of documents that considered the tuple "poor". If the tuple occurred more times in "excellent" query, than "poor" then it is considered a positive orientation. Likewise, if the tuple occurred more times in "poor" query, then it will be negative.

3.7 Data presentation and analysis methods

The general purpose of the analysis is to convert unstructured fragmented text into meaningful information. Once the analysis is completed, several conventional options are used to display the result of text analysis. Chief among them is the use of graphical displays such as pie charts, bar charts and line graphs. The polarity is segmented on colour, frequencies, percentages and size. The format of presentation depends on the research interest. Data scrapped from twitter was analysed quantitatively using python mathematical and visualisation libraries (pandas, matplotlib). The results were expressed in terms of inferential statistics, graphs, tables and proportions.

Figure 7 Graph Plotting

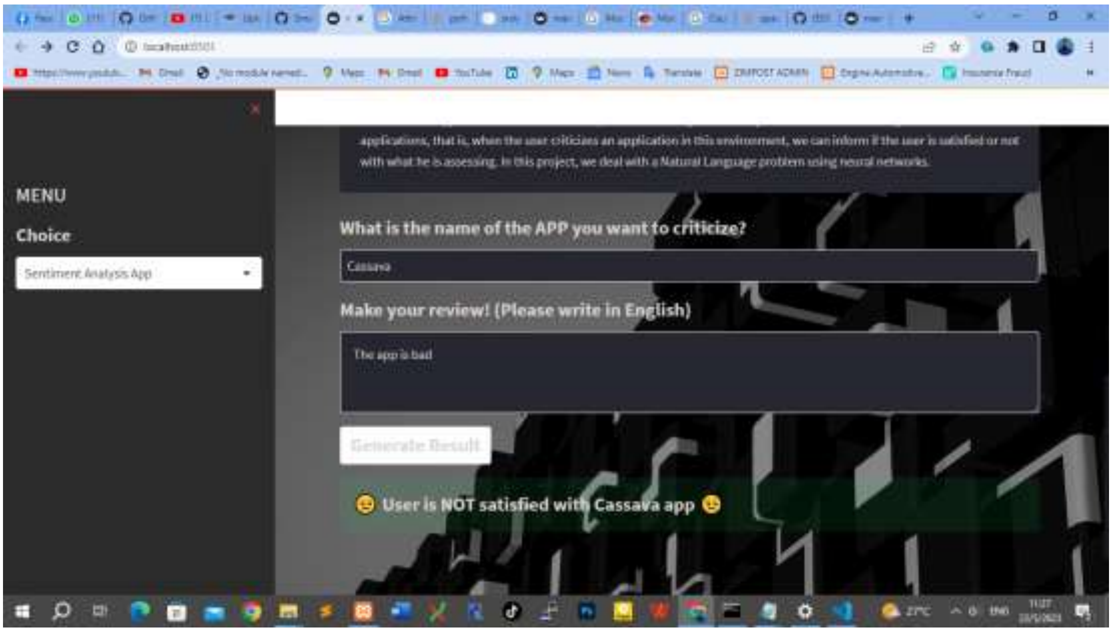
```
fig, ax = plt.subplots(figsize=(8, 8))

# Plot horizontal bar graph
fd.plot.barh(ax=ax,
              color="purple",
               x='Word',
               y='Frequency',
            )

ax.set_title("Common Words Found (Including All Words)")

plt.show()
```

Figure 8 Analysing commonly used words



This above graph will help us analyse the commonly used words that can be used when engaging with customers on twitter and possible find a way of choosing the words that will improve sentiment.

Word cloud is the informative visual representation of text datasets, highlighting the most popular and trending keywords in text datasets based on the frequency of occurrence and importance. It was used by the researcher to display the keywords that were most actively present in the scrapped text dataset.

Dataset

	id	myTweets	tweet_date
0	1365589888448479235	hie jamesmaseko kindly note that we have respo...	2021-02-27 09:09:35
1	1365589596344627201	hie jamesmaseko our apologies for the delay pl...	2021-02-27 09:08:25
2	1365587528900870144	hello ajuda the bundles work like an ordinary ...	2021-02-27 09:00:12
3	1365586710344708099	makadini tafarapalesa tinokumbirawo mutarise m...	2021-02-27 08:56:57
4	1365585901452226561	hey morgenmukuli please note that the transact...	2021-02-27 08:53:44
5	1365585645339635713	hie munyamusy we have since responded to your ...	2021-02-27 08:52:43
6	1365585321031835650	hi leisleyb jermainematth muleyaelijah we have...	2021-02-27 08:51:26
7	1365584297466429443	hi vinlyn leisleyb we have reversed the money ...	2021-02-27 08:47:22
8	1365583952673660929	kwazivai prayer tinokumbira mutarise mhinduro ...	2021-02-27 08:46:00
9	1365583358894440448	hi vinlyn we have responded to your dm mbm	2021-02-27 08:43:38

Figure 9 Word Cloud visualisation

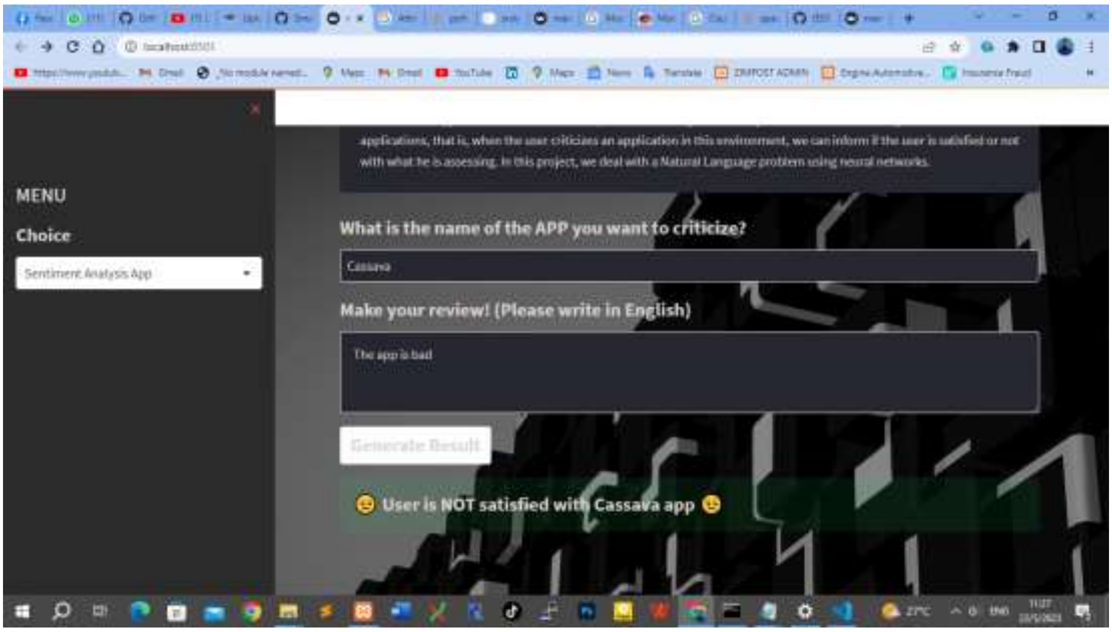
Word Cloud visualisation

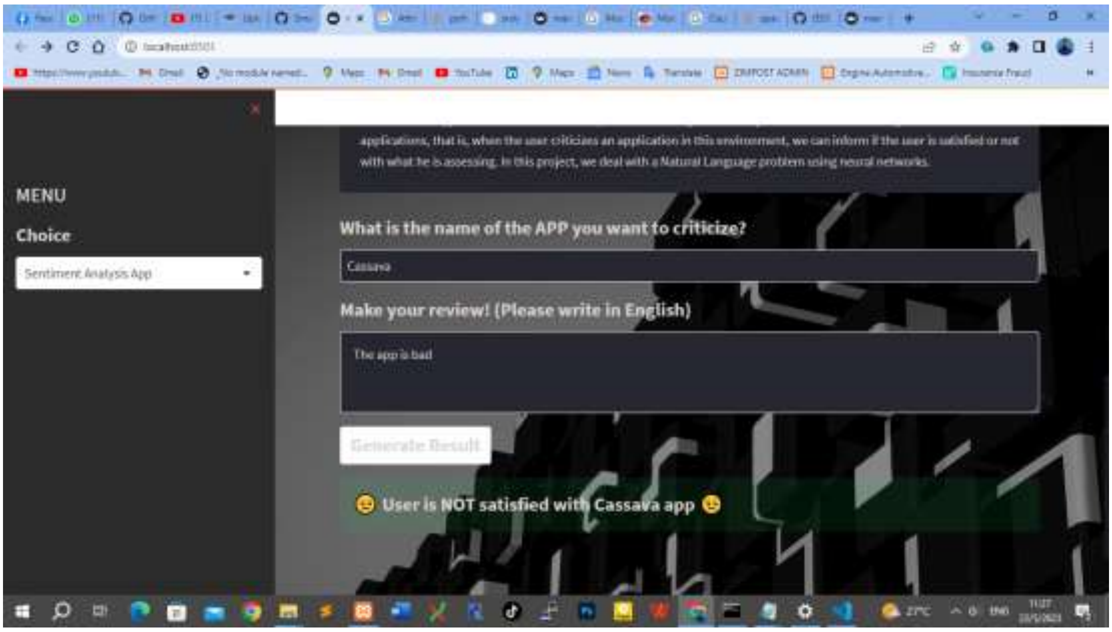
```
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator

def word_cloud(wd_list):
    stopwords = set(STOPWORDS)
    all_words = ' '.join([text for text in wd_list])
    wordcloud = WordCloud(
        background_color='white',
        stopwords=stopwords,
        width=1600,
        height=800,
        random_state=1,
        colormap='jet',
        max_words=80,
        max_font_size=200).generate(all_words)
    plt.figure(figsize=(12, 10))
    plt.axis('off')
    plt.imshow(wordcloud, interpolation="bilinear");
```

```
word_cloud(df['myTweets'])
```

Figure 10 Model Variables





3.8 Ethical considerations

Ethical considerations are one of the major considerations of any research study. Crosswell (2003) asserts that when conducting a study, the researcher has the mandate to observe the desires, needs, rights and values of participants. It therefore means that respondents have the ultimate right to making reasonable decisions in as far as responses are concerned (Graziano and Raulin, 2004) as well as ensuring that the respondents identify the findings of the study as their experiences (Streubert and Carpenter, 2011). All users' personal identifying information was strictly protected according to Twitter's user privacy terms and all user identity-related text content from user tweets was not presented in any tables or graphics. The information gathered was considered for academic use only.

3.8 Section summary

In this chapter, attention was given to the crucial elements that make up the research methodology applied in this study. The next chapter, Results and discussion, the task was to present the data that has been collected and analyzed using the instruments discussed in this chapter.

CHAPTER 4: RESULTS AND ANALYSIS

4.0 INTRODUCTION

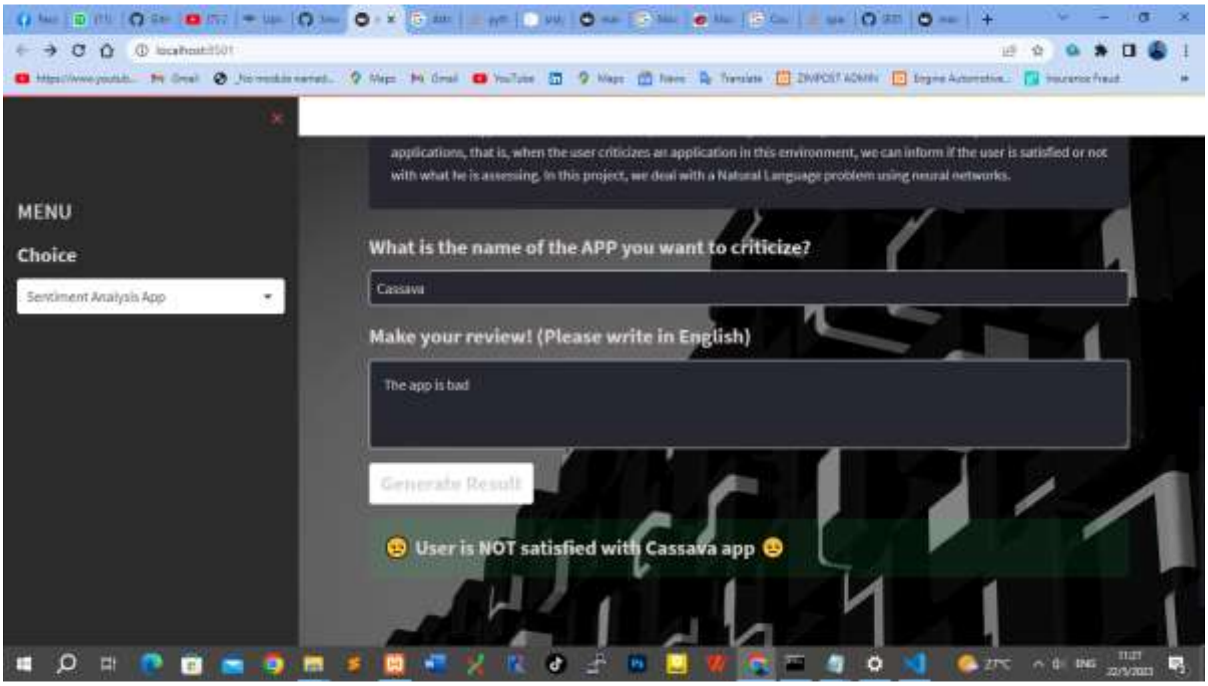
After the author had successfully implemented the system there arose the need to analyze the efficiency of the developed solution. Accuracy, performance and response time were the matrices used to determine the efficiency and effectiveness of the developed solution. The developed solution's behavior was also well observed under the different times and the outcome was presented in a table format.

4.1 TESTING

Testing is a vital part of the development process and this chapter shows the tests that were undertaken and the result they produced. The testing is thus measured against the functional and non-functional requirements as outline in the previous chapter.

4.1.1 BLACK BOX TESTING

Black box testing enables a user without the knowledge of the internal structure of the system to test it against the functional and sometimes the non-functional requirements of the system. It mainly focused on predicting if the user is satisfied or not. Thus, the main purpose of black box testing was to test if the system worked as per expected in requirement document.



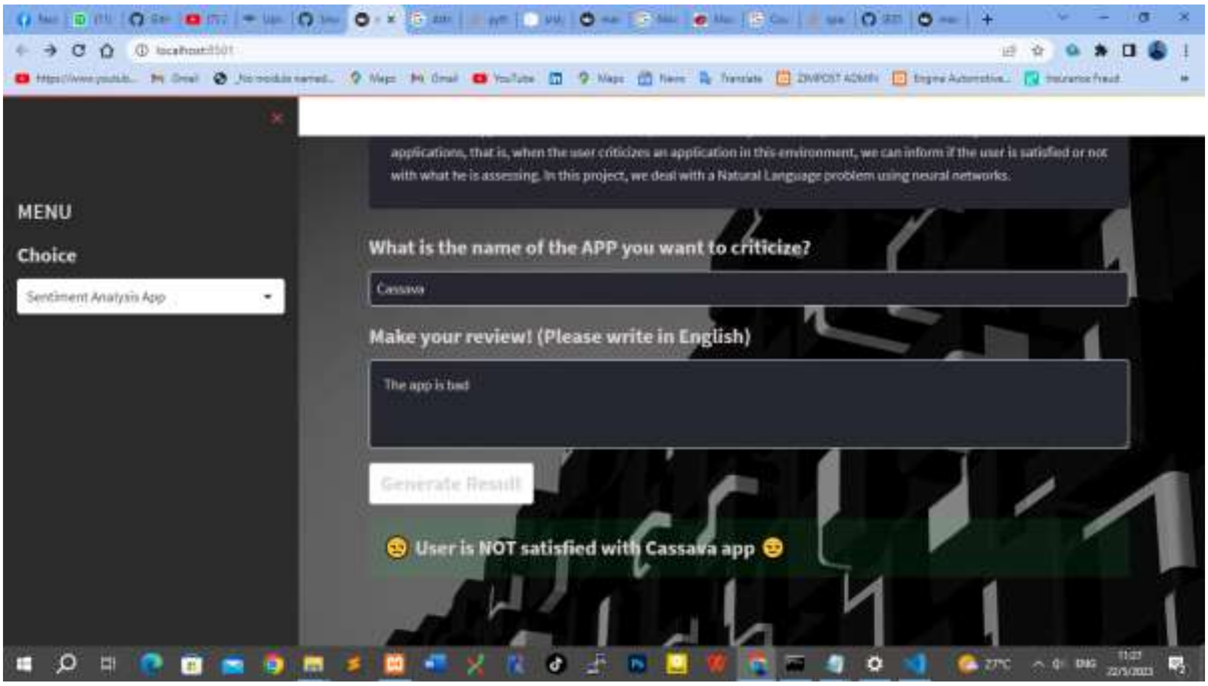


Figure 11 Black box testing

4.1.1.1 FUZZY TESTING

Fuzzy testing is a black box testing technique which the researcher used on the Weather Forecasting application to check if the system is accurately responding and giving the correct results as per given coordinates.

4.2 EVALUATION MEASURES AND RESULTS

An evaluation metric measures the performance of a classifier (Hossin & Sulaiman, 2015). Moreover, according to Hossin & Sulaiman (2015), model evaluation metrics can be grouped into three types namely threshold, probability and ranking.

4.2.1 Measuring System Performance

The performance of the system is ranked according to its ability to give a real time feedback as per given dataset.

Machine 1(4 gig Ram,Core i3 500gb)

Test Runs	1	2	3	4	5
Time(s)	150	145	151	164	149

Table 2 Measuring system perfomance

Mean Value for the performance of the system on machine 1

150+145+151+164+149=759/5

=151.8 seconds

Machine 2(8 gig Ram,Core i3 1terabyte)

Test Runs	1	2	3	4	5
Time(s)	69	78	76	67	80

Mean Value for the performance of the system on machine 1

69+78+76+67+80=370/5 =74 seconds

4.2.2 Measuring Supervised Machine Learning to previous algorithms

Algorithms	**Linear Regression**	**Decision Tree**	**Random Forest**
Accuracy	0.99	0.98	0.99

Table 3 Confusion Matric

Type	Bad Experience	Good Experience
Bad Experience	True Positive	False Negative
Good Experience	False Positive	True Negative

Two scenes and test environment were created for observation of the system. On each scene the system was observed on 40 occasions 20 cases were good experience and 20 cases were bad experiences and the behavior of the system was observed. All the analysis on the scenes was carried out to test for the solution's accuracy and elimination of false prediction. The tables below show the observed results from the tests carried out.

Table 4 During Good Experiences

Test cases	**Good Experience**	**Number of cases**	**Correct readings**	**False Readings**	**Classification**
1	Yes	20	16	4	True positive
2	No	20	18	2	True negative

Table 5 During Bad Experience

Test cases	**Good Experience**	**Number of cases**	**Correct readings**	**False Readings**	**Classification**
1	Yes	20	14	6	True positive
2	No	20	17	3	True negative

4.2.3 Accuracy

Accuracy is the number of right predictions divided by the total number of forecasts in each category. It is then multiplied by 100 to get the percentage of correctness. It is calculated using the equation below:

Equation 1: Accuracy calculation as adopted from Karl Pearson (1904)

Accuracy = (TP+TN)/ (TP+TN+FP+FN)*100

Accuracy during good experience = (16+18)/ (20+20+0+0)

=0.85

=0.85*100= 85%

Accuracy during bad experience = (14+17)/(14+17+3+6) *100

= 76%

Average Accuracy rate = Accuracy at (good + bad) /2

= (85+76)/2 *100 = 295/3 *100

=80.5 %

4.3 Conclusion

The test results indicated the solution had a high level of accuracy on 2 scenes it produced 85 % and 76 % rate of accuracy respectively which was a result of the analysis of the confusion matrix. However, the solution had eighty-point five (80.5%) percent accuracy on the overall this was due to the high levels of wind and insufficient training data and proper environment exposure. The high levels of accuracy of the system indicate a reduction of false prediction on air pollution index.

CHAPTER 5: SUMMARY, CONCLUSIONS AND IMPLICATIONS

5.1 Introduction

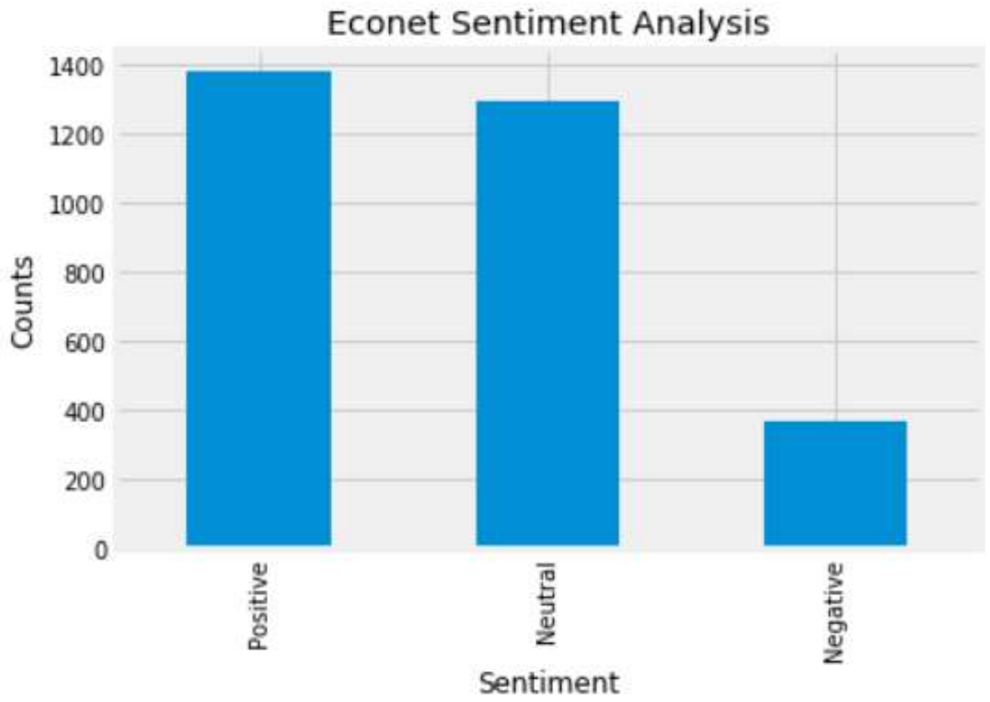
This chapter concludes the research study. Answers to research questions raised in the first chapter will be outlined and conclusions will be clearly stated. For future studies, recommendations are going to be provided. The recommendations and suggestions are based on the key findings obtained in the previous chapter and the objectives of the study.

5.2 Summary of research findings

Based on the objectives of the study the research was able to meet the objectives of the study and answered all research questions.

Research Objective	Research Question
To measure customer satisfaction by analysing customer sentiment from tweets	How do we measure customer satisfaction using sentiment analysis?

```
# Plotting and visualizing the counts
plt.title('Econet Sentiment Analysis')
plt.xlabel('Sentiment')
plt.ylabel('Counts')
df['Analysis'].value_counts().plot(kind = 'bar')
plt.show()
```



Research Objective **Research Question**

To extract the most prevalent words that contribute to a negative or positive sentiment.	What words can be used to improve customer engagement?

```
word_cloud(df['myTweets'])
```

Research Objective **Research Question**

To identify the most suitable words that can be used to improve customer engagement.	What words can be used to improve customer engagement?

How can we improve overall customer engagements and Influence customer behaviour?

Randomly sample 10% of your dataframe

```
datasetC = df.sample(frac=0.1)
```

```
datasetC
```

	id	myTweets	tweet_date	Subjectivity	Polarity	Analysis
2012	1362681659330605059	hi docmoodsie elsamplero kindly refer to your ...	2021-02-19 08:33:19	0.900000	0.600000	Positive
2239	1362207539115552769	hie babangwenya kindly check our dm response gfk	2021-02-18 01:09:20	0.900000	0.600000	Positive
463	1365216000573079552	hey tendainherera we sincerely apologise for t...	2021-02-26 08:23:53	0.700000	0.000000	Neutral
2128	1362393042490122242	wakuraa hey buddie please check your dm for ou...	2021-02-18 13:26:28	0.000000	0.000000	Neutral
1455	1363833277044428804	hie tinodzikiti kindly confirm if the provided...	2021-02-22 12:49:26	0.700000	0.300000	Positive
2044	1362663874487586816	makoreaddmore hi buddie merchant reversals are...	2021-02-19 07:22:39	0.888889	0.500000	Positive

Randomly choosing 10% of the dataset and running the sentiment analysis model 4 times gave us 4 different results. Which proved that certain words can be identified and used to improve customer engagements.

Research Objective	**Research Question**
To develop a twitter sentiment predictive model	How do we develop a sentiment analysis model ?

```
def getAnalysis(score):
    if score < 0:
        return 'Negative'
    elif score == 0:
        return 'Neutral'
    else:
        return 'Positive'

df['Analysis'] = df['Polarity'].apply(getAnalysis)

# Show the dataframe
df.head()
```

	id	myTweets	tweet_date	Subjectivity	Polarity	Analysis
0	1365672925534294016	hi tiniezoey kindly refer to your dm for our r...	2021-02-27 14:39:33	0.90000	0.60000	Positive
1	1365671143294787595	makadini giftvocure chagumukaa demarcusmhalo t...	2021-02-27 14:32:28	0.00000	0.00000	Neutral
2	1365670345773092866	makadini chagumukaa takupindurai kudm kwenyu mbm	2021-02-27 14:29:18	0.00000	0.00000	Neutral
3	1365667945372860426	hie maiteeteebi we are glad that the issue has...	2021-02-27 14:19:45	0.81875	0.44375	Positive
4	1365667876544393218	hi ultimatekagz demarcusmhalo kindly refer to ...	2021-02-27 14:19:29	0.90000	0.60000	Positive

5.3 Practical implications

This study may lead businesses in Zimbabwe to incorporate sentiment analysis techniques when evaluating customer satisfaction as it provides more insights as compared to old traditional methods. If these insights are acted upon, this will improve their revenues significantly since a satisfied customer is a loyal customer.

Advantages of using customer satisfaction metrics obtained from sentiment analysis

1. Loyal customers

Happy customers stay loyal and increase revenue. They always return when the like a product or service and are satisfied with the offered performance and customer service. Using these metrics, you can find out your loyal and satisfied customers. You can reach out to dissatisfied ones to know their reasons and take actions to make them happy.

2. Promoters

With NPS surveys, you can understand who your promoters, detractors, and passives are. With your promoters, you can use them to amplify your brand and positives. They are your brand's best advocates, and you should leverage them as such. For passives, you can take measures to nudge them into becoming promoters. This could be via discounts, offers, early product previews, various benefits, etc. It would help if you worked more on detractors, going to the core reasons behind their dissatisfaction and less than favorable experience. This will help improve the overall CX and satisfaction levels.

3. Brand reputation

Customers with great experiences may talk to their friends and family about their experiences, but those with bad experiences will talk about it. This not only seriously hampers your brand reputation but also bottom line. Conducting CSAT surveys can help alleviate some of these concerns as you can actively track these customers and make amends. With so many social media channels available at fingertips, users can easily upload information about their less than favourable experiences or bad reviews. You can avoid this with timely actions and take the necessary actions to improve their experience and satisfaction.

4. Usability and experience

Conducting Customer Effort Score (CES) surveys, you can collect the quantitative and qualitative data put by your users. You can use these studies to ensure you make their lives easier and keep that in mind for future feature rollouts or new offerings. As you can see, all these metrics offer their own benefits and can be used to elevate your customer satisfaction.

5.4 Conclusions

The article discusses the growing interest in sentiment analysis, which involves extracting meaningful information from large volumes of text-based data. However, the field is still relatively new, and researchers may face challenges related to the nature of classification. These challenges include the limit to the number of groups and subgroups that can be extracted and the fact that text-based data are usually context-specific and domain-dependent. Additionally, the techniques employed in sentiment analysis, such as machine learning, can be expensive and time-consuming to develop, and the accuracy of classification depends on the classification data, which may not be transferable to other domains. The article notes criticisms of sentiment analysis, such as the reliability of automated sentiment classification and issues of ethical research, such as voluntary participation, privacy, and confidentiality. Despite these challenges, sentiment analysis has the potential to provide a systematic alternative in extracting and analyzing a large volume of textual data in real-time, removing subjectivity and individual biasness. By integrating sentiment analysis with existing research design methods, researchers can bridge the gap between qualitative and quantitative research and gain a richer, more integrated perspective into online consumer research. The article concludes that sentiment analysis can provide a valuable contribution to real-time conversion of mass volumes of textual data into meaningful information and is worth academic attention as online purchase, consumption, and conversations continue to grow.

5.5 Recommendations

The findings from the study addressed the gap on the existing literature regarding application of sentiment analysis in studies done in Zimbabwe. The results of the study could spur more research on sentiment analysis linguistic models especially those that incorporate native languages such as Shona and Ndebele.

References

Kaplan AM, Haenlein M (2010) Users of the world, unite! The challenges and opportunities of social media. Bus Horiz 53(1):59–68

Patino, A., Pitta, D.A. and Quinones, R. (2012), "Social media's emerging importance in market research", Journal of Consumer Marketing, Vol. 29 No. 3, pp. 233-237. https://doi.org/10.1108/07363761211221800
https://sproutsocial.com/insights/listening-vs-monitoring/

Market Research. (2020, November 14). In *Wikipedia*. https://en.wikipedia.org/wiki/Market_research

Komariah, K. S., Machbub, C., Prihatmanto, A. S., & Sin, B.-K. (2016). A Study on Efficient Market Hypothesis to Predict Exchange Rate Trends Using Sentiment Analysis of Twitter Data. Journal of the Korean Multimedia Society, 19(7), 1107–1115. https://doi.org/10.9717/KMMS.2016.19.7.1107

De Mauro, A., Greco, M. and Grimaldi, M. (2016), "A formal definition of Big Data based on its essential features", Library Review, Vol. 65 No. 3, pp. 122-135. https://doi.org/10.1108/LR-06-2015-0061

Tyagi, Priyanka and Chakraborty, Sudeshna and Tripathi, R.C. and Choudhury, Tanupriya, Literature Review of Sentiment Analysis Techniques for Microblogging Site (March 15, 2019). International Conference on Advances in Engineering Science Management & Technology (ICAESMT) - 2019, Uttaranchal University, Dehradun, India, Available at SSRN: https://ssrn.com/abstract=3403968

Perumal, S. (n.d.). LITERATURE REVIEW ON SENTIMENT ANALYSIS. Retrieved November 29, 2020, from Ijstr.org website: http://www.ijstr.org/final-print/apr2020/Literature-Review-On-Sentiment-Analysis.pdf

J. Carvalho, A. Prado and A. Plastino, "A Statistical and Evolutionary Approach to Sentiment Analysis," 2014 IEEE/WIC/ACM International Joint Conferences on

Web Intelligence (WI) and Intelligent Agent Technologies (IAT), Warsaw, 2014, pp. 110-117, doi: 10.1109/WI-IAT.2014.87.

Rambocas, Meena. (2013). Marketing research: The role of sentiment analysis. FEP WORKING PAPER SERIES.

Liu, B. (2012). *Sentiment analysis and opinion mining*. Williston, VT: Morgan & Claypool Publishers.

Liu, B. (2015). *Sentiment analysis: Mining opinions, sentiments, and emotions*: Cambridge University Press.

Tsvetovat, M., Kazil, J., & Kouznetsov, A. (2012). Implicit sentiment mining-New approach overcomes inherent problems while exploring media bias and electoral sentiment. *OR/MS Today*, 39(6), 20.

Leung, D., Law, R., Van Hoof, H., & Buhalis, D. (2013). Social media in tourism and hospitality: A literature review. *Journal of Travel & Tourism Marketing, 30*(1-2), 3-22.

D'Andrea, A., Ferri, F., Grifoni, P., & Guzzo, T. (2015). Approaches, tools and applications for sentiment analysis implementation. *International Journal of Computer Applications*, *125*(3), 26–33.

Twitter.Inc . Twitter privacy policy. 2017. https://twitter.com/en/privacy.

Google Scholar

POTRAZ, (2019), *Abridged Postal and Telecommunications Sector Performance Report Second Quarter 2019*

Medhat, W., Hassan, A. & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey, pp. 1093-1113, Vol. 5.

Vivek, S. D., Beatty, S. E., & Morgan, R. M. (2012). Customer engagement: Exploring customer relationships beyond purchase. The Journal of Marketing Theory and Practice, 20(2), 122–146.

McCall, T. (2015). Gartner predicts a customer experience battlefield. Retrieved from https://www.gartner.com/smarterwithgartner/customer-experience-battlefield/. Accessed 27 December 2020.

Homburg, C., Jozié, D., & Kuehnl, C. (2015). Customer experience man-agement: toward implementing an evolving marketing concept.Journal of the Academy of Marketing Science, 45(3), 377–401.

Carbone, L. P. and Haeckel, S. H. (1994). "Engineering Customer Experience." Marketing Management 3(3): 8-19

Voss, C. and Zomerdijk, L. (2007). Innovation in Experiential Services -An Empirical View. Innovation in services. London, DTI: 97-134.

Berry, L. L. and Carbone, L. P. (2007). "Build Loyalty Through Experience Management." Quality Progress40(9): 26-32

Holmlund, M., Van Vaerenbergh, Y., Ciuchita, R., Ravald, A., Sarantopoulos, P., Ordenes, F. V., & Zaki, M. (2020). Customer experience management in the age of big data analytics: A strategic framework. Journal of Business Research, 116, 356–365.

Keiningham, Timothy, Joan Ball, Sabine (neˊe Moeller) Benoit, HelenL. Bruce, Alexander Buoye, Julija Dzenkovska, Linda Nasr, OuYi-Chun, and Mohamed Zaki (2017), "The Interplay of Customer24Journal of Service Research 22(1) Experience and Commitment,"Journal of Services Marketing,31(2), 148-160.

Lemon, Katherine N. and Peter C. Verhoef (2016), "UnderstandingCustomer Experience throughout the Customer Journey,"Journalof Marketing, 80 (6), 69-96

Verhoef, Peter C., Edwin Kooge, and Natasha Walk (2016),CreatingValue with Big Data Analytics:Making Smarter MarketingDecisions. New York, NY: Routledge.

Villarroel Ordenes, Francisco,Babis Theodoulidis, Jamie Burton,Thorsten Gruber, and Mohamed Zaki (2014), "Analyzing Cus-tomer Experience Feedback Using

Text Mining: A Linguistics-based Approach,"Journal of Service Research, 17 (3), 278-295.

McColl-Kennedy, Janet R., Stephen L. Vargo, Tracey S. Dagger,Jillian C. Sweeney, and Yasmin van Kasteren (2012), "Health CareCustomer Value Cocreation Practice Styles,"Journal of ServiceResearch, 15 (4), 370-389.

Macdonald, Emma K., Michael Kleinaltenkamp, and Hugh N. Wilson(2016), "How Business Customers Judge Solutions: Solution Qual-ity and Value in Use,"Journal of Marketing, 80 (3), 96-120.

Verhoef, Peter C., Katherine N. Lemon, A. Parasuraman, Anne Rog-geveen, Michael Tsiros, and Leonard A. Schlesinger (2009),"Customer Experience Creation: Determinants, Dynamics andManagement Strategies,"Journal of Retailing, 85 (1), 31-41.

STELZNER, M. 2013. 2013 SOCIAL MEDIA MARKETING INDUSTRY REPORT :How Marketers Are Using Social Media to Grow Their Businesses, Social Media Marketing Examiner.

GUY, R. 2012. The use of social media for academic practice: A review of literature. Kentucky Journal of Higher Education Policy and Practice, 1, 7.

KAPLAN, A. M. & HAENLEIN, M. 2010. Users of the world, unite! The challenges and opportunities of Social Media. Business horizons, 53, 59-68.

KAPOULAS, A. & MITIC, M. 2012. Understanding challenges of qualitative research: rhetorical issues and reality traps. Qualitative Market Research: An International Journal, 15, 354-368.

MAYES, L. 2011. Effectively Incorporating Social Media: A Case Study on Coca-Cola. Expedition, 206, 27.

Df

LAROCHE, M., HABIBI, M. R. & RICHARD, M.-O. 2013. To be or not to be in social media: How brand loyalty is affected by social media? International Journal of Information Management, 33, 76-82.

LEVINSON, J. C. & PERRY, D. E. 2011. Guerrilla marketing for job hunters 3.0: How to stand out from the crowd and tap into the hidden job market using social media and 999 other tactics today, John Wiley & Sons.

ZHOU, L. & WANG, T. 2014. Social media: A new vehicle for city marketing in China. Cities, 37, 27-32.
RUDDELL, R. & JONES, N. 2013. Social media and policing: matching the message to the audience. Safer Communities, 12, 64-70.

POSTAL AND TELECOMMUNICATIONS REGULATORY AUTHORITY OF ZIMBABWE(POTRAZ) (POTRAZ). (2020). ABRIDGED POSTAL & TELECOMMUNICATIONS SECTOR PERFORMANCE REPORT. Retrieved fromhttps://t3n9sm.c2.acecdn.net/wp-content/uploads/2020/12/Abridged-Sector-Performance-report-3rd-Q-2020.pdf

Marumbwa, J. and Mutsikiwa, M.(2013) 'An Analysis of the Factors Influencing Consumers' Adoption of Mobile Money Transfer Services (MMTs) in Masvingo Urban, Zimbabwe', British Journal of Economics, Management & Trade, Vol. 3(4), pp. 498-512.
http://www.potraz.gov.zw/wp-content/uploads/2017/03/Annual_Sector_Perfomance_Report_2017.pdf

Gate, T. (2017). *Investigation on the impact of customer relationship management on customer retention*. BUSE.

Makudza, F. (2020). Augmenting customer loyalty through customer experience management in the banking industry. *Journal of Asian Business and Economic Studies*

Cajetan, C. (2018), “Digital banking, customer experience and bank financial performance: UK customers' perceptions”, International Journal of Bank Marketing, Vol. 36 No. 2, pp.
230-255.

Zeithaml, V.A., Parasuraman, A. and Berry, M. (1990), Delivering Service Quality, The Free Press, New York.

Karim, Rashed & Chowdhury, Tabassum. (2014). CUSTOMER SATISFACTION ON SERVICE QUALITY IN PRIVATE COMMERCIAL BANKING SECTOR IN BANGLADESH. British Journal of Marketing Studies. 2. 1-11.

Shahin, A. and Janatyan, N. (2011) Estimation of Customer Dissatisfaction Based on Service Quality Gap by Correlation and Regression Analysis in Travel Agency. International Journal of Business Management, 6, 99-108.

Biza, P. (2019). Factors that affect customer satisfaction in telecommunications industry. A case of Telone Bindura. BUSE.

Mazikana, A. T. (2020). The impact of quality service and customer satisfaction on consumer purchasing decisions in Zimbabwe telecommunications industry. SSRN Electronic Journal. doi:10.2139/ssrn.3715253.

Makanyeza, C., & Chikazhe, L. (2017). Mediators of the relationship between service quality and customer loyalty: Evidence from the banking sector in Zimbabwe. International Journal of Bank Marketing, 35(3), 540–556.

Hwambo, L., Shamhuyenhanzva, R. M., & Sandada, M. (2017). An assessment of churn determinants in Zimbabwe’s mobile telecommunication services. International Journal of EBusiness and EGovernment Studies, 9(2), 106–120.

Jena, R. (2017). An evaluation of the contribution of Information and Communications Technology (ICT) to customer satisfaction in the banking sector in Zimbabwe: A case study of MBCA Bank (2010 - 2013). Retrieved from http://41.175.146.201/handle/10646/3595

Gwambuka , W.(2017). An assessment of the contribution of internet banking to customer satisfaction in the banking sector in Zimbabwe Retrieved February 20, 2021, from Buse.ac.zw:8080 website: http://liboasis.buse.ac.zw:8080/xmlui/handle/123456789/5872.

Viriri, Piason & Phiri, Maxwell. (2017). Determinants of Customer Satisfaction in Zimbabwe Telecommunication Industry. Journal of Communication. 8. 101-104. 10.1080/0976691X.2017.1317495.

Al-Otaibi, S., Alnassar, A., Alshahrani, A., Al-Mubarak, A., Albugami, S., Almutiri, N., & Albugami, A. (2018). Customer Satisfaction Measurement using Sentiment Analysis. International Journal of Advanced Computer Science and Applications : IJACSA, 9(2). doi:10.14569/ijacsa.2018.090216

Anastasia, S., & Budi, I. (2016). Twitter sentiment analysis of online transportation service providers. 2016 International Conference on Advanced Computer Science and Information Systems (ICACSIS), 359–365. IEEE.

Gitto, S., & Mancuso, P. (2017). Improving airport services using sentiment analysis of the websites. Tourism Management Perspectives, 22, 132–136.