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An Overview of the Application of Sentiment Analysis in Quality Function Deployment

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Abstract. Customer feedback is important in continuous improvement of products and services for businesses to stay ahead of competition. With the advent of the internet, online product reviews from various platforms attracts a lot of comments from customers as they share their sentiments from experiences with the different products and services. The sentiments shared online are an important resource for mining opinions that can help businesses to improve on their products and services. Online sentiment analysis has brought about endless possibilities to incorporate these sentiments in product development in continuous improvement. However, most sentiments analysis research done seem to muzzel the customer comments into three points of view that are positive, neutral and negative. Though this approach is excellent in providing a general perception of customers about a particular product or service, it falls short in outlining specific product features that may require improvement in order to increase customer satisfaction from the Quality Function Deployment (QFD) perspective. This paper presents an overview of how sentiment analysis has been applied to a number of products and services reviews. The aim being to highlight the gaps in sentiment analysis output data and how QFD can be integrated with sentiment analysis to make the sentiments valuable. An integration conceptual framework is proposed to stimulate research into the area.

Keywords: Sentiment Analysis, Quality Function Deployment, Opinion Mining.

1 Introduction

The world has become one big room in which many conversations and transactions are taking place simultaneously, thanks to the internet and social media. These interactions generate a lot of data. The data can be collected, analyzed and processed into useful information for decision making. This collection of data repositories is known as Big Data [1]. In its raw form the data characteristics are summarised by the four Vs namely; Volume, Velocity, Variety and Veracity [2]. Volume refers to the huge quantity of the data while Velocity denotes high speed at which data accumulates in real time. Variety indicates that the data is composed of different types and Veracity brings the aspect of uncertainty and unreliability of the data [2], [3]. Big data is therefore a mixture of mainly

unstructured data and a bit of structured data [4], [5]. This data resembles mineral deposits that require mining and processing for further purification to make the mineral useful. Data mining is thus defined as a process of knowledge discovery from large databases using data analysis and discovery algorithms [6]. In conventional mining various tools and methods are used to get the precious mineral out of the ore. Data mining likewise also uses different types of machine learning algorithms for extracting valuable information from the datasets [7]. This study reviews one of the techniques used in data mining called Sentiment Analysis or Opinion Mining. This method is employed to extract customers opinions about a product or a service from online platforms. The sentiments are categorized into positive, neutral and negative [8]. In this paper it is argued that these three may not provide sufficient information to assist in research and development to improve the product as the sentiments are muzzled together. A conceptual framework is proposed for integration of Sentiment Analysis and Quality Function Deployment.

2 Methodology

To develop the conceptual framework, the authors used the integrative literature review methodology to get an overview of the application of Sentiment Analysis in reviewing customer perceptions on different products and services. The aim being to find general ideas and the related procedures in order to collect relevant data and deduce the common stages and procedures used in Sentiment Analysis. The same is done for QFD to give readers a contextual perspective of the application of QFD in product development. The two processes are then superimposed on each other and a logical conceptual framework structure is developed in which sentiment analysis can provide input data for QFD.

3 Sentiment Analysis Overview

Sentiment analysis is one of the many data analytics tool used determine opinions expressed on online platforms about a particular topics, product or service [9]. This technology has become a game changer in marketing as companies are able to determine customers' opinions on brands and services and thereby understanding consumer attitudes towards the product or service [10]. Customer feedback is important for product research and development and these sentiments can play a major role in providing the much-needed voice of the customer as it is the key input in Quality Function Deployment processes. The process is only an insight into the general measure of the ambience [9]. To date sentiment analysis has been applied to review a number of disciplines, products and services. To mention a few examples Isah et al. [11] used sentiment analysis from Facebook and Twitter to compare customer perception on the safety of skin care products. In another study Hu et al [12] discovered that while online feedback reviews may influence potential buyers, some of the information available is subject to manipulation. Be that as it may, Schuckert et al. [13] applied sentiment analysis to determine various customer perceptions in the hospitality and tourism industry while

Alamoodi et al. [14] suggest that sentiment analysis could be used to fight pandemics like COVID 19 as an information tool. The variety of applications for sentiment analysis has also been proved by Ceron et al. [15] who applied it to predict election outcomes, Wang et al. [16] to forecast cellphone purchase decisions and Brunova and Bidulya [17] to customer satisfaction surveys for banking services. There is also a potential to develop a universal sentiment analysis tool that can automatically rank products based on consumer expectations, costs, convenience and communication issues in any product or service [18]. Investors may also use such tools to decide on their next business portfolios and location to set up their businesses, for example Lamba and Madhusudhan [19] used sentiment analysis productivity hashtags with results showing a number of sectors and countries that have high productivity. These applications indicate that sentiment analysis can be adopted as an interdisciplinary tool and the scope can be expanded beyond the polarity of sentiments. Sentiment Analysis involves a number of stages, Micu et al. [10] suggest that the process consists of four stages that are sentiment extraction; classification; retrieval, and reporting to decision makers. Kriegel et al. [6], Kennedy [9] and Isah et al. [11] reaffirm these stages, but describe them as data retrieval, preprocessing, sentiment analysis and reporting. A more holistic description of the process is given by Alamoodi et al. [14] in their four stage process that include search strategy, data collection, preprocessing and analysis. The presentation stage is added to the process and adopted as a standard process in this overview. The next section expands on these stages and reviews the applicable tools that can be used at each stage as summarised in **Fig 1**.

3.1 Developing a search strategy in Sentiment Analysis

Most literature reviewed in this study does not document this important step of developing a search strategy in Sentiment Analysis. It is assumed to be obvious that the researcher knows what to look for and from which sites to search for the information. However, the best approach is to start from a position of ignorance and develop a plan of execution [20]. This stage is suggested and explained in detail by Alamoodi et al. [14]. The planning stage involves outlining the aim of the study and its accompanying objectives. It is also important to decide on the time period for carrying out the sentiment analysis [21]. This then directs the researchers to the different sources of mines from which they can extract their data from and these are often social media sites like YouTube, Facebook, Twitter, Instagram or any other product review sites. Deciding where to mine is critical at this stage because it determines the mining algorithms to be used as data is structured differently on different sites. There is need for developing a strategy mapping tool for data exploration. Beale [22] developed a tool that interacts with the user in order to understand information at different levels of detail for iterative exploration. However, the suggested tool in this overview is one which is user friendly and can be used by the less tech-savvy professions who would also want to apply sentiment analysis in their fields without having to rely on coding. The tools may culminate into a search engine specifically for sentiment analysis for example if there is Google Scholar there can be “Google Sentiments”, Yahoo!, Bing and many more.

3.2 Data Retrieval in Sentiment Analysis

After the search strategy, the next phase is data retrieval. This stage is also known as data collection or data extraction [10], [14]. Application Programming Interfaces (APIs) and web crawling software programmes are used to collect data from the identified sites [11], [23]. Most social media sites like Twitter, Facebook and You Tube have got APIs on the developers side that help with authentication, extraction and data sharing [11]. Other websites like Amazon do not support developer APIs, hence a web crawler has to be developed to retrieve data from such sites [24]. In a study on sentiment analysis for medical data applications Meena and Bai [25] used python tweepy and Twitter developer API to extract tweets from twitter for their study while Chong et al. [23] had to develop a web scrapping tool for their study to retrieve information from the Amazon site. It therefore follows that both APIs and web crawlers can be used for the same project and the results can be compared if the websites allow [26]. The data collected at this stage is usually noisy and requires further processing or cleaning [11].

3.3 Data Preprocessing in Sentiment Analysis

The data collected in the retrieval stage consists of structured and unstructured data [6]. Sentences and phrases usually contain joining words without meaning, symbols, misspelt words, word spacings and a lot of punctuation and these are the foundation of noise signals that need to be removed during processing [18]. According to Zhang et al [27], some of the preprocessing steps include changing all words in a sentence to lowecase letters, removing stop-words and punctuation. In addition, during the preprocessing stage the data retrieved may need to be split into sentences and sentences into words and filtering stop words. This is possible through the application of Parts Of Speech (POS) tagging in which the words are classified into nouns, verbs, adjectives, pronouns and other POS tags [2]. Bag of Words (BoW) binary vectorization may also be used for preprocessing [11]. There could be information loss during processing and researchers must be careful [2]. Another challenge is that one sentence may carry multiple sentiments [28] and can also be written in a multi-linguistic manner [29]. Therefore corpus filtering for language preprocessing is always necessary [30]. Zhang et al. [27] proved that information losses can be avoided at the preprocessing stage by incorporating deep learning algorithms in the data retrieval stage to maintain the sentence structure.

3.4 Data Feature Extraction in Sentiment Analysis

Feature extraction is also the key process in sentiment analysis as it is the actual process of deriving the sentiments contained in the data. Alaei et al. [2] describes feature extraction as the process of discriminating information from nonredundant values to numerically represent a review or text. In other words, the process involves both statistical and semantic approaches [31]. This implies that words that have similar meaning are grouped together and represented statistically as it is described by Rambocas and Pacheco [32] as sentiment grouping. Features can be classified into three morphological

types namely; semantic, syntactic and lexicon. In feature extraction researchers are concerned with frequent features and implicit features in order to analyse the sentiments [33]. Feature extraction is also possible in audio-visual sentiment analysis [34]. Artificial Intelligence algorithms play a vital role in sentiment extraction.

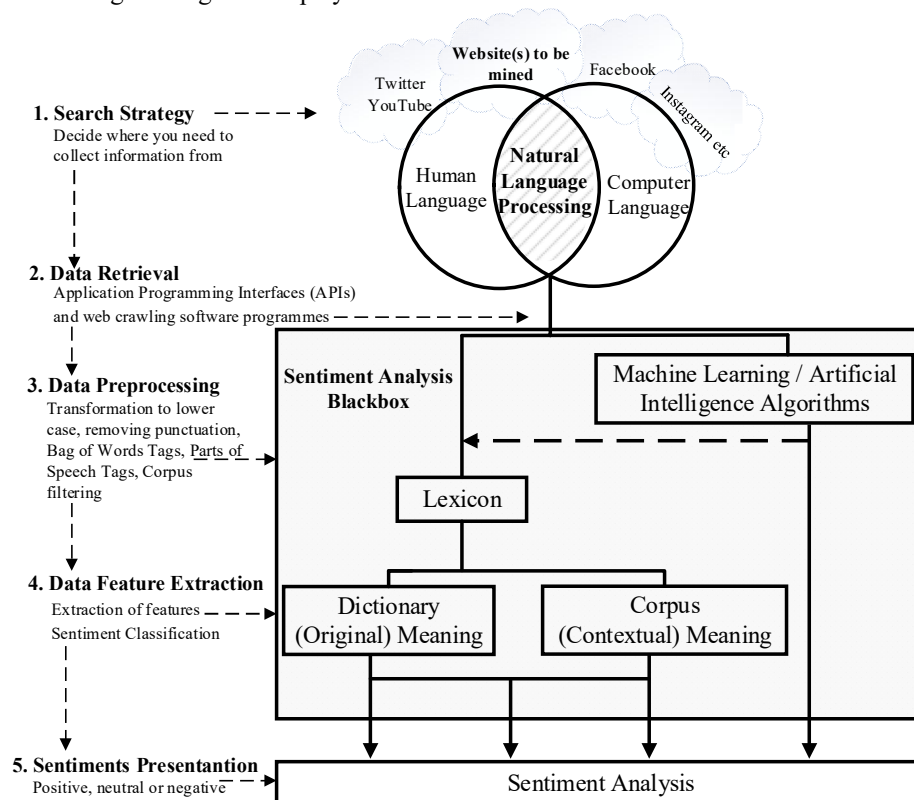


Fig 1. Sentiment Analysis Procedures Summary

3.5 Reporting findings in Sentiment Analysis

As previously discussed, sentiment analysis findings are presented in a semantic and statistical format [31]. The features identified are the basis from which the sentiments are drawn from while the statistics indicate the number of opinions in different categories. A number of statistical manipulations of the data can be used in sentiment analysis for example averages, weighted averages, standard deviations, distribution analysis, relative importance and feature ratings. The data can be presented in a number of visual formats like bar charts, bubble charts and original lists separating the positive, neutral and negative reviews. Marrese-Taylor et al [35] postulates that the development of a Results Visualization Module can better assist users in the manipulation of data for presentation.

3.6 Sentiment Analysis Algorithms

There are a number of artificial intelligence or machine learning algorithms available to use for sentiment analysis, but the decision on which ones to use is a very complicated [24]. It follows that the algorithms or combination thereof should be able to retrieve, preprocess, extract sentiments. There are a number of factors that should be considered in order to select or develop sentiment analysis algorithms. Some of the factors include the website from which sentiments are to be drawn, availability of developer API platforms, the length of the data, the structure of the data, the expected results and the complexity of the algorithm [24]. In order to fully comprehend the background and basics of sentiment analysis algorithms, it is necessary to understand that the sentiments are drawn from human language using computer language. The area of interaction between the human language and the computer language has led to the development of the field called Natural Language Processing (NLP) [31]. This implies that first and foremost the human language semantics and syntax have to be properly understood for correct interpretation of the sentiments. The interpretation would be based on the meaning of words which is also known as lexicon analysis [18]. Lexicon analysis is subdivided into two categories that are the dictionary and the corpus approach [31]. According to Ravi and Ravi [1] the dictionary approach is built on the original words meaning together with their synonyms and antonyms while Lin et al. [31] say the corpus approach is based on the aggregated semantic orientation that seeks to understand the contextual meaning of the words. **Fig 1** summarizes the link between NLP and Sentiment Analysis.

4 Quality Function Deployment Overview

The decision to buy a product or service by customers is often a complex one, it involves the evaluation of competing products against the customers preferences or expectations. Research and development in quality and innovation helps businesses to improve their products and services to match customer requirements. Business and service providers need to effectively use customer feedback to obtain responses from users or customers to improve services. This form of response is to explore the level of satisfaction or dissatisfaction with a product or service [31]. In most cases the customer requirements are fuzzy and would need to be transformed to the technical specifications of a product. Quality Function Deployment (QFD) is one of the methods that is used for transforming customer requirements into the product technical specifications leading to the development of customer-oriented products [36]. According to Franceschini [37], the QFD approach consists of five stages that are; determining customer requirements, product specifications, sub-systems or part specifications, process specifications and quality control specifications. Ginting and Widodo [38] further proposes another five step approach to QFD that is composed of processes that include; identifying customer needs, determination of priorities, determination of technical specifications, determination of relationships between technical specifications and finally the relationship between customer needs and technical specifications. These stages are similar and this implies that the QFD process is pretty much standard. In all the stages, the House

of Quality (HOQ) tool is used to link all the processes as shown in **Fig 2**. Alsaadi et al. [39] describes the QFD process in eight stages of HOQ that are identifying customer needs, determination of priorities in the needs, identification of technical requirements, identification of relationships between the technical requirements, creation of relationship matrix between customer requirements and technical requirements, competitive benchmarking, technical requirements prioritization and determination of technical requirements to deploy. This paper reviews these stages in QFD with the aim of creating integration points with Sentiment Analysis stages in order to apply Sentiment Analysis to product development through Quality Function Deployment.

4.1 Identifying customer needs

In order to deliver on customer expectations, it is necessary for organisations to identify customer needs through capturing the voice of the customer [39]. The demand for mass customized products is increasing and this requires businesses to shorten the product development phase so as to quickly launch their products on to the market [40]. This implies that customer feedback has to be captured into product design for companies to remain competitive. Traditionally the process of soliciting feedback from customers involved a lot of market research using tools like questionnaires and interviews [41]. The availability of online reviews makes it possible to apply sentiment analysis in quality function deployment since sentiment analysis can be used to capture the voice of the customers using opinion mining [8]. Identifying customer needs answers the “What” questions in terms of the features to be incorporated into a product [39].

4.2 Determination of customer needs priorities

The advantage of using sentiment analysis in online reviews is that customers freely express feedback without any reservations. The next step after the identification of customer needs is to prioritize the needs. Prioritization is traditionally done with customers having to rank the needs or allocate some weights or scores in order for the product development team to determine the most important needs that should be prioritized [39]. When applying sentiment analysis after the retrieval of the sentiments from various sources that represent the voice of the customer, the needs can be extracted, organized and sorted in order of importance [42]. The voice of the customer is often elusive and fuzzy in nature and application of artificial intelligence can help in the defuzzification of the customer sentiments. Hybridization of this process with the Kano model can help to priorities the product attributes by splitting them into three categories that are Basic attributes, Performance attributes and Excellence attributes [8]. Thus the sentiments or customer needs can be split into product sub systems or critical paths [37].

4.3 Determination of technical specifications

After determining the customer priorities in terms of product quality, the next step is to determine how these specifications would be provided using the technical specifications of the product or service [39]. Technical specifications are also known as the

product design requirements [43]. The technical specifications are simply responses on how the business intends to respond to the customer needs. This response can also be subjected to the manufacturing constraints such as regulatory requirements, environmental sustainability factors, materials availability, technology capability and logistical challenges [44]. Questions that remain to be answered are whether sentiment analysis is still applicable to this stage of QFD. Song et al. [45] demonstrated that the inclusion of the Kano model in sentiment analysis can help in theme extraction if the product can be decomposed into its constituent features.

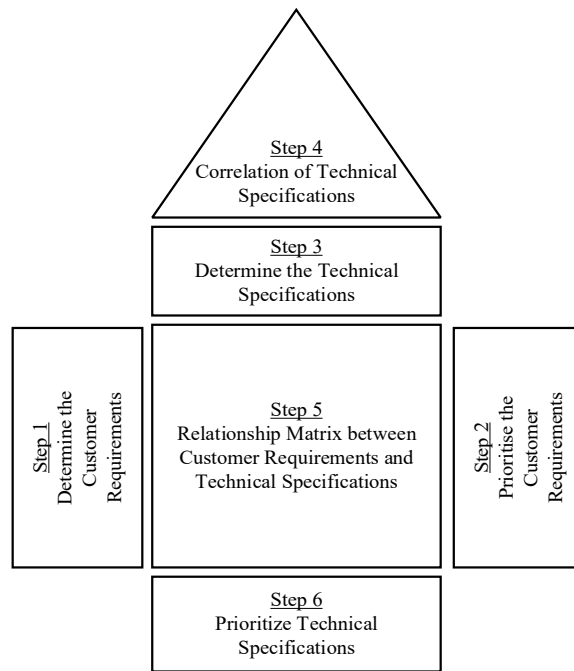


Fig 2. Quality Function Deployment House of Quality, adapted from Natee et al. [46]

4.4 Correlation of technical specifications

The next step after determining the technical specifications is to develop a correlation matrix of the technical specifications [44]. This forms the roof of the HOQ as shown in Fig 2. The correlation seeks to quantify the relationships between the technical specifications themselves and their impact on each other. Like sentiment analysis the relationships are classified as strong positive, positive, neutral, negative and strong negative and different score can be allocated for each kind of relationship [39]. Positive correlation means that the technical specifications are complementary while negative correlation is a sign of conflict. Highlighting the correlations between the technical specifications means that complementing and conflicting specifications can be identified. This helps in determining the priorities and equitable trade-offs between conflicting specifications [37]. Focus must be on the conflicting specifications to allow for equitable trade-offs in order to maintain the product features that delight the customers [43].

4.5 Relationship matrix between customer needs and technical specifications

The most important part of the House of Quality in Quality Function Deployment is its ability to show the relationships between the customer requirements and the technical specifications. This is the biggest part in the matrix and the work and uses the priority matrix method [47]. The relationship matrix provides a comparison between the customer requirements and engineering characteristics. The number of comparisons depends on the number of the customer requirements and the number of engineering specifications [46]. Ginting and Satrio [47] recommends coupling the process together with value engineering in order to properly evaluate alternatives to the technical specifications. The relationships between customer requirements and technical specifications can be strong, mild or weak [37].

4.6 Technical specifications priorities

After having determined the nature of relationship between the customer requirements and the technical specifications, the next process is to determine the priorities for the technical specifications. Application of the Analytical Hierarchical Process (AHP) can be used to generate a meaningful degree of importance in the prioritization of technical specifications [37]. Competitive technical benchmarking can be used to inform the priorities of the technical specifications against competitors' products in order to set the technical targets and develop performance targets for the technical requirements for the product or service under review [47].

5 Proposed Integration Framework for Sentiment Analysis and Quality Function Deployment

In this paper, the authors provide an overview of Sentiment Analysis procedures and how Quality Function Deployment can be integrated with sentiment analysis to improve the product development process. The authors combine insights from the work of previous authors on the stages of sentiment analysis for example Isah et al. [11], Hu et al. [12], Schuckert et al. [13] and Alamooodi et al. [14] among others and the framework of Quality Function Deployment as discussed by Natee et al. [46], Ocampo et al. [44], Dehe and Bamford [43] and Ginting and Satrio [47] among others. In the conceptual framework a number of integration points have to be considered for the sentiment analysis and quality function deployment to work together seamlessly. **Fig 3** represents the proposed integration in this paper. The first step is having the objectives of the QFD inform the search strategy. This will guide the researcher to the correct websites where the reviews are to be extracted for sentiment analysis. When retrieving the data, preprocessing and extracting features it is also advisable to split the data into the different product or service features using the Kano model. The feature keywords should also be taken to be the voice of the customer into the process of determining the customer requirements in the QFD process. The sentiments expressed from the reviews should then guide the target areas of improvement during the product development

stage. These sentiments should inform the prioritization stage for the customer requirements and loop back to the search strategy until the all the customer requirements have been captured.

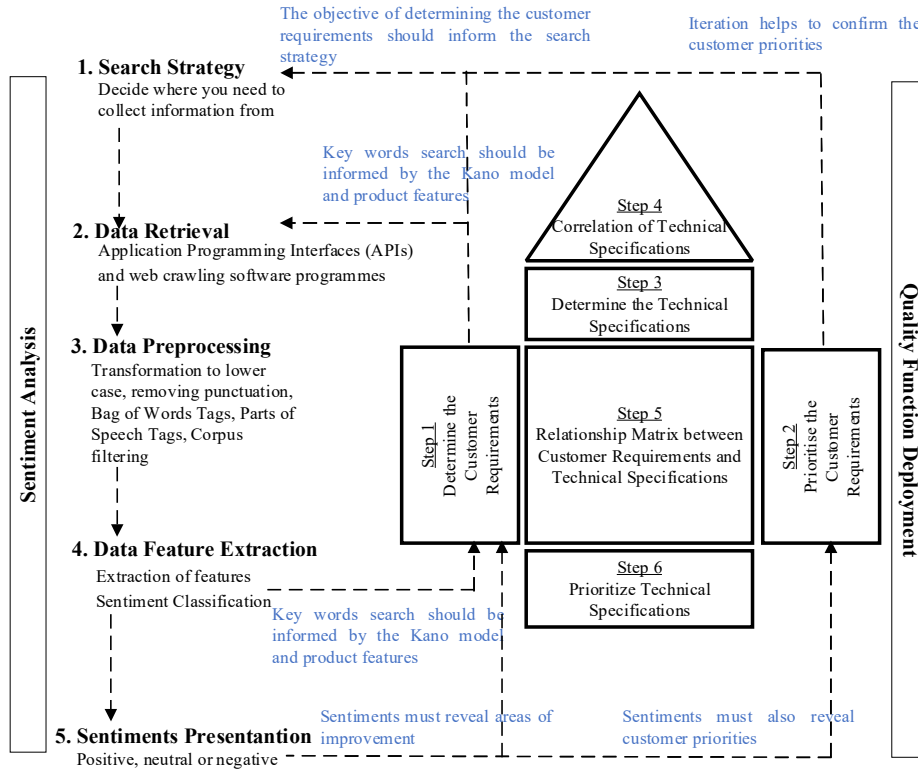


Fig 3. Proposed conceptual framework of integration between Sentiment Analysis and QFD

6 Conclusion

In conclusion, the linkage between sentiment analysis and quality function deployment is an interesting field of research capable of shortening the product development process as well as a game changer in market research. The process may be used to augment the traditional market research approaches that are long and winding. As more and more consumers get connected to the internet in future the process may eventually replace the traditional market research process. More research needs to be done and this paper is a teaser to stimulate thinking towards that area. This overview is preliminary work for the authors to use sentiment analysis in the redesign of overlanding roof-top tents as future work. The framework is presented for adoption, further scrutiny, elaboration and revision by other scholars to suit specific needs for the products and services under review.

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