Predicting STC Customers' Satisfaction using Twitter

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Abstract

The telecom field has changed accordingly with the emergence of new technologies. This is the case with the telecom market in Saudi Arabia, which expanded in 2003 by attracting new investors. As a result, the Saudi telecom market became a viable market [1]. The prevalence of mobile voice service among the population in Saudi Arabia for that, this research aims at mining Arabic tweets to measure customer satisfaction toward Telecom company in Saudi Arabia. This research is a use case for the Saudi Telecom Company (STC) in Saudi Arabia. The contribution of this study will be capitalised as recommendations to the company, based on monitoring in real-time their customers' satisfaction on Twitter and from questionnaire analysis. It is the first work to evaluate customers' satisfaction with telecommunications (telecom) company in Saudi Arabia by using both social media mining and a quantitative method. It has been built a corpus of Arabic tweets, using a Python script searching for real-time tweets that mention Telecom company using the hashtags to monitor the latest sentiments of Telecom customers continuously. The subset is 20,000 tweets that are randomly selected from the dataset, for training the machine- classifier. In addition, we have done the experimented using deep learning network. The results show that the satisfaction for each service ranges between 31.50% and 49.25%. One of the proposed recommendations is using 5G to solve the "Internet Speed" problem, which showed the lowest customer satisfaction, with 31.50%.

This paper's main contributions are defining the traceable measurable criteria for customer satisfaction with telecom companies in Saudi Arabia and providing telecom companies' recommendations based on monitoring real-time customers' satisfaction through Twitter.

1 Introduction

Global competition for telecommunication services 'drives companies to enhance their customers' satisfaction. Therefore, the enhancement of customer satisfaction is a popular topic in marketing literature as much research correlates customer satisfaction with customer loyalty [2]. Information about customer satisfaction is attained by examining customers' expectations of companies' products [3]. Customers who are satisfied with a company's services make a company more profitable because the cost of attracting new customers is five times greater than retaining existing customers [2]. Traditionally, customer satisfaction has been measured using customer interviews and questionnaires, but these cannot measure customer satisfaction in real time [4]. Currently, public policies and the standardisation of mobile communications allow customers to easily switch from one service provider to another. Therefore, one of the most critical challenges for the data and voice telecommunication service industry is retaining customers. Because the cost of gaining a new customer is higher than keeping an existing customer, service providers have now shifted their focus from customer acquisition to customer retention. As a result, satisfaction prediction has emerged as an essential Business Intelligence (BI) application.

Social media is a key part of many people's lives today, and approximately 67% of all active Internet users use social media platforms [5]. Social media is a type of communication tool that permits people to share their sentiments, thoughts, opinions and moods [6]. By mining these conversations, a database of emotions can be created to analyse the sentiments and related subjective contexts of these conversations. In addition, social media is a more cost-effective marketing communication method [7].

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Several studies have highlighted the benefits of sentiment analysis for organization [8]. According to Sohangi et al. [8], sentiment analysis can help organizations support decision makers predict stock markets by identifying the feelings of social network users about financial matters. Other researchers consider that mining social media data is important for marketers and customers for several reasons, including that it produces an abundance of useful data, which provides a wealth of information about customers for a company [9].

Twitter is a popular and widely used messaging service categorised as a microblogging website [10]. By mining the tweets, a database of emotions can be created to analyse the sentiments and related subjective contexts of microblogging conversations [11]. Analysing subjective contexts and emotions can help create real-time analytics and mine information about public opinions of and emotions felt towards products, leadership, decisions, cultures and events [4]. It has been shown that sentiment analysis (SA) can be used by management to take timely actions to improve the experience of customers to raise customer satisfaction and create positive customer sentiments about the brands customers prefer; this was reflected in the higher growth rates of new subscribers within the study period [12].

The telecom field has changed accordingly with the emergence of new technologies. This is the case with the telecom market in Saudi Arabia, which expanded in 2003 by attracting new investors. As a result, the Saudi telecom market became a viable market [1]. The prevalence of mobile voice service among the population in Saudi Arabia is 124,6% [13], indicating that many individuals subscribe to more than one mobile service. Over 31% of customers registered complaints in 2018 alone. [13] representing over 13,103M complaints. The percentage of mobile internet subscribers in 2019 in Saudi Arabia is 80% of the total population (STC, 2020). In Saudi Arabia, 11 M used Twitter in 2018 [14].

Therefore, this research seeks to capture users' satisfaction with one of the biggest Saudi telecom companies, STC by mining Twitter. It then aims to use these insights for the application of social media mining techniques to make recommendations for the company.

This paper performs analyses in order to achieve the paper objective.

• To propose recommendations to improve the services of STC telecom company.

In addition, to answer the research questions:

RQ1. What are the *traceable measurable criteria for customer satisfaction* with telecom companies in Saudi Arabia?

RQ2. What kinds of services are mentioned in tweets for customers of telecom companies in Saudi Arabia and what is the customers' sentiment about these services?

This paper's main contributions:

- Defining the *traceable measurable criteria for customer satisfaction* with telecom companies in Saudi Arabia.
- Providing telecom companies' recommendations based on monitoring real-time customers' satisfaction through Twitter.

2 Related Research

2.1 Questionnaire elements

The most popular means to gather and measure customer satisfaction is through surveys. The business criteria used to construct the survey elements were based on the performance indicators specified by the Saudi Communications and Information Technology Commission [15]and another related research. Some research that guided the development of the questionnaire, [16] found that price perceptions had positively affected overall customer satisfaction.

In addition, [17] examined the behaviour of mobile telecommunication customers in Hong Kong. They found that transmission quality and network coverage were the most important factors driving customer satisfaction in their study. Athanassopoulos and Iliakopoulos [3] considered a positive recommendation to be the most useful loyalty indicator in the European Telecommunications Company. They defined specific measures, such as quality of voice transmission, access at peak time, speed of service and correct operation, which affected customer satisfaction.

2.2 Customer Satisfaction and Sentiment Analysis

Most studies examined data mining techniques to measure customer satisfaction in the telecommunication industry. However, there are only a few studies in the literature that measured customer satisfaction, particularly in the telecommunication industry, using social media mining. With the advent of the 'big data' phenomenon and the widespread use of social web globally, sentiment analysis (SA) has recently become a highly popular research area in the academia during the past decade. Sentiment analysis or so-called 'opinion mining' refers to a computational process of gathering the individuals' opinions, feelings or attitudes towards a particular event or issue [18], [19]. Therefore, SA helps to reveal the polarity of a text by identifying whether its fragment has a positive, negative or neutral impression [20]. SA has an essential function for real-life applications and decision-making process in various domains [20]. These include marketing and e-commerce, customer relationship management, market intelligence, strategic planning, political polls, employment, sociology, health care, education and scientific research, humanitarian assistance and disaster relief (e.g., earthquakes) [18], [21].

Literature has witnessed much research attempts that address SA from different perspectives, either in general [22], [23] or for specific challenges [18], [24] techniques [25], [20], [21] or even for specific language [26].

The majority of previous research has paid more considerable attention to investigating SA in the English language, whereas Arabic Sentiment Analysis (ASA) [27] in the existing literature is still scarce [28], [29]. All languages around the world have different levels of the expressive power of sentiments. The detection of sentiment polarity is a challenging task due to the sentiment lexicon limitations in different languages [30]. This issue is complicated to solve because natural language is unstructured, interpreting sentiment a tiresome task [31]. Recently, ASA has received considerable attention as an emerging topic from researchers. Early ASA research addressed the SA in newswire [32], [33], whereas the most recent studies focused more on ASA in social media [34], [35], [36]. Although plethora survey studies extensively addressed the SA in the English language [18], [37] ASA survey research is still modest [38]. Some ASA research studies addressed specific issues [39], [40], while others focused only on specific SA techniques [41], [42]. However, these studies provide only slight insights into ASA, as they did not comprehensively address it [43].

2.3 Deep Learning

There are a lot of papers reviewed in this study that used deep learning models [44], [41], [28]. Particularly, they used Long Short-Term Memory (LSTM) in their Arabic sentiment analysis [12], [26], [27], [28], [29], [30], [31], [32]. Al-Smadi et al. [52] used two implementations of LSTM - the first one was a bidirectional LSTM with a conditional random field classifier (Bi-LSTM-CRF) for aspect opinion target expressions and the second one was an aspect-based LSTM for aspect sentiment analysis. These approaches were trained in reviews of Arabic hotels. They used character and word embedding features. The result showed that their approach outperformed in comparison with the state-of-the-art.

Moreover, Sohangi et al. [8] used deep learning to enhance the performance of sentiment analysis in the financial social network called Stock Twits. They used LSTM, convolutional neural networks and doc2vec. Their results showed that deep learning raised the accuracy of financial sentiment analysis. In addition, the convolutional neural network model outperformed the other models.

3 Research Approach

The methodology composed of two parts: Twitter mining and questionnaire construction. Then, we aggregated both results in the importance analysis to achieve the paper goal.

3.1 Data Collection

The questionnaire in this paper was uploaded via an online survey website: www.qualtrics.com. In addition, the questionnaire in this study was sent to participants through some social media platforms and by e-mail to the staff and students at many Saudi universities to avoid bias in the outcomes and generalise results. To avoid bias in the sample [45], we have:

- Identified the population.
- Specified the sample frame.
- Chosen the right sampling technique.

The population in this study is STC customers. The sample frame is an adult over 18 years old, using STC telecom com panies for post-paid voice service. The total number of participants after filtering (to remove unreliable answers), the sample contained 297 answers. The responses and results were stored automatically when a participant finished the questionnaire.

To measure the validity and reliability of all the questionnaire elements, Cronbach's alpha test was used through the Statistical Package for Social Science (SPSS). The rate of reliability and validity for the questionnaire in terms of the Cronbach's alpha [46] was 0.853, which is a greater than the 0.7 cut-off point [47] and indicates the degree of consistency and clarity of questions of the questionnaire. The questionnaire was ready for distribution after it was evaluated and modified based on feedback.

Regarding the Twitter data set, we fetched 20,000 Arabic tweets based on specific search keys, similar to the ones used in [6]. We used Python to connect with Twitter's search application programming interface (API) [42]. We used Twitter accounts and some hashtags in Arabic and English that mentioned the company, such as #STC and #الاتصالات_السعودية. Furthermore, the company Twitter accounts were used as keywords. The collecting started from January 2017 until June 2017.

3.2 Data Set Cleaning and Pre-processing

To clean the data set, eliminate the non-Arabic tweets. Also, re-tweets were discarded. We filter all the features that unnecessary and will decrease the classifiers accuracy, e.g., links, user mention, punctuation marks, and stop words.Then, applying pre-processing producers on the data set (tokenisation and normalisation). Normalization such as removing Kishida and uniting the same letters with different shapes. The cleaning and pre-processing were done using Toolkit (NLTK) library in Python.

3.3 Data set Annotation

It has been defined the services that reported as customer satisfaction standard determined by the Saudi Communications and Information Technology Commission [13] andfrom related research. The services as follows: 'network coverage', 'quality of voice transmission', 'customer service', 'successful calls', 'billing price, 'offers', 'reasonable fees when calling another telecom company' and 'internet speed'. They found 4380 tweets from the 20,000 tweets that mentioned the services. In addition, we explored some new services through the annotation process. We asked the annotators as we referred to define the service mentioned in the tweet and the sentiment toward it if it found. They can specify more than one service. In addition, they use the five-way sentiment analysis (Strongly Positive, Positive, Neutral, Negative, Strongly Negative). They listed the services that were mentioned in the tweets as follows: Network Coverage, Phone Network, Quality of Voice Transmission, Customer Service, Successful Calls, Billing Price, Good Offers, Reasonable Fees when calling another Telecom Company, Browsing Speed, and Hiring Section. The Network Coverage and Phone Network were subsequently merged, as they pointed to the same service. Additionally, we merged Internet speed and Browsing Speed. We excluded the Hiring Section, because it was out of scope for this research. After that, we listed the final list of services that we will predict the satisfaction toward it as follows: ‘network coverage’, ‘quality of voice transmission’, ‘customer service’, ‘successful calls’, ‘billing price, ‘offers’, ‘reasonable fees when calling another telecom company’ and ‘internet speed’.

Table 1. Sample of the data set with one service label

Tweet	Label	Service
سددت فاتورة جوالي من أمس وإلى الآن خرا	Negative	Bill Accuracy
غير معقول ابدا ان هذه السرعة ادفع عليها , ٠٥٣ اير	Negative	Internet Speed

We defined the number of services per tweet as follows in the Python code snippets provided, where *df* means the data frame, *Num_ser* is the number of services:

df['Num_ser'] = df. Service. apply (lambda x: len(x.split(','))) (1)

Creating a data frame which has one service:

df_ = df[df['Num_ser’] ==1] (2)

Creating a data frame which has 2 services:

df2 = df[df['Num_ser']>1] (3)

We then generated 8 column data frames, one column for each service:

table = pd. pivot_table (df_, values='Label', index=df_. index, columns=['Service'])(4)

Table 2. Sample of the data set with two services labels.

Tweet	Service1	Label-service1	Label-service2	Service2	Num_ser
والله نتكم مجنون و السعر الحلو	Internet Speed	Positive	Positive	Billing Price	2
تغطيه وانترنت زي الخرا	Network Coverage	Negative	Negative	Internet Speed	2

After that, we merged any sample with two services or more; then, we converted the data frame df2 with all services as columns filled with the services that mentioned in the tweet and the sentiment where (5 for Strongly positive, 4 for positive, 3 for Neutral, 2 for Negative,1 for Strongly negative) (Table 2).

4 Model Construction

4.1 Our model

Due to the nature of our sequential data, in which there is a time/position dimension in the data, e.g. the word you see in the future is not independent of the words you have seen before. We use the most popular deep-learning-based model, two inputs Gated Recurrent Unit (GRU) [48] [49] with attention mechanism that approved high result in [9]. The attention mechanism model with two inputs (word embedding) and (character embedding) to represent each word/character in a tweet as a vector. It is worth mentioning that LSTM can. The GRU is the same as the LSTM architecture which can overcome the vanishing gradient through the forget gate, which lets the memory update except it combines the two gates “forget” and “input” into one “update” gate. It is less complicated than the LSTM model and widely used [50].

The experiment starts by using some libraries such as Panda, Keras and Sklearn and reading the file (Table1).

Next, we split the data to Train, Test, Validation by 65,20,15. Then, we applied our model. For oversampling, we used the popular Synthetic Minority Over-Sampling Technique (SMOTE). We got Average F1 score on all services, as shown in Table 3. After that, we used our model to calculate Customer satisfaction toward each service for STC company, as shown in the equation (I).

First, we calculated the customer satisfaction as follows:

$$cust_{sat} = \frac{\sum_{\forall i} rating_i}{4 * len(ratings)} \quad (I)$$

where:
num_customers = len(ratings)
total_ratings = sum(ratings) (the summation of all ratings)
rating: multi-way rating.

Table 3. F1 for each service

Service	FI score
Bill Price	0.96
Call Quality	0.98

Customer Service	0.88
Hiring section	0.99
Internet Speed	0.88
Network Coverage	0.96
Good Offers	0.88
Reasonable fees when calling someone uses another telecom company	0.85
Successful Calls	0.91
Average F1 score on all services	0.93

4.2 Questionnaire Construction and analysis

The questionnaire referred to surveying the customers of STC telecom company who published on Twitter for widely distributed public consumption. The aim of this survey was:

- **To define the user satisfaction metrics from the user's perspective.**

The questionnaire has one question: The standards of customer satisfaction for the mobile phone or Internet access providers which contained nine statements that identify the standards of customer satisfaction towards the services provided by a telecommunication company. The customer could choose one item that describes the importance of the customer satisfaction standard towards the services offered by a telecommunication company from his/her perspective.

The Statistical Package for Social Science (SPSS) software tool generally used for the analysis of social science surveys [19]. Hence, the SPSS was used to conduct a correlation analysis to investigate the relationship between the variables in this study. The mean, frequencies, percentages and standard deviation are the most popular statistical tools used in the descriptive approach [19] and [16].

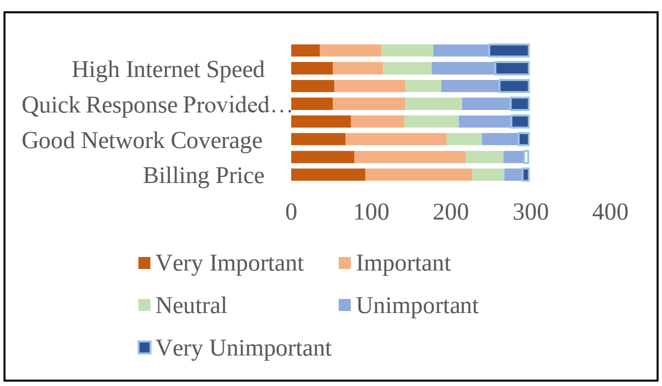

Figure 1. The importance of the standards for STC customer satisfaction

Additionally, in this study, the Kolmogorov-Smirnov Normality test [53] was used to check the normality distribution of the sample. The aim was to choose appropriate correlation tests for both questions and respondents. The correlation analysis tests, chi-square and Kruskal-Wallis tests were applied to find out whether there were significant relationships between the variables.

A 5-point Likert-scale was used in the questionnaire to record the importance of customer satisfaction standards towards the services provided by a telecommunication company from the customer perspective. The questionnaire used a scale ranging from 1 = not important to 5 = very important, as follows:

- Very important, weighted (5)
- Important, weighted (4)
- Neither important nor unimportant (Neutral), weighted (3)
- Unimportant, weighted (2)
- Very unimportant, weighted (1)

The relative importance index (RII) [51] to rank the criteria based on their importance for each telecom company. We calculated the *RII (m)* based on the equation, where *m* is the metric:

$$RII(m) = \frac{\sum i*Wi}{A*N} \quad (II)$$

where Wi is the weight of index i, with $i \in \{1 \; to \; 5\}$, $A = 5$ (the highest weight) and N is the total number of respondents for all weights.

We tested the normality of the sample per standard for STC telecom company, using the Kolmogorov-Smirnov Normality test [53], to check the normality distribution of the sample. The purpose of that was to choose the appropriate correlation test for the question and respondents. We found that all standards were significant and smaller than the significant level $\alpha = 0.05$, which indicated that the sample is not normally distributed. Therefore, the non-parametric Kruskal-Walli's test was applied to test more than three independent groups not normally distributed. The test aimed to find out whether there are significant relationships between the variables. We found the P-value for 'Reasonable fees when calling someone who uses another telecom company', and 'High browsing speed for Internet' standards are .025 and 0.03 < 0.05, respectively, this indicates that these two standards are significant.

It is shown in Figure 1 that the 'Quality of voice transmission' standard was the most important standard for 140 STC customers. Then, the 'Successful calls' standard was allocated the second highest importance by 134 customers. In addition, the 'Successful calls' standard was considered a very important by 78 customers, while the 'Internet speed' standard was considered a very unimportant standard by 40 customers and an unimportant standard by 76 customers. Additionally, 'Reasonable fees when calling another telecom company' was considered very unimportant by 40 customers.

For ranking the importance of the standards for STC telecom company from the customer's point of view, we calculated RII as mentioned before. We then listed them in ascending order from 1 to 9. It is noted in Table 4 that the top three most important standards for STC customers were: ,'Billing Price', 'Quality of voice transmission' and 'Network coverage'. In contrast, the least important standard was 'Reasonable Fees when Calling another Telecom Company'.

Table 4: Ranking the Importance of Customer Satisfaction Standards.

Standard	RII	Rank
Billing Price	0.789	1
Good Quality of Voice Transmission	0.774	2
Good Network Coverage	0.728	3
Number of Successful Calls	0.672	4
Quick Response Provided from Customer Service	0.659	5
Good Offers	0.634	6
High Internet Speed	0.602	7
Reasonable Fees when Calling another Telecom Company	0.586	8

5 Discussion

This section discusses the results that were obtained through our analysis of the responses provided by participants. The results of the analysis are used to answer the research question.

RQ1: What are the traceable measurable criteria for customer satisfaction with telecom companies in Saudi Arabia?

As we mentioned before, we defined the customer satisfaction standards using a report from the Saudi Communications and Information Technology Commission Saudi Communications and Information Technology Commission [13], related research and the tweet annotation process. Then, we measured the importance of these standards using statistical analysis for the responses obtained from the questionnaires providing us with the customers' point of view. We can define the standards as follows: 'network coverage', 'quality of voice transmission', 'customer service', 'successful calls', 'billing price, 'offers', 'reasonable fees when calling another telecom company' and 'internet speed'. We analysed the importance of each standard for each telecom company using RII. Our questionnaire analysis. has found that the 'Billing Price' and 'Quality of voice transmission' are the most important standards for customer satisfaction for STC customers. The least important standard for STC customers was 'Reasonable Fees when Calling another Telecom Company' because STC has led the free calls to another telecom providers.

RQ2: What kinds of services for customers of telecom companies in Saudi Arabia are mentioned in tweets, and what is the sentiment of customers about these services?

It is shown in Table 5, that the STC customer satisfaction between 31.50% and 49.25%. That's under 50%, which is consistent with the customer satisfaction percentage overall toward the company, which is 31.06%.

Table 5: CS of STC customer toward the services

Service	CS percentage
Network Coverage	47.01
Quality of voice transmission	48.09
Customer Service	33.01
Successful Calls	47.01
Billing Price	42.17
Reasonable fees when calling another telecom company	49.25
Good Offers	44.12
Internet Speed	31.50

Research Objective: To propose recommendations to improve the services of Saudi telecom companies.

To achieve research objective, it has been correlated between the answers of the **RQ1** and the **RQ2**. We used tableau software to visualize the service importance VS. Customer satisfaction toward the service because there are enormous potentials of tableau and its ease of use. The reason behind the visualizing this correlation to set the recommendations for the decision-makers on the STC telecom company.

As shown in Figure 2, all the services of the STC company are placed on the Low satisfaction and High importance area. All the services are important from the customers' point of view, yet the customer satisfaction towards these services is lower than 50%. Therefore, STC decision-makers need to pay attention to all these services, especially Internet Speed where customer satisfaction is 31.50% and its service importance rating is much higher at 60.2%. In addition, the Customer

Service scored 33.01% customer satisfaction and 65.9% service importance. That means these services are highly important to STC customers, but the satisfaction was low. Billing Price and Quality of Voice Transmission scored 78.9% and 77.4% as the most important services, while the satisfaction was 42.17% and 48.09%; this is better than the satisfaction towards other standards, but there is room for improvement.

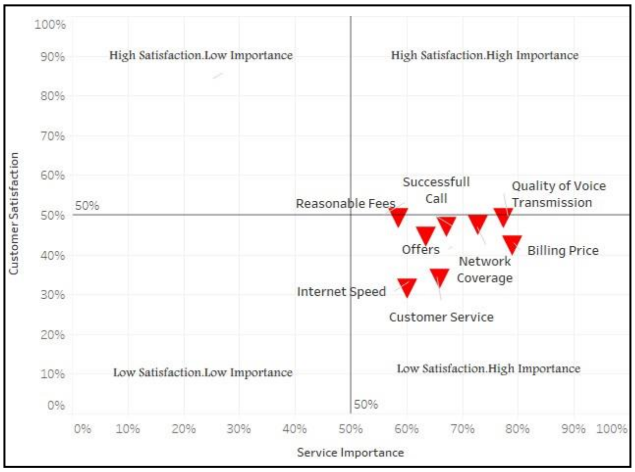

Figure 2 The importance VS. customer satisfaction for STC customers

6 Conclusion

This research used Twitter mining to measure STC customers' satisfaction toward the STC services, besides, the questionnaire analysis to provide the recommendations to the company. It has been built a corpus of Arabic tweets, using a Python script searching for real-time tweets that mention Telecom company using the hashtags to monitor the latest sentiments of Telecom customers continuously. The subset is 20,000 tweets that are randomly selected from the dataset, for training the machine- classifier. In addition, we used 2-inputs GRU with attention mechanism to predict the satisfaction per predefined service, and we got from 99 to 85 F1. The satisfaction for each service ranges between 31.50% and 49.25%. One of the proposed recommendations is using 5G to solve the "Internet Speed" service because it got the lowest customer satisfaction with 31.50%.

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