

Sentiment Analysis of the Saudi Digital Library (SDL) Tweets Interactions

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Abstract. In July 2011, the Saudi Digital Library (SDL) created a Twitter account to serve as a primary means for customer interaction, support, and a Q&A page. The SDL account actively tweets about SDL news, recently-added databases, and training venues, dates, and times. It is interesting to see SDL users interact with the SDL account on Twitter, but how beneficial is it? This study investigates the reactions of people who use the SDL to SDL tweets via Twitter, using a manual sentiment content analysis approach to analyze the interactions. The content analysis consists of counting the number of likes and retweets, whether the questions posted receive answers, and lastly categorizing the sentiment expressed in tweets as “positive,” “negative,” and “neutral.” The students’ interaction with SDL through Twitter ranges between positive and neutral. Students seem to like tweets about news and instructions about the SDL. However, students do not seem to find solutions to the problems they are having; instead, they are directed elsewhere to find help.

Keywords: Saudi Digital Library, Twitter, Digital Library, Arabic Text, User’s Needs.

1 Introduction

In 2010, the ministry of education in Saudi Arabia established the Saudi Digital Library (SDL) to provide its services to staff and students in all the Saudi universities. The SDL, however, is a consortium of academic libraries than a digital library in the ordinary meaning of the term. Some of the critical known issues are: “subscriptions to appropriate scholarly sources; customization and authentication problems; statistical reporting mechanisms; and strong communication and customer support from vendors” [1].

One year after, the SDL created a Twitter account to serve as a primary means for communication with its users. The SDL account is very active in tweeting about SDL news, recently added databases, training venues, dates, and times; in some cases, they provide who is offering the training. Often, the SDL account on Twitter provides recordings of training workshops they have provided at some point in time. It is interesting to see SDL users interact more with its Twitter account, but how beneficial are the interactions?

2 Research Questions

This short study aims to evaluate the SDL users' interaction with the SDL Twitter account and whether or not using the SDL's Twitter services is an alternative to the FAQ section of its website provides adequate assistance to the users. The researcher looked at the tweets of the SDL account on Twitter and evaluate the users' reactions to it. The broader research question is how practical the SDL's customer support is through Twitter. To answer the research question, the researcher looked at how many users retweet, like, reply or directly tweet to the SDL account?; what do the users say in the comment or reply box?; when users ask questions of SDL account representative/s, are their questions answered?; how long does it take the representative to answer SDL users' questions?; and do users complain about or praise the SDL and its services?

3 Related Work

3.1 Twitter (API) Content Analysis of Tweets

Yi, Choi, and Kim [15] used the Twitter Application Programming Interface (API) to perform content analysis on tweets. This work produced a large dataset collected between February 1, 2013, and April 30. Similarly, but with a specific use of Vista Sentiment 140 analysis, Hoeber et al. [11] performed sentiment content analysis, focusing on positive, neutral, and negative language in the collected tweets. Both Yi, Choi, and Kim [15] and Hoeber et al. [11] eliminated some contents after data collection due to spam tweets or/and non-English language tweets during their analysis.

3.2 Manual Content Analysis of Tweets

Hewis [10] performed an in-depth qualitative content analysis of individual patients' tweets. The native Twitter search engine was employed using the advanced search functions, focusing on tweets containing "MRI" or "magnetic resonance imaging" from May 1 through the 31. The content analysis process comprised three stages which began with 1) a manual review of each tweet to meet some criteria; 2) manual coding of each tweet, with photographs and images coded separately; and 3) the identification of emergent themes from the coded tweets. Al-Daihani and AlAwadhi [2] and Hewis [10] differ in their analyses of the data. For example, in Hewis [10], the coding and thematic analysis were an iterative process, and a symbiotic relationship existed between the writing and data analysis that occurred concurrently. Al-Daihani and AlAwadhi [2] performed the data analysis after they completely collected the data. Xie and Ann Stevenson [14] conducted an open coding analysis of Tweets from 15 different Digital libraries (English-speaking only) over the course of one year (June 30, 2012 – July 1, 2013). Five types of functions of DL Twitter accounts were selected and discussed that represent the problems, promotion, related resources, social connection, and social identity of DLs. Lee et al. [12] performed their study using two different datasets where they chose Twitter accounts of doctors and then randomly chose 200 public tweets. In comparison,

Gul et al. [9] chose random tweets, and then from those tweets, they developed 16 categories that they later narrowed down to 10.

3.3 Mixed Method Twitter (API)

Greaves et al. [8] performed a mixed-methods study, including a quantitative analysis of all 198,499 tweets sent to English hospitals over a year and qualitative, directed-content analysis of 1,000 random tweets. Twitter sentiment and conventional quality metrics were compared using Spearman's rank correlation coefficient. Authors performed a simple descriptive analysis of the entire set of tweets collected by measuring the frequency of tweets by day, and by the hour of the day, and by hospital organizations (known as trusts in England) to see if there were observable patterns of activity. Two hundred and fifty random tweets were coded thematically. An iterative discussion between the reviewers developed a codebook. Additional codes were added to reflect several other topics discovered.

3.4 Arabic Text Analysis

Several studies discuss the analysis of Arabic text on Twitter. Aldayel and Azmi [3] conducted a content analysis of public tweets in Saudi Arabia. While doing so, they mentioned issues in the content analysis process and proposed a solution to overcome these issues. The problem with Arabic text on Twitter is that the tweets made by the public are in dialectal Arabic rather than the formal Modern Standard Arabic (MSA). Similarly, Refaee and Rieser [13] found dialectal Arabic a challenge in the process of the content analysis of Arabic text on Twitter. Researchers in both studies, Aldayel and Azmi [3] and Refaee and Rieser [13], used a systematic content analysis but found that there were some errors due to the dialectal Arabic, causing them to choose manual review in some instances. Other issues they found were that many people use the dialect of their country instead of using MSA. Those various diacritics in the Arabic language make it difficult to systematically analyze the content of tweets on Twitter [7]. The Arabic language is a synthetic language (i.e. derivational, flexional, and Agglutinative) where an Arabic morpheme may consist of a stem and affixes (to refer to tense, gender, and/or number) and clitics (including prepositions, conjunctions, determiners, and pronouns), explaining the difficulties of analyzing Arabic texts. Moreover, articles, prepositions, pronouns, etc. can be affixed to adjectives, nouns, verbs, and particles. Arabic language processing and mining is a challenge, and it requires reliable, publicly-available tools, and resources [6]. With these complexities, research addressing the issue is encouraged to overcome the challenges above [3, 6, 7, 14].

4 Methodology

This study uses a qualitative method called sentiment content analysis. Based on the research questions mentioned above, the researcher used manual content analysis to analyze the interaction between the SDL Twitter account tweets and the public who use the SDL services. The content analysis consists of counting the number of likes, retweets, whether the questions posted receive answers and lastly measuring “positive,” “negative,” and “neutral” reactions to tweets or replies. The researcher analyzed the sentiment reaction of SDL users. Some studies like Al-Rubaiee, Qiu, and Li [5] study investigated the sentiment analysis of Arabic tweets. Since Twitter allows people to express their opinions, the researcher chose to analyze the sentiment analysis as a method for this study to answer the research questions. And due to the technical expertise during the time of the study, the researcher decided to take the manual sentiment analysis approach. Sentiment analysis “is mainly the process of classifying text into two classes, positive and negative, to conclude the writer’s orientation towards a certain topic or subject” [4].

4.1 Data Collection and Procedure

The timeframe for collecting data used in most studies in the literature review is one month to three months, and thus several tweets were randomly chosen from within that timeframe. The timeframe for this study is from January 1st, 2017 to March 1st, 2017, during which 300 tweets were collected. The process started from the first tweet on January 1st and ended when 300 tweets had been reached in March. As the SDL Twitter account produces an average of 8 tweets per day, the researcher decided to collect 150 tweets from January 1st until January 31st, and 150 tweets from February 1st until March 1st. The researcher analyzed the public reactions toward 300 tweets, which is the target number for this study.

4.2 Data Analysis

The researcher analyzed and quantified numbers of likes, retweets, and positive, neutral, and negative reactions noted and documented during the data collection process of the analysis.

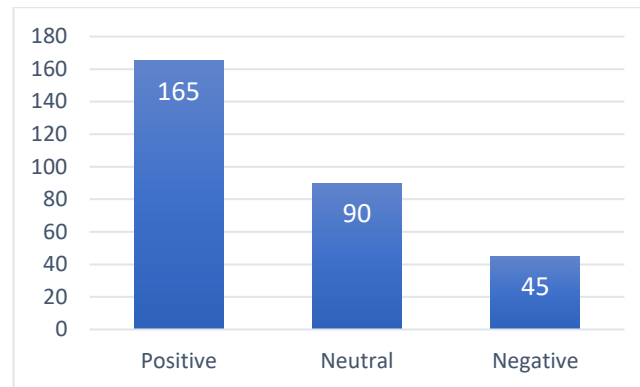


Fig. 1. Users' Reactions Toward SDL Tweets

Figure 1 shows the majority of users' reactions toward the SDL account's tweets were positive. Nearly 55% of tweets showed positive sentiment, 30 percent showed neutral sentiment, and as low as 15 percent showed a negative sentiment towards the tweets.

It was found that the public sentiment toward SDL tweets was not dependent on the content. When the SDL tweeted information about databases to which the library is subscribed, people tended to show approval by clicking like and retweet. However, when a person asked for help with logging in difficulty or other technical issues, there was no reaction implied from people other than the ones who asked for help. There were minimal instances where the SDL account provided answers directly to users, but this motivated other users to indicate a positive reaction by liking or retweeting that reply.

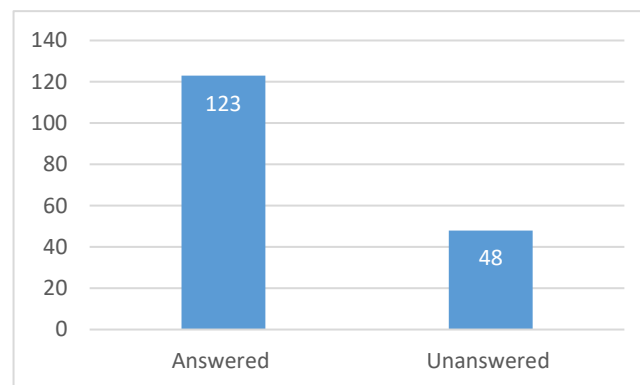


Fig. 2. Answered and Unanswered Questions Asked by SDL Users

Figure 2 shows the questions tweeted or replied to by the SDL Twitter account. It shows that nearly 48 questions, approximate 28%, were not answered. Around 123 questions, about 72%, were responded to. All of the answered questions were either referrals to the universities' representatives or referral to the SDL website to create a ticket for

technical investigation. The answered questions are those that received a reply from the SDL representatives on Twitter. It is worth mentioning that there are questions that some people asked which did not receive answers. It cannot be determined if the users received responses by other means or if the SDL account directly contacted them via the direct message feature on Twitter. Such interactions could not be measured due to the lack of public response to the questions that were posted by the users. In this case, it cannot be determined if the user opened a ticket as advised or ignored the advice and did not have his/ her issue resolved. The duration of time between users' questions and SDL answers was somewhat high, but in general, the response for questions seems to be within a normal range with an average of 1.8 days. However, it does not seem practical as the users were instructed to go elsewhere to seek help and did not benefit from the speedy response. In other words, the user(s) who asked for help had been referred to the SDL website to create a ticket or to contact the university representative at which they are studying. This kind of response does not solve the problem entirely and whether or not these students proceed to seek help as directed or not is a mystery.

4.3 Reliability

The researcher and three doctoral students met and checked the data analysis process of the 300 tweets and the sentiment analysis agreement on each tweet. The first step was that the researcher handed the analysis of the 300 tweets to the three raters and asked them to mark tweets as positive, neutral, or negative based on their judgments. After the raters completed the review, the researcher presented and compared his analysis with the raters'. There was discussion over whether or not to consider tweets that were news or announcements made by the SDL positive, natural, or negative. Because the user intention cannot be determined, raters have come to a resolution that the news or announcements tweets that had more likes and retweets are considered positive and those who have little or none are considered neutral. The percentage of agreement and disagreement on tweets are shown in table 1.

Table 1. Percentage of Agreement and Disagreement on Tweets Analysis

Rater	Agreement	Disagreement
<i>Rater 1</i>	255 (85%)	45 (15%)
<i>Rater 2</i>	273 (91%)	27 (9%)
<i>Rater 3</i>	261 (87%)	39 (13%)
Total	789 (87%)	111 (12%)

5 Limitations

Some challenges and issues came up during the analysis process. One of the issues was that most of the replies by the SDL account directed students to contact either their

university or a designated person within the school at which they study. Because most students did not reply to their original posts or indicate whether they found the reply useful or not, it was difficult to capture the sentiment of the students towards the tweets. The other issue was that tweets by the SDL account included some spam tweets, which made it difficult to rely on counting the replies to the tweet. For this study, the researcher decided to eliminate those tweets from the analysis. Also, the small number of tweets may not be sufficient to conclude the interactions.

6 Conclusion

The reaction toward the SDL Twitter account is mostly positive only when the SDL account tweets about SDL news, recently- subscribed databases, training workshops opportunities, instructions on how to conduct an SDL search, and other SDL-related news. However, the neutral and negative reactions toward the SDL occur when students ask questions, or the SDL replies to a tweet posted by students. The use of Twitter to replace an "ask-the-librarian" service for the SDL users does not seem practical and helpful. Most students who had questions or problems were referred to the SDL website to create a ticket for the SDL staff to investigate the issue, or they were referred to contact the university coordinators. The SDL should consider using its Twitter account for promoting the library and spreading news and workshops to the users and dedicate the SDL website to provide the support to avoid frustration and confusion that may be caused. It is essential to study the students' information-seeking behavior within the SDL website. The results indicate there are cases where students did not find answers, or possibly received answers from different sources, like friends or classmates.

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