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Customer behavior using food delivery services in GCC: studying engagement using sentiment analysis during COVID-19

Abstract

Online food delivery services have become very important during COVID-19 given that many people cannot dine in at restaurants. This study does sentiment analysis on data collected from Twitter and Youtube on food delivery services focused in the GCC region. Raw data is collected from Twitter and Youtube API and then filtered to get sentiment polarity. Cross-platform analysis is done on this data over a period of before and during the COVID-19 pandemic and co-relations are also found between metadata. Crucial reasons are identified for the changing customer sentiment and also suggestions to use the right social media are provided based on those findings

Keywords: Sentiment Analysis, Food delivery service, Youtube, Twitter, GCC

1. Introduction

Covid-19 has affected almost every aspect of our daily life. Especially, this global pandemic has affected many businesses negatively, whereas, in some cases, it has affected some businesses positively. Online food delivery business is something that has seen a growth during these Covid-19 times given that many people cannot dine in at restaurants. Lately there has been a lot of online feedback from customers about the performance of food delivery services. This is due to an increase in social media activity during the pandemic. Alrazaq (2020) quote "social media can play an important role as a source of data for detecting outbreaks but also in understanding public attitudes and behaviors during a crisis as a way to support crisis communication and health promotion messaging". Publicly accessible data posted on social media platforms by users around the world can be used to quickly identify the main thoughts, attitudes, feelings, and topics that are occupying the minds of individuals in relation to the COVID-19 pandemic (Alrazaq and Hamdi, 2020) It is very important to study this customer feedback because "consumer–company interactions in food delivery platforms differ largely from interaction in traditional restaurant visits" (Teichert, 2019) and also by studying this data, we can look for insights into customer likings and behavioral change.

The purpose of this study is to study customer engagement online with food delivery services focused in the GCC region by using sentiment analysis. COVID-19 has increased the demand for food delivery services and hence one of the main focus of this research is to identify any change in sentiment for a period of pre and during COVID, and also identify the reasons for those changes. Cross platform analysis is done across Youtube and Twitter and co-relations are also found between some metadata to investigate the data in detail.

The remainder of the paper will focus on the literature review, methodology adopted to collect and prepare data, results based on the data analysis, discussion and findings based on those results, limitations and conclusion of your work.

2. Literature review

Consumer feedback and their likings are considered very important since it can help businesses improve their business. Predicting consumers liking thanks to emotion-based measurements is a hot topic in sensory science (Visalli, 2020) Predicting consumers likings can be done effectively using a method called 'Sentiment Analysis'.Sentiment Analysis automatically determines the emotions of the author of a text from that text (Visalli, 2020) Mostafa (2019) defines it as 'Sentiment analysis studies emotions, evaluations, and attitudes toward a specific subject'. Sentiment analysis relies on 'the exploitation of a large corpus of text coming from, for example, social networks' (Visalli, 2020) Unlike traditional social media, such as newspapers, online social media contains a large amount of multimodal data that can provide a considerably large number of clues for estimating sentiments when compared with that provided by words alone (Lui and Tang, 2020) This data collected from social media is studied using sentiment analysis to look for insights into consumer behavior. In the previous decade, there has been a lot of research going on around the use of sentiment analysis. Abd-alrazaq (2020) did sentiment analysis on top concerns of tweeters during COVID-19. Ainin and Abdullah (2020) did sentiment analysis on halal tourism. Mostafa (2019) did twitter sentiment analysis on halal food consumers. Mostafa (2019) also highlighted many other researches on sentiment analysis in his paper.

Engagement is related to customer review text, likes, retweets and total no. of replies. Ibrahim and Wang (2017) studied the effect of user engagement in online brand communities. Their analysis showed that 'engagement has an effect on sentiments that associate with brand image, perception and customer service of the online retailers.' Their research also indicated that 'Engagement does not only influence customers but also has implications for companies in consideration of their brand building and product development.' This shows how important it is to study customer engagement with a product/brand in order to develop or promote a business.

However, there has been limited research that captures both sentiment analysis and customer engagement in the food delivery service industry.

Mostafa (2019) expressed limited research done on consumer halal food to carry out their research, whereas Ibrahim and Farizah (2017) expressed limited research done on customer engagement in online retailing to carry out their research. After doing our literature review, we saw that sentiment analysis has been used in many applications, but no research has been done to study online food delivery services, specially no research is done in a GCC region context. Our research will help try to fill that gap in.

3. Methodology

In order to understand the sentiment of customer satisfaction on food delivery services in the Middle East region on social media, we chose two platforms: YoutTube and Twitter to find trends across platforms. We choose both Twitter and Youtube to get a diverse set of sentiments

3.1 Youtube

3.1.1 Data retrieval

We used *YouTube Data API* to retrieve data from youtube. We identified the available food delivery services in the GCC countries and created a list of the most popular of them. These are Talabat, Zomato, Carriage, UberEats and Deliveroo. Next keywords were identified prior to the data retrieval in accordance with the chosen services. Also, *Youtube Data API* has a feature of retrieving results from keywords based on a specific region. By using this feature, we searched for videos with our previously identified keywords from GCC countries. We collected videos, comments of each video, likes of each comment, published date of comment and replies for each comment. Finally, the extracted data were saved into a JSON file. Initially, we extracted 518 videos which contained 99,500 comments. The data collection and verification process were conducted over a period of two weeks.

3.1.2 Data pre-processing

The videos that we collected were not all relevant to our project. Our final dataset contained 142 videos after removing all the irrelevant videos and also videos other than English and 1265 comments form these videos. Not all the comments were in English. Also, there were comments that were undetectable as languages such as only numbers, symbols and emojis. Firstly we removed the undetectable comments. Then we created a new dataset with pure English comments which can be detected by the langdetect library in Python.

The final dataset was imported to our working notebook as a dataframe with Pandas library from python. Moving on, URL's, punctuations, stop-words and collection words were removed for a better result in our analysis. Taking one step further, the data frame was split into two different data frames, one for comments made before COVID-19 and another for comments made during COVID-19 where 1st March 2020 was the splitting date.

3.2 Twitter

3.2.1 Data Collection

Tweepy and TwitterSearch libraries from python were used to collect data from Twitter. The Names of the delivery services were used as keywords to retrieve tweets. These delivery services were the same as those used in Youtube (Talabat, UberEats, Zomato, Deliveroo, Carriage). The tweet, total likes, total retweets and date of the tweet published were collected. The data for during COVID-19 and before COVID-19 were saved in 2 separate files so that both datasets can be studied easily. Initially, approximately 2000 tweets were collected but they were filtered later to work on only the relevant ones.

3.2.2 Data pre-processing

Tweets collected initially were not all relevant to food delivery service. Also, there were twitter handles, alpha-numeric characters, numbers, URL's, emojis, mentions, punctuations and hashtags all of which would compromise our result. There were also some Arabic comments. Due to limited sentiment analysis tools, we removed arabic comments along with other textual barriers.

Finally, all the stop-words and collection words were removed and all words were transformed to lower-case to maintain the uniqueness of each word as similar words with the different case are treated as different words and would increase the complexity of the result. Initially, the dataset had a number of retweets, promotional/advertisement tweets etc. They were removed to finally work on a dataset containing relevant tweets. The final dataset consisted of approximately 400 tweets and this dataset was imported as a dataframe using Pandas library from Python.

3.3 Sentiment Analysis

Sentiment analysis can provide valuable insights on social media platforms by detecting emotions from texts (Hasan et al., 2018). Nakayama (2019) divided review sentiment into two categories: positive sentiment and negative sentiment. In sentiment analysis, polarity is measured by assigning a score between -1 to +1 for each tweet/comment. Negative score indicates negative sentiment, positive score refers to positive sentiment and zero being neutral. We used a Python library named **Textblob** for processing textual data and identifying sentiments. To get further insight on sentiments, we used **bigrams** to clarify the accuracy of sentiments in word level. Bigrams are used to get the frequency of words occurring together in a text.

4. Results

The results of sentiment analysis across platforms over the period of before and during COVID-19 are presented below

4.1 Sentiment analysis on Twitter vs YouTube

While conducting sentiment analysis we found that a large number of comments and tweets fall in the neutral zone of polarity. We removed those texts and again analyzed the dataset. Firstly, the percentage of sentiment for comments and tweets were identified and found that the percentage of Positive:negative sentiment was 41.6:58.4 for Twitter and 80.9:19.1 for YouTube. Then, we divided the sentiments into 8 bins and drew histogram with the mean line. Here we found the mean of sentiment for Twitter was -0.114 and for YouTube was 0.267. Overall, we can conclude that sentiment on Twitter was more negative while sentiment on YouTube was highly positive.

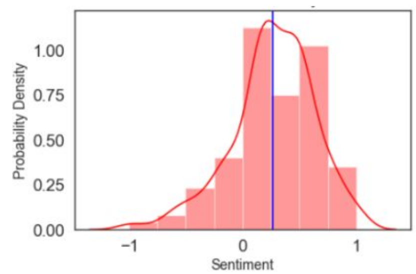

Figure 1: Distribution of sentiments on food delivery services on Youtube

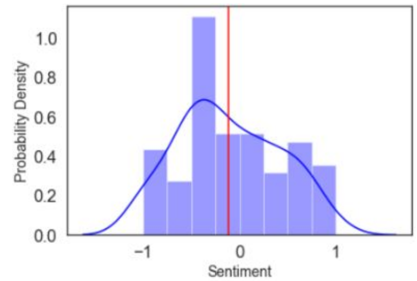

Figure 2: Distribution of sentiments on food delivery services on Twitter

4.2 Sentiment analysis on Youtube before and during COVID-19

Following the steps from the previous part, this time, we splitted the dataframe into before and during COVID for YouTube and did sentiment analysis on them individually. From this analysis, it was found that the percentage ratio of positive:negative sentiment is 81:19 before COVID and 80:20 during COVID. The sentiment has slightly moved towards negative. To further verify our findings, we used bigrams to find the frequency of co-occurring words and it supported our initial finding.

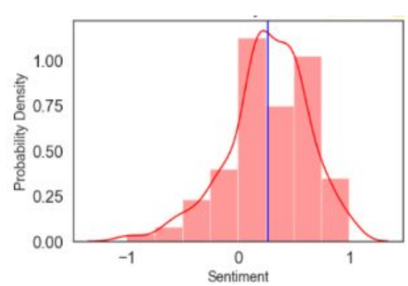

Figure 3: Distribution of sentiments on food delivery services on Youtube before COVID

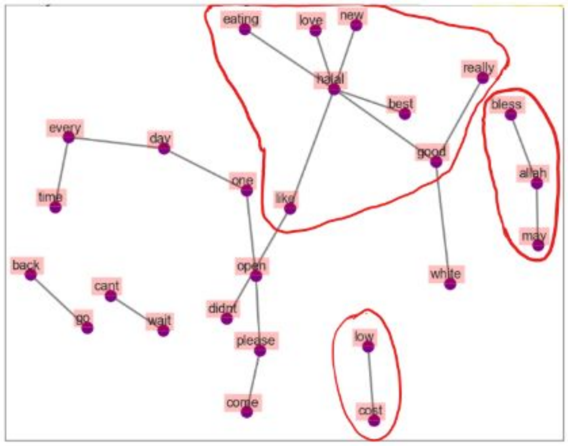

Figure 4: Frequency of words occurring together on Youtube before COVID

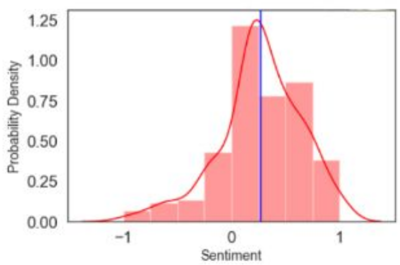

Figure 5: Distribution of sentiments on food delivery services on Youtube during COVID

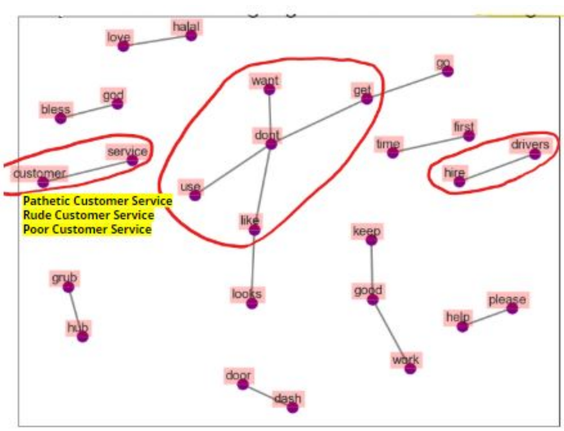

Figure 6: Frequency of words occurring together on Youtube during COVID

4.3 Sentiment analysis on Twitter before and during COVID-19

Similar to YouTube, percentage ratio of sentiments were calculated for before and during COVID on Twitter and then bigram was used to justify the result. It was found that the percentage of sentiment before COVID was 42% positive & 58% negative and 46% positive & 56% negative during COVID. For Twitter, the sentiment change is opposite of YouTube as it is changing from more negative to less negative. Again, we used bigram to justify our result and found that this was indeed the case.

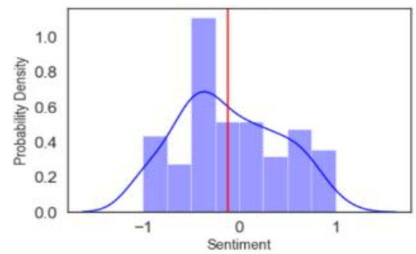

Figure 7: Distribution of sentiments on food delivery services on Twitter before COVID

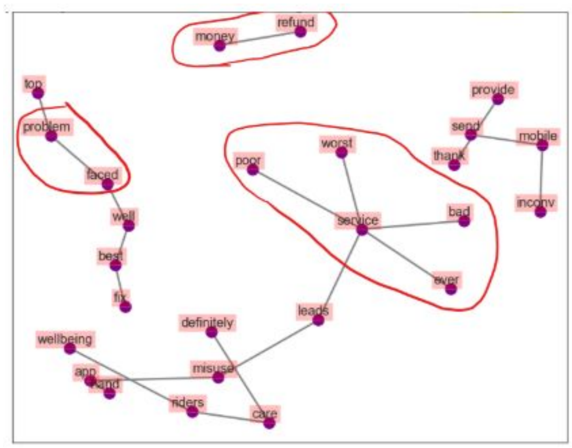

Figure 8: Frequency of words occurring together on Twitter before COVID

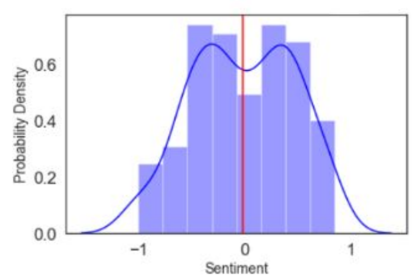

Figure 9: Distribution of sentiments on food delivery services on Twitter during COVID

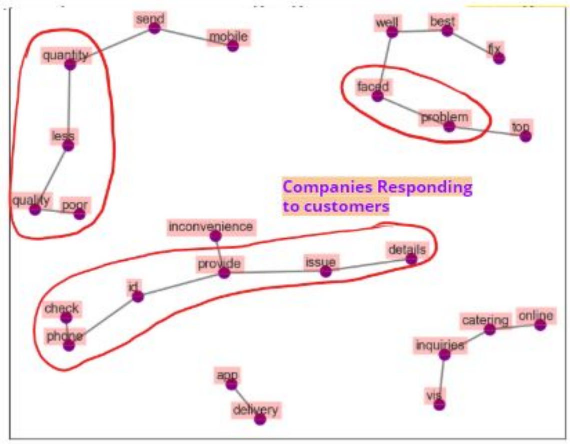

Figure 10: Frequency of words occurring together on Twitter during COVID

5. Discussion

In this section, we will discuss the results from sentiment analysis, provide suggestions to restaurant and food delivery services based on our findings in terms of choosing the right platform, limitations of our research and future research scopes.

5.1 Interpretation

YouTube is considered as a social media platform, but it is mostly used for recreational purposes. Therefore, people don't actually engage on YouTube and is found from sentiment analysis. Most comments on YouTube were one or two words such as (nice, good etc.). These words contain positive polarity but yet don't contain the social aspect of engagement. On the other hand Twitter is a social interaction platform where individuals share their views, feedback, concerns etc. and interact with others. Negative overall sentiment tells that the consumers are complaining about the services on Twitter.

As time changed from before COVID to during COVID, sentiment changed on both platforms. The change was positive for Twitter and negative for YouTube. Negative sentiment on Twitter decreased by 2% and also the density of negativity was reduced in word level. Additionally it was found that the service providers were responding to the complaints on Twitter, thus taking in account the customers feedback. For YouTube, negative sentiment increased by 1% and during COVID contained highly negative comments (which were complaints), suggestions for the service providers and their opinions as found from the bigram. Therefore, we can conclude that people started engaging on YouTube during COVID and service providers are more active on Twitter to identify their drawbacks.

We also identified many reasons for the change in sentiment from a period of pre to during COVID. The major reasons for the change in sentiment were due to: delivery timeliness, food quality and food quantity. We saw a lot of customer complaints about these things in the bigrams. Bigrams contained a lot of words that expressed negative sentiment (poor delivery, hire more drivers, poor quality etc) The negative sentiment was more on Twitter before COVID, however, we saw an increasing trend of negative sentiment on Youtube during COVID. This shows that customer engagement is increasing on Youtube and customers have started to express their feedback on Youtube too.

5.2 Practical Implication

Consumers were found complaining and providing feedback on Twitter more than YouTube. Businesses can utilize the Twitter platform to identify problems with their products. Also, they can take suggestions from users to improve their product/service.

On the other hand as people do not engage in YouTube but use it to watch videos, thus this can be a good platform for marketing. Restaurants can upload snippets from their kitchens to ensure the quality and quantity of foods. Other businesses and/or services can also adapt to this strategy by uploading videos related to advertisement and promotions of their product.

Both of these platforms are very helpful for any business in the GCC region, especially for young entrepreneurs. They can utilize these platforms to identify their niche, customers, potential competitors and their drawbacks.

5.3 Limitations

Our research was limited by the limited amount of relevant data availability. This was due to API restrictions from both Twitter and Youtube. We also had no authorized access to both Instagram and Facebook API. During the time of this research, Facebook and Instagram had limited staff (due to COVID pandemic) and hence we could not get access to their APIs. We also did not consider Arabic comments in your research given the complexity and time constraints.

5.4 Future Research Opportunities

The limitations in our research open up paths for future research opportunities. Future work can be done on a larger dataset, considerinig data availability from both Facebook and Instagram. Arabic comments can also be considered in future research work to get a better understanding of customers in the GCC region. Additionally, more data during COVID scenario can be studied in future research work (This research was done in July-2020 so future work can consider COVID data from months of July onwards)

6. Conclusion

Online food delivery constitutes a major trend in the food industry (Teichert, 2019) This trend and demand for online food delivery services has increased during COVID-19 pandemic. It is very important for businesses to listen to customer feedback and improve their service in order to remain competitive in the food delivery business. Our research has helped food delivery businesses in GCC to identify the main customer feedback platform and use that feedback to improve their service. Our research also helps provide businesses digital guidance on which social media platform is best suitable and for which purpose.

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