# The Rise of Food Delivery Culture during COVID-19: Sentiment Analysis of Food Delivery Services in the Gulf

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## Plain Language Summary

The COVID-19 pandemic profoundly affected all aspects of society and economy, including online food delivery services as restaurants limited dine-in options to reduce risks. Little is known about the quality of these delivery services, especially in the Gulf area, or how they were affected by the pandemic. Analyzing customer feedback on social media can help businesses gain insight into the services they provide. This paper presents a cross-platform sentiment analysis of Twitter and YouTube data to examine customers' attitudes on social media towards food delivery services in the Gulf region before and during COVID-19. Only minor sentiment changes occurred in both platforms and were related to many factors including delivery timeliness, food quality and food quantity. This study provides insights into the specific usefulness of each platform for businesses seeking to engage with users about services and satisfaction.

## Publication Category

Course-based Assignment

## Academic Context

In a summer special projects course entitled *Data Analysis for Social Commerce Platforms in the Gulf Area During COVID-19*, students designed and conducted an analysis of social commerce platforms. Students determined a research question and developed their approach based on a literature review and the Gulf context. Students accordingly collected, processed, analyzed, and visualized data. They crafted a formal research report to present their findings.

## Introduction

The COVID-19 pandemic affected almost every aspect of our daily life, pushing most regions to implement lockdowns. These lockdowns, along with the fast-paced and unknown variables of the pandemic, introduced significant challenges to many businesses. However, some businesses experienced a positive impact. Online food delivery, for example, saw growth during pandemic times as on-site dining was not allowed; delivery services were used in an effort to limit the virus spread. Food delivery services (FDS) gained more and more attention, and along with consumers' increasing use of social media during the pandemic (Abd-Alrazaq et al., 2020), they increasingly shared their feedback about FDS performance, often describing their experience with different delivery companies (i.e., Talabat, Deliveroo, UberEats, etc.). Publicly accessible and naturally occurring data posted on social media platforms by users around the world, such as tweets and YouTube comments, can be used to quickly identify main thoughts, attitudes, feelings, and topics occupying the minds of individuals in relation to COVID-19 and the affected businesses (Abd-Alrazaq et al., 2020).

Customer feedback is important to study because consumer–company interactions in food delivery platforms differ largely from interaction in traditional restaurant visits (Teichert, 2020). By analyzing this data, researchers can look for insights into customer public attitudes and behaviors (Abd-Alrazaq et al., 2020). This paper presents a study of customer social media engagement with FDS in the Gulf region by using sentiment analysis. COVID-19 increased the demand for FDS, hence by collecting and analyzing tweets and YouTube comments using text mining techniques, I aim to quantify the customer engagement with FDS throughout the coronavirus outbreak and identify any change in sentiment for a period before and during COVID-19. To the best of my knowledge, this is the first work that studies the effect ofCOVID-19 on the FDS in Gulf region using consumer opinion on social media.

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This paper is structured as follows: I present a literature review on consumer feedback and its impact on businesses. Then I describe data collection, processing, and the sentiment analyses. Finally, I discuss the findings, as well as limitations and a future research agenda.

## Literature Review

Social media can help researchers understand various aspects of a society. COVID-19 saw a surge in overall social media engagement from users, as users regularly expressed their sentiment and opinions. Many researchers have used social media as a way to understand COVID-19's effects on society. For instance, Li et al. (2020) explored the impacts of COVID-19 on people's mental health by analyzing Weibo active user posts in China and using sentiment analysis to detect cases of anxiety, depression, and happiness. Barkur et al. (2020) explored the feelings of Indians on Twitter caused by COVID-19. They conducted a sentiment analysis on tweets to gauge the feelings of Indians towards a lockdown announcement. Abd-Alrazaq et al. (2020) presented a study that identifies the main topics posted by Twitter users related to the COVID-19 pandemic and did sentiment analysis on top concerns of tweeters during COVID-19. These and other studies suggest that social media is an important source for understanding public attitudes and behaviors during a crisis (Jordan et al., 2018).

Consumer feedback and their opinions towards a brand are considered particularly important since analyzing them can help companies understand their business and service quality. Predicting consumers' sentiments and attitudes towards a brand, a product or a service using sentiment analysis has shown to be effective in sensory science (Visalli et al., 2020) and in the fields of natural language processing and text mining (Liu, 2022). Companies analyze people's posts on social media and leverage their opinions about products or services to identify possible problems and improve its quality (Jain et al., 2020). For example, ecommerce companies like Amazon use customer reviews and feedback to assess satisfaction towards their service.

The high demand for FDS during COVID-19 and its increased online customer attention suggests an analysis of that engagement could yield useful results. Pre-pandemic customers' experiences and attitudes towards FDS have been addressed in numerous research projects using sentiment analysis. Yeo et al. (2017) examined consumers' experiences and behavior towards online FDS and found that customers' online food delivery experience depends on various factors. A customer's satisfaction impacts their loyalty to the business, which ultimately affects profitability. Sing et al. (2020) presented a social media analytics framework to process tweets in real-time to identify the influences of generated insights on e-commerce decision making in metropolitan cities. They also highlight the sentiment and brand reputation of four online food delivery applications in India, namely Zomato, Swiggy, Ubereats, and Foodpanda. Nagpal et al. (2020) presented an approach with several steps for extracting sentiments from a large set of tweets on three online food delivery apps. They mainly focused on building a large-scale dataset and explaining the process for finding the relevant tweets that can help a company analyze its customer experience.

Most of the work presented in the literature on analyzing user's sentiment about FDS is done on a specific food delivery application in regions like India and China. To the best of my knowledge, this is the first work that aims at analyzing customer attitudes towards FDS on Twitter and Youtube in the Arab Gulf region before and during the COVID-19 pandemic.

## Methods and Procedures

To study customer sentiment on FDS in the Gulf region, I explore customers' feedback on two social media platforms: YouTube and Twitter. Customers express their reviews and feedback on Twitter through tweets and Youtube through commenting on videos. I chose both Twitter and YouTube to get a sense of which platform might be more suitable for businesses to focus on if they are interested in studying customers' opinions about their service. I conduct a cross platform analysis across Twitter and Youtube to compare sentiment and engagement over two-time intervals—before COVID-19 and during COVID-19—to assess the change in sentiments that might be caused by the lockdown, quarantine, and the increase in delivery demand.

### Data Collection

I collected pre-COVID-19 FDS-related tweets from 1 November 2019 to 29 February 2020. For the during COVID-19 interval, I collected tweets from 1 March 2020 to 15 July 2020. Tweet collection was done using the Twitter standard search API. As I am focusing the study on the Gulf countries (Qatar, Bahrain, Saudi Arabia, Kuwait and UAE), I first identified the FDS available in these countries, and created a list of the most popular ones in the area including Talabat, Carriage, UberEATS, Zomato, and Deliveroo. The set of search terms related to the chosen services include their names in addition to keywords related to COVID-19. I also apply a region filter to keep only tweets from the Gulf.

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I extracted the text and metadata of the tweets (number of likes and retweets, publishing date) used the Tweepy[1] Python library for accessing the Twitter API and. I first collected 2,000 tweets and then filtered them (detailed below) to keep only the relevant ones.

In order to collect YouTube video comments on FDS in the Gulf, I used the YouTube Data API.[2] This API allows users to search for videos that match specific criteria and retrieve video comments and user profiles including a geo-location feature. I collected the list of matching videos using the same list of keywords used for collecting tweets. I limited the search to videos posted in the Gulf region. Then I extracted video text comments as well as their metadata, such as the number of likes, date of comment, and comment replies. I initially obtained 518 videos with 99,500 comments. The data collection and verification process were conducted for the same dates as Twitter.

### Data Pre-Processing

I first filtered out non-English tweets and video comments using the langdetect library.[3] I then identified and removed retweets from the analysis. I also removed punctuation, URLs, and non-printable characters such as emojis from the tweets. I also removed user mentions, hashtags, and stopwords such as *a*, *an*, and *the*. Collection words (keywords used to collect tweets and Youtube comments) were removed from the video comments and tweets and all words were lowercased to avoid data sparsity. The final dataset consisted of approximately 900 comments and 400 tweets.

### Sentimental Analysis

I analyzed the polarity of the processed tweets and video comments. In sentiment analysis, polarity is measured by assigning a score between -1 to +1 for each tweet/comment. Negative scores indicate negative sentiment, positive scores indicate positive sentiment and zero marks neutral sentiment. For detecting the polarity of each tweet/comment, I used Textblob[4], a library for processing textual data and performing common natural language processing tasks such as sentiment analysis. I removed neutral tweets and comments and analyzed the remaining dataset independently.

To gain further insight on the data polarity, I analyzed the tweets and YouTube comments using word frequencies of bigrams and visualized them through a graph using NetworkX[5], a Python library for the creation and study of the structure of complex networks, such as a social network. These networks allow us to identify the most frequent co-occurring words in tweets and comments that could be further analyzed and interpreted to understand customers' satisfaction towards FDS in the Gulf.

## Results

This section presents the results of sentiment analysis across platforms before and during COVID-19.

### Overall Sentiment on Twitter vs YouTube

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. I divided the sentiments into 8 bins and drew histograms with the mean line (Figures 1 and 2).

**FIGURE 1.** Distribution of Sentiments on Food Delivery Services on YouTube

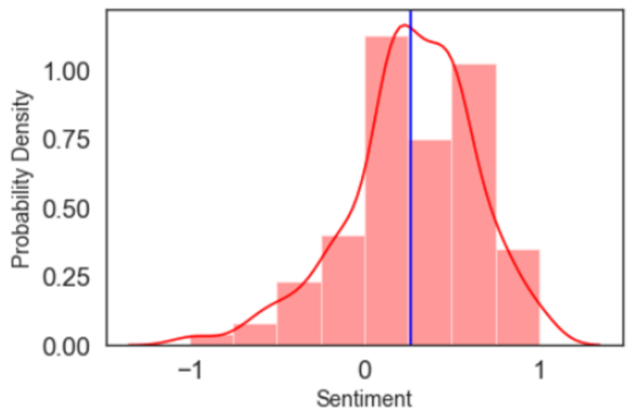
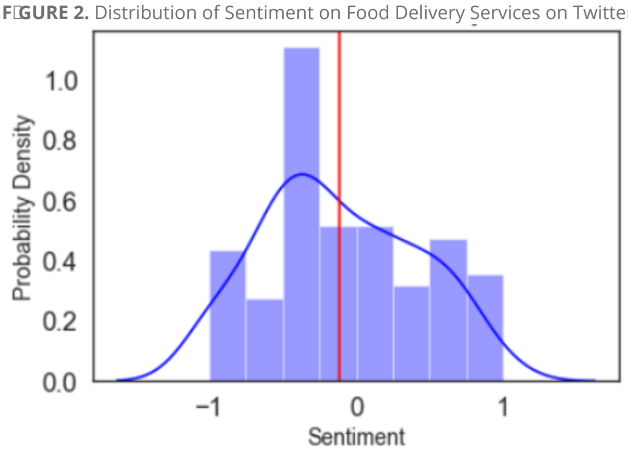



**FIGURE 2.** Distribution of Sentiment on Food Delivery Services on Twitter




Here I found the mean of sentiment for Twitter was -0.114 and for YouTube was 0.267. Overall, I can conclude that user feedback on FDS on Twitter was more negative while it is highly positive on Youtube.

[1] https://www.tweepy.org/
[2] https://developers.google.com/youtube/v3
[3] https://pypi.org/project/langdetect/
[4] https://textblob.readthedocs.io/en/dev/
[5] https://networkx.github.io/

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## Sentiment Analysis on YouTube before and during COVID-19

Using the filtered dataset, I split the data into before and during COVID-19 using the date feature for YouTube and analyzed their polarity. I found that the percentage sentiment of positive and negative comments is 81% positive and 19% negative before COVID-19 (Figure 3) and 80% positive and 20% negative during COVID-19 time (Figure 4) showing that the customer attitude towards FDS in the Gulf was minimially affected on YouTube.

To further verify the findings, I used bigram analysis to find the frequency of co-occurring words representing the topics and concerns mentioned by the customers in their feedback (Figures 5 and 6). Although the sentiment change was found negligible in histogram for before and during COVID-19, bigram shows that the most frequent words occurring together during COVID-19 is higher in negative sentiment found in the comments (e.g., “pathetic service,” “rude service,” etc.) compared to higher positive sentiment comments before COVID-19 (e.g., “best,” “really good”).

**FIGURE 3.** Distribution of Sentiments on Food Delivery Services on YouTube Before COVID-19

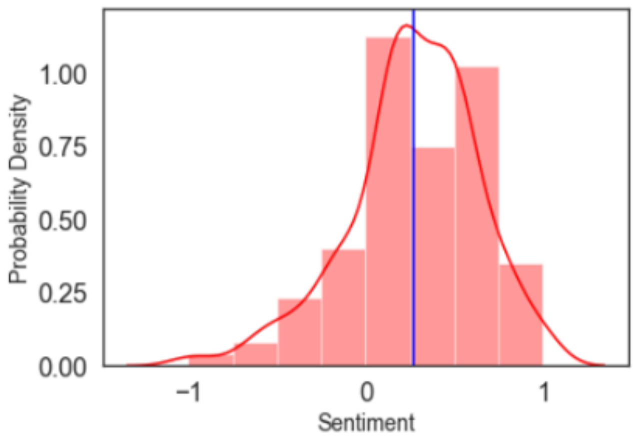



**FIGURE 4.** Distribution of Sentiments on Food Delivery Services on YouTube During COVID-19

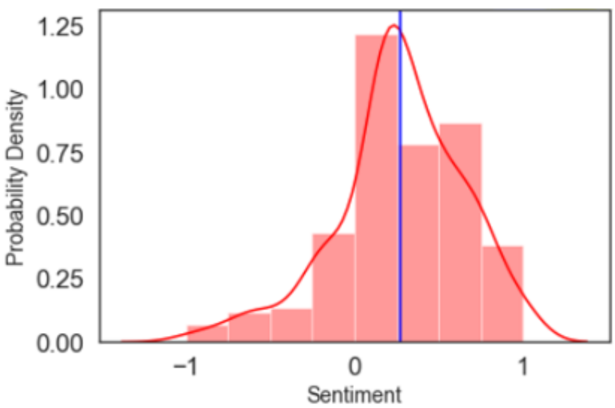



**FIGURE 5.** Most Frequent Bigrams on YouTube before COVID-19

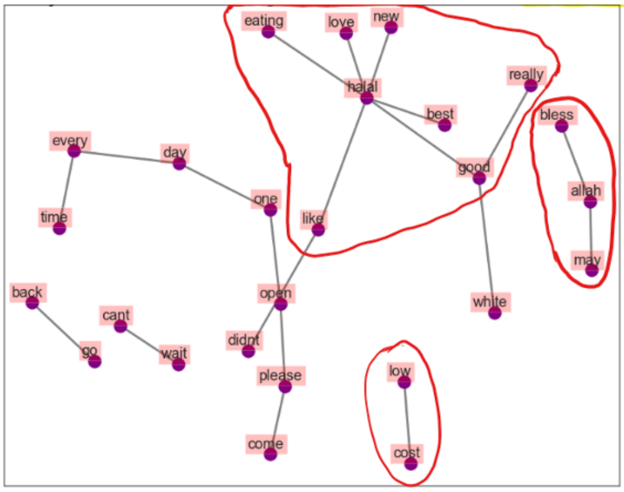
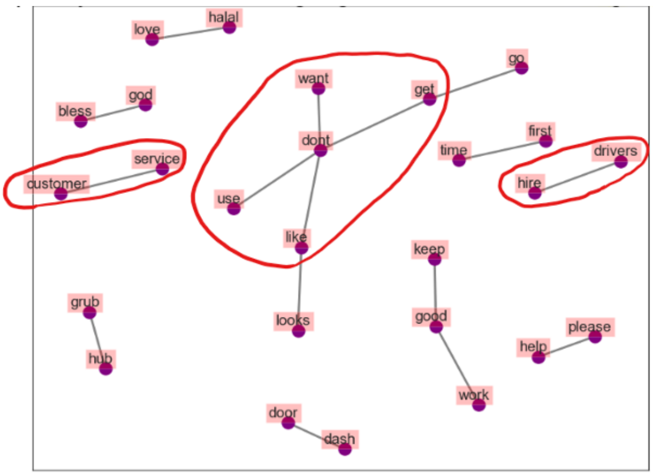



**FIGURE 6.** Most Frequent Bigrams on YouTube During COVID-19




## Sentiment Analysis on Twitter before and during COVID-19

Like the analysis I carried out on the YouTube comments, I calculated the percentage ratio of tweet sentiments before and during COVID-19, and then a bigram co-occurrence analysis (Figures 7 and 8) was used to further understand the results. Sentiment before COVID-19 was 42% positive and 58% negative and 44% positive and 56% negative during COVID-19. For Twitter, the sentiment change is opposite to that observed on YouTube, changing from more negative to less negative.

Unlike YouTube, the frequency of most co-occurring words was observed to be consistent with the percentage ratio, where during COVID-19 bigram contained less negative sentiment (e.g., “poor quality,” “less quantity”) than before COVID-19 bigram (e.g., “worst service,” “faced prob-lem,” etc.). Also, the service providers were found engaging with the customers during COVID- 19 bigram (e.g., "provide issue details").

**FIGURE 7.** Most Frequent Bigrams on Twitter Before COVID-19

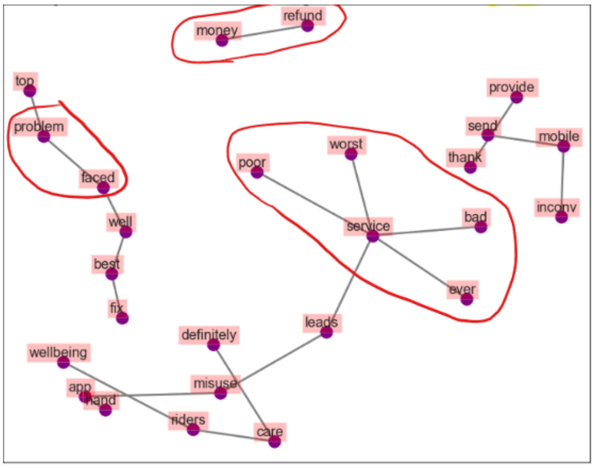
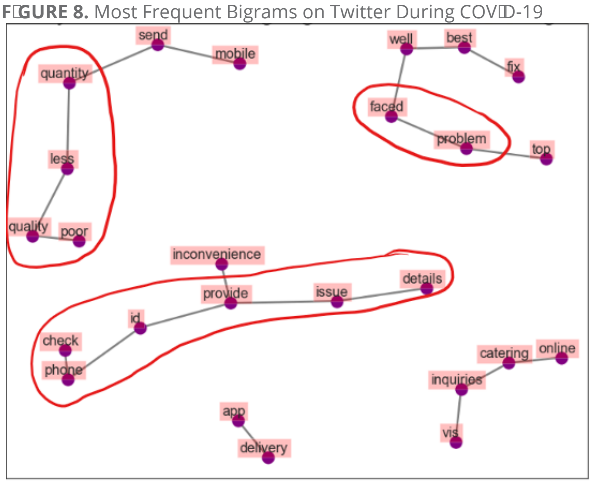



**FIGURE 8.** Most Frequent Bigrams on Twitter During COVID-19




## Discussion

Social media are important tools that can enhance customer engagement with online retailers and ease online activities like branding and customer service. Also, the advent of social media has led to an explosion of interest in customer engagement and opportunities for developing close relationships with customers (Ibrahim et al., 2017). This phenomenon is reflected in the findings. The COVID-19 pandemic had a minor impact on consumers' sentiment towards FDS in general on both platforms. The change was positive for Twitter and negative for YouTube. Negative sentiment on Twitter decreased by 2% and the density of negativity was reduced at the word level. As indicated previously, "worst service" and "bad service" occurred more frequently on tweets before COVID-19 and "poor quality" and "bad quality" were mentioned more frequently during COVID-19. Though the sentiment change in Twitter is minor, service providers were engaged with consumer feedback during COVID-19, which may have helped improve overall sentiment. By further exploring the replies to the tweets, I observed that food delivery providers were responding to the complaints, thus taking into consideration their customers' feedback. This finding reflects Ibrahim et al.'s (2017) position that negative tweets should be handled conse-quently by companies until it turns into positive since it will induce more replies and feedback from customers, helping to sustain positive image of company.

The sentiment change for YouTube was also minor with a 1% increase in negative sentiment during COVID-19. Further exploration showed that YouTube comments contained highly negative comments, which were mostly delivery operation complaints, such as "pathetic customer service," "rude customer service," etc., as found in Figure 6. Companies are not engaging with customer feedback in the YouTube comment section.

Results suggest that YouTube is used as a one-way communication platform. Users do not appear to provide relevant feedback about delivery services on YouTube. Most comments on YouTube were short, including 1 or 2 words such as "nice" and "good," which is interesting for sentiment analysis but does not provide much detail about the service and user experience. This may be because users choose YouTube to watch videos as a relaxing form of entertainment (Khan, 2017), and user engagement in the comments is passive (Carvache-Franco et al., 2023). On the other hand, Twitter is a platform where individuals share their views, feedback, and concerns, and they interact more with delivery services. Individuals express their opinions more on Twitter compared to YouTube.

These cross-platform differences hold a lot of practical and managerial implications for companies. Businesses can analyze Twitter to identify problems with their products and address them. YouTube can be a suitable platform for marketing and advertising campaigns. Businesses and/or services can adapt this strategy by uploading videos related to advertisement and promotions of their product to YouTube. Whereas Twitter can be a suitable platform to monitor brand community discussions and convey information to customers.

Business owners can can utilize both YouTube and Twitter to identify their niche customers, potential competitors, and their drawbacks. Both platforms can be used to address customer complaints. Special attention must be given to YouTube engagement in the form of viewership and

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comments section. Both platforms had sentiment variation based on delivery operations.

## Conclusion & Future Work

This paper presents an analysis of customer social media engagement with FDS in the Gulf region before and during the COVID-19 pandemic using sentiment analysis. The main finding is that the pandemic only minorly affected consumers' sentiment towards FDS in general on both platforms. Findings also produced useful insights regarding the customer use of each platform. On Twitter, users tend to post tweets to express their satisfaction about FDS quality or to complain about them, while on YouTube, they do not engage significantly with FDS and instead provide passive comments. Companies should continue to engage with Twitter to interactively addressing customer issues and reflect on FDS services; they should also consider customer sentiment on YouTube for insights to ensure the best service is provided to customers.

It is important to note that the research was limited by the availability of relevant tweets and comments. Due to technical restrictions from both Twitter and YouTube and time constraints, I could not gather a larger amount of data that could give further insights, but I believe that using the medium-scale dataset I could understand user behavior towards FDS in the Gulf to investigate change due to the COVID-19 situation. I did not consider Arabic comments given the complexity of processing this language and time constraints. These limitations open paths for future research opportunities. This work could be extended to a larger dataset covering more social media platforms and on a larger time frame and including Arabic feedback. The present analysis holds practical and managerial implycations for food delivery businesses in the Gulf. Twitter and YouTube can be used complementarily to advertise, convey necessary information, and monitor customer feedback. Overall, this research helps provide businesses digital guidance on which social media platform is best suitable and for which purpose.

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