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RESEARCH ARTICLE

AN ANALYSIS OF UTILITY COMPANY CUSTOMER SERVICE DURING THE COVID-19 PANDEMIC

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Abstract

Many companies have fared badly in service due to COVID-19 restrictions and changes in the lifestyle around the United States. Consumers within the United States are potentially faced with service interruptions and the inability to resolve issues for services that are necessary for daily life; this is exacerbated by many Americans working from home during the pandemic. The purpose of this research is to analyze the public opinion of Americans living with these service issues via social media. Through the collection and interpretation of this data, we hope that changes may be brought to light. The data was analyzed using natural language processing utilities, and finally, using various inferential statistical methods. The potential implications of the results will be practical for companies moving forward in a post-COVID-19 society. We aimed to show the overall satisfaction of customers during this adjustment period. The research conducted reflected the minimal effect presented by moratoriums ending during our capture dates. Significant results were found between utility types and the overall polarity of customer satisfaction, and possible conclusions are discussed.

Introduction:-

Historically epidemics have shaped the societies they appear in; with the COVID pandemic, the effects are global and long-lasting (Ceylan et al., 2020). The COVID-19 pandemic has had an unprecedented impact on psychology, sociology, economics, and many other areas of study (Ceylan et al., 2020). Impacts directly related to COVID-19, such as unemployment, may currently be underestimated (Ceylan et al., 2020). This crisis has triggered the fall of many companies, a loss of jobs, and the sprouting of new online industries (Donthu& Gustafsson, 2020). Meanwhile, social media has become a prominent feature in connecting with others (Donthu& Gustafsson, 2020). The internet has become a way to get necessary supplies and services (Donthu& Gustafsson, 2020). Internet connection challenges, especially in rural areas, have created inequality in the daily life of many in the United States (Nuechterlein&Shelanski, 2020). People from all over the world have become dependent on the internet for regular actions such as work, education, entertainment, and social activities (Feldman et al., 2021).

During the pandemic, there is heightened pressure on individuals living in areas that suffer from connectivity issues (Lai &Widmar, 2020). Additionally, residential internet subscribers suffer from low bandwidth; internet service providers cannot support the digital demands of the pandemic (Lai &Widmar, 2020). Stay-at-home orders have forced many individuals to work and educate remotely; this has changed the demand for energy services (Bielecki et

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al., 2021). Though at the start of the COVID pandemic, electricity hit its lowest demand in March of 2020, the following stay-at-home orders resulted in around a 30% increase in residential sectors by the end of stay-at-home orders (Krarti&Aldubyan, 2021). Important aspects of sanitation that help slow the spread of the virus include access to water (Switzer et al., 2020). Water utilities have been affected specifically by social distancing policies, a shift in water demand, financial losses, and delayed repairs for needy infrastructure (Spearing et al., 2020). Even before the COVID-19 pandemic, millions of households were disconnected from utility services due to their inability to pay; this also burdens those who are now incapable of paying because of COVID-19 (Kowanko&Harak, 2021). Utility companies are under moratoriums, which allow the customer to keep service on when they are unable to pay (Kowanko&Harak, 2021). The national unemployment rate is still enlarged; because of this, utility bills that could be in the thousands come due as we come towards the end of the pandemic (Kowanko&Harak, 2021).

Meeting customer needs during the pandemic has been a severe challenge for all utilities, especially the energy sector (Nayak et al., 2021). Companies in the energy industry were forced to reduce or even halt spending in all areas (Nayak et al., 2021). Bills that go into default will further the economic struggle of the utility companies (Nayak et al., 2021). Studies have shown that a consumer's satisfaction can predict a company's potential prosperity (Bhattacharya et al., 2021). Social media can be used to depict the feelings and satisfaction of consumers; the potential impact for businesses attracting attention on such platforms is gaining credence (Lin & Luo, 2014). Twitter, one of the largest social media sites, can deliver upwards of 400 million tweets per day (Rathod et al., 2020). Recent progress in machine learning techniques has opened the way for specialized natural language processing research (Rathod et al., 2020). These advancing techniques and methods have enabled hybrid approaches with classification methods that are leading to greater accuracy in the field (Rathod et al., 2020). A sufficient model would encompass more than just the polarity of positive or negative opinions; this type of model would enable the researcher to pinpoint the details of why the customers lean one way or the other (Kazmaier& van Vuuren, 2020). In March of 2020, sentiment analysis was conducted on the first few months of the pandemic to ascertain public perception (Rajput et al., 2020). From March 11th to March 30th, over 4 million tweets a day were mined pertaining to the virus outbreak (Rajput et al., 2020). The study used a combination of word frequency patterns and sentiment analysis to determine the public polarity concerning the pandemic (Rajput et al., 2020). Research showed that to recover from this pandemic, companies would need to adapt to changes brought to light by evaluating public opinions mined from social media data (Senthil & Goswami, 2020).

Method:-

The purpose of this research is to determine the overall polarity of the customers of utility companies during a time when moratoriums are ending, companies are attempting to recover, and everyday life is reaching a new normal in a post-COVID-19 society. Companies were found using a mixture of online company rankings and NARUC (National Association of Regulatory Utility Commissioners) for the perspective regulation agencies.The search for appropriate companies started with a search for utility companies that have an internet presence and top utility companies through the Utility Dive, Reuters, and Statista for the largest energy companies by stock in the United States. Searches were done on BizVibe, the FCC member list by state, as well as Broadband Now for the top ten cable/broadband companies. For gas companies, the American Gas Association, Utility Connection’s list of natural gas utilities, as well as FERC (Federal Energy Regulation Commission) were used. For water companies, a list of the largest water conglomerates was located on the Society for Environmental Journalists, a stock listing on IG, and the National Association of Water Companies member list were used.

The companies that would be used for this research would need to be primarily owned and operated in the United States. Companies that encompassed utilities as well as other outside services, such as automobile fuel distribution or wireless phone services, would need to be able to be tracked by utility services alone. These companies would not only need to be large enough but have a great enough internet presence to generate the amount of data needed. It was originally intended that the data would be able to be separated by each distinctive utility; however, very few companies existed that solely provided a single residential utility service while having an internet presence large enough to provide the data needed. Because of this, companies that encompassed multiple types of utilities were also used.

The perspective pages and affiliates were investigated to verify our requirements for each company. Some companies encompassed too many non-utility-related businesses; however, some of these larger corporations led to appropriate subsidiaries. Few gas companies were found that solely provide residential natural gas, and of these, only two had an online presence. There were similar issues with water companies. Though there were more accounts for water companies, there was very little social media interaction. Data was collected from these companies that focus on a single utility along with other larger multitype utility companies that operate solely in the United States. For broadband and multitype utility companies, the companies with the largest online presence were chosen. Companies that offered services such as wireless service or automotive fuel suppliers were only used if the Twitter account was separate for the utility services only. A full list of companies used for analysis can be found in Appendix A.

Data was collected from Twitter every week from 1 June 2021 to 13 July 2021. Each Tuesday, data was collected from the previous Tuesday through Monday. The Twitter data had to be collected due to time limits set forth by Twitter, allowing only seven days past of tweets. To ensure data was collected seamlessly, a buffer of one extra day was allotted. Posts deleted by the user or Twitter staff before each data collection are not included in our data. There were two methods used to collect data from Twitter. For the first method, a search was performed for all Tweets directed to each perspective company. To ensure enough data was retrieved, a secondary method of obtaining data was used. For the second method, searches were performed by doing an exact match search for each company's full name. This was problematic for certain companies with names that are frequently used in other contexts such as Frontier, Optimum, and Spectrum. For searches that did not result in tweets about the company, adjustments were made, such as appending appropriate words to ensure useable data was collected. A full list of search terms can be found in Appendix B. The data was pulled using NCapture through NVIVO. A total of 163,967 tweets were pulled for six weeks.

After data collection, all of the data was then combined into excel files. Unnecessary columns such as user's name, number of followers, number of tweets, and row ID, username, and all location sections were removed. Duplicate tweets and bot tweets (outage, bitcoin, stocks, and job post bots) were removed. Tweets that were not in English, advertisements, and all tweets by the perspective companies were removed. For the final step, the data was cleaned using the tm (text mining) R package. All punctuation, URLs, and stop words were removed. The only remaining data after this step were the cleaned tweets and any hashtags. This portion of the data was used to obtain the polarity scores, which were then appended onto the step one data sets to compile the master set which was used in our statistical analysis.

Results:-

A one-way between-subjects ANOVA was conducted to compare the effect of type of utility (cable, electric, gas, multi-type, and water)based on polarity. There was a significant difference at the $p < .05$ level for the five conditions, $F(4, 78537) = 103.587$, $p <.001$, $\eta^2 = .005$. Post hoc comparisons using the Bonferonni test indicated that the mean score for each utility type was significantly different, excluding cable and gas and gas and multi-type. A chart depicting the differences can be found in Figure 1.

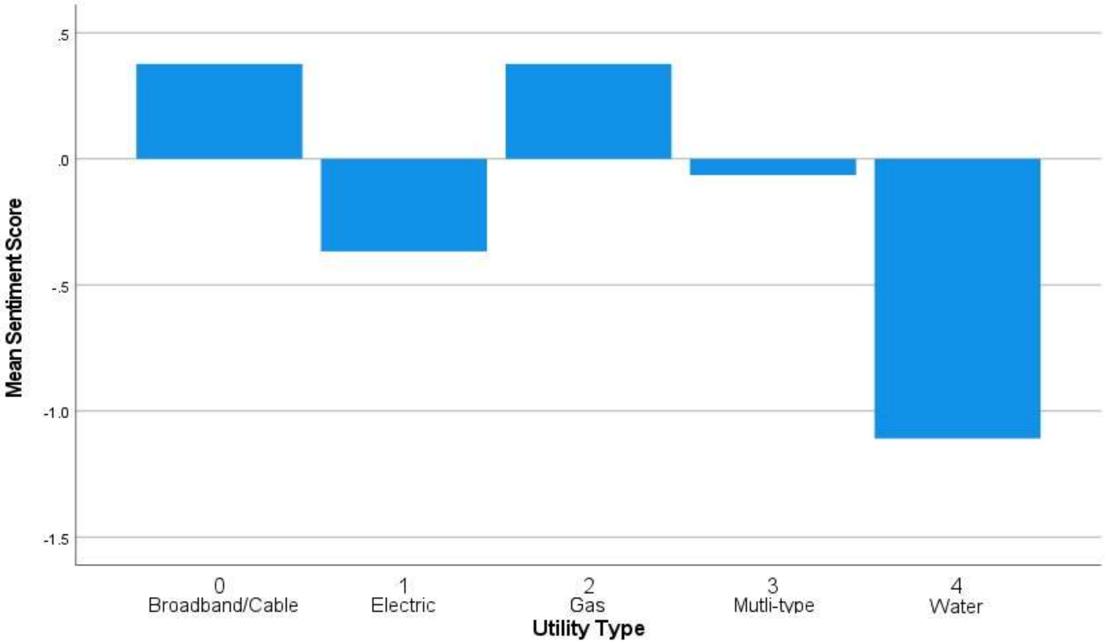

Figure 1:-

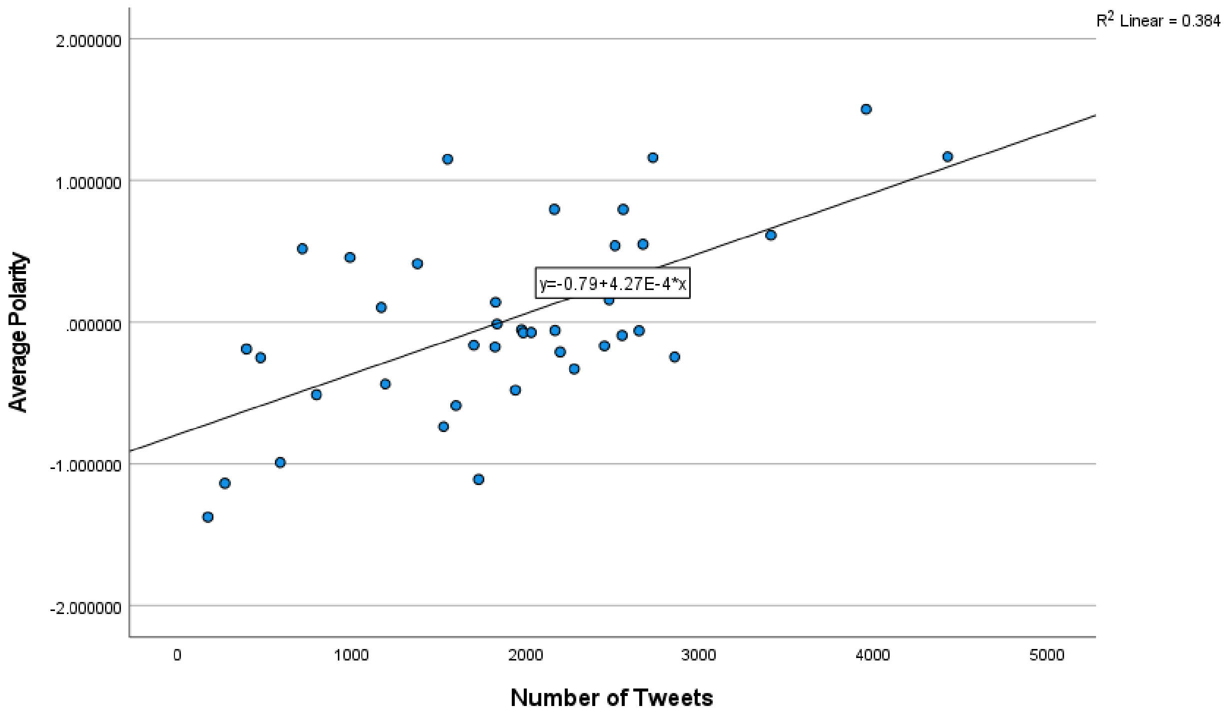

Figure 2

A one-tailed independent samples t-test was performed to see if the polarity of the Tweets on the days the COVID-19 moratoriums ended was lower than the polarity of the Tweets on the days that the COVID-19 moratoriums did not end. There was not a significant difference in the polarity of Tweets on days that COVID-19 moratoriums ended and those days those moratoriums did not end, $t(78540) = -2.698$, $p = .999$.

A simple linear regression was calculated to predict the average polarity of Tweets based on the number of Tweets each day.A significant regression equation was found, $F(1, 39) = 24.330$, $p < .001$, with an R^2 of.384. The polarity of Tweets is equal to $0.043x + 0.79$, where x is the number of Tweets. A scatterplot with a regression line can be found in Figure 2.

A simple linear regression was calculated to predict the average polarity of Tweets each day based on time, but a significant regression equation was not found, $F(1, 39) = 0.878$, $p = .354$, with an R^2 of .022. A simple linear regression was calculated to predict the number of Tweets based on time, but a significant regression equation was not found, $F(1, 39) = 0.371$, $p = .546$, with an R^2 of .009.

Conclusions:-

The first analysis was completed to find a difference in polarity of Tweets based on the type of utility that the company focuses on. While there was a significant difference in polarity for many of the utility types, the result was not practically significant, with a small effect size of 0.005. This analysis suggests that there may be some differences in polarity based on the type of utility, but the differences are so small that they would not matter in real-world scenarios. The findings also suggest that external influences may have a strong impact on polarity; many of the positive Tweets from the cable utility were relating to a popular NASCAR race that was sponsored by Xfinity. On the other hand, many of the negative Tweets from the water utility were relating to a drought.

The second analysis yielded surprising results. A t-test was performed to see if customers expressed more negative opinions on Twitter on the dates that moratoriums ended. Despite three moratoriums ending during the dates of data collection, there was not a significant difference that suggested customers were more negatively polarized during these dates. There were a total of 6 moratoriums that ended on these three dates; it was hypothesized that Tweets from these days would be significantly more negative than days when moratoriums ended, but that was not the case. This result may suggest that customers had adequate time to prepare for the end of the utility moratoriums, and many customers were able to resolve issues beforehand.

The next three analyses were simple linear regressions; only one of the three linear regressions yielded significant results. The first regression suggested that as more users Tweeted, there was a higher positive polarity in the Tweets on average. This can be seen with popular events such as the Xfinity-sponsored NASCAR race. The other two regressions were performed to see if polarity or the number of Tweets changed over time. Neither of these variables significantly correlated with time. This may suggest that despite prior COVID-19 related issues, the quantity and polarity of Tweets were not changing over time during the 41-day period that data was collected. By only collecting data for 41 days, there may be a pattern to the data that was not discovered with this relatively small sample size.

Limitations

There were many limitations to this project. First, the sentiment analysis package used was not perfect. When the authors reviewed the results, many Tweets with low, positive sentiment scores seemed to still be expressing negative opinions. Additionally, some of the Tweets with high, positive scores seemed to be sarcasm. Some topics, such as the NASCAR race sponsored by Xfinity and the drought, were loosely related to the companies that the Tweets were about, but this sentiment is not exactly what the research wished to examine. Despite this issue, these are still external sources that influence public opinion when collecting data, so they were included in the analysis. These are common limitations when applying sentiment analysis to real-world situations (Ashgar et al., 2014).

Another limitation that should be addressed is time. Twitter only allows users to collect data from the previous two weeks; this means that our analysis was very limited. Data was collected over six weeks; although this was an adequate sample size for many of the analyses performed, a larger sample size would have allowed for more in-depth discussion and results. Additionally, since data collection was not performed during the initial COVID-19 lockdowns, there is no easy way to compare the Twitter data from the beginning of the COVID-19 pandemic to the Twitter data from the end of the COVID-19 pandemic.

Future Work

One surprising find was the positivity that Xfinity received from sponsoring the NASCAR race. An interesting future direction of this work may be examining how events sponsored by utility companies impact customer perception of the company. Other work in this field could examine similar topics on other social media sites. Other social media sites, such as Reddit, allow a user to go back further in time, and more relevant data may be available

(Hutto & Gilbert, 2014). Lastly, despite not obtaining significant results in current research, as we continue to move away from the COVID-19 pandemic, time could have an impact on the polarity or quantity of social media posts.

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Appendix A

Cable

1. Xfinity
2. Google Fiber
3. Suddenlink
4. Mediacom
5. Spectrum
6. Frontier
7. Verizon Fios
8. Cox Communications
9. Dish Network
10. Optimum

Electric

1. Southern California Edison
2. Southern Company
3. AEP
4. NRG Energy
5. Oncor
6. Entergy
7. Delmarva Power
8. Atlantic City Electric
9. Commonwealth Edison Company

Water
1. American Water
2. Aqua America
3. York Water
4. California Water Services
5. Suez Water
6. San Jose Water Company
7. Golden State Water
8. Connecticut Water
9. Middlesex Water

Gas
1. Southern California Gas
2. Atmos Energy

Multitype
1. Itron Inc.,
2. Duke Energy
3. Pacific Gas & Electric
4. DTE Energy
5. Constellation
6. Baltimore Gas and Electric
7. PECO Energy
8. Sempra Energy
9. Center Point
10. PSEG
11. Consumers Energy
12. Eversource
13. TVA
14. Dominion Energy
15. San Diego Gas & Electric

Appendix B
Cable Companies
1. Cox Communications
2. Dish Network
3. Frontier Internet
4. Google Fiber
5. Optimum Cable
6. Optimum Internet
7. Optimum TV
8. Spectrum Cable
9. Spectrum Internet
10. Verizon Fios

Electric Companies
1. Oncor Energy

Multitype Companies
1. Center Point Energy
2. Constellation Energy.